Geld – Banken – Börsen

Hrsg.: Wolfgang Bessler

Peter Lückoff

Mutual Fund Performance and Performance Persistence

The Impact of Fund Flows and Manager Changes

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Geld – Banken – Börsen

Herausgegeben von
Prof. Dr. Wolfgang Bessler

Mit der Schriftenreihe Geld – Banken – Börsen wird der zunehmenden Bedeutung der kapitalmarktorientierten Sichtweise innerhalb der Betriebswirtschaftslehre Rechnung getragen. In diese Reihe sollen Dissertationen und Habilitationen aufgenommen werden, die aktuelle Fragestellungen in den Themengebieten Finanzierung und Geldanlage sowie Finanzmärkte und Finanzinstitutionen behandeln und sich durch neue, für Theorie und Praxis relevante Forschungsergebnisse auszeichnen.

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With a foreword by Prof. Dr. Wolfgang Bessler

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Bibliographic information published by the Deutsche Nationalbibliothek
The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available in the Internet at http://dnb.d-nb.de.

Doctoral thesis, Justus-Liebig-Universität Gießen, 2010

1st Edition 2011

Editorial Office: Stefanie Brich | Sabine Schöller

Gabler Verlag is a brand of Springer Fachmedien.
Springer Fachmedien is part of Springer Science+Business Media.
www.gabler.de

Cover design: KünkelLopka Medienentwicklung, Heidelberg
Printed on acid-free paper
Printed in Germany

ISBN 978-3-8349-2780-4

Foreword

The institutionalization of the asset management industry and the delegation of portfolio management decisions to professional fund managers have gained in importance during the last decade. Consequently, asset management in general and the evaluation of the investment performance of managed portfolios in particular have evolved into important topics in the mutual fund industry as well as in academic research. Most of the empirical studies on mutual fund performance and performance persistence have concluded that, on average, mutual funds do not outperform their respective benchmark after costs. These results lead to a number of interesting and important research questions. Peter Lückoff addresses these issues by analyzing theoretically and empirically the investment performance and the performance persistence of about 4,000 U. S. equity mutual funds. Instead of focusing only on performance measurement, his objective is to investigate the factors that may be responsible for the empirical findings in the academic literature of no persistent abnormal performance. His main research question is therefore: Why is persistent mutual fund performance so difficult to achieve?

Peter Lückoff conducts his analysis of mutual fund performance and performance persistence very carefully in that he first discusses and analyzes how to correctly measure the risk-adjusted performance of mutual funds. He then investigates the relevant risk factors that contribute to and are able to explain differences in mutual fund performance by employing state-of-the-art statistical techniques. In this context, the critical issue is whether the superior performance of a portfolio manager in one period was due to his superior investment skills or simply the result of luck. Therefore, the pivotal question is whether or not portfolio managers are, on average, able to outperform persistently an appropriate benchmark model or whether certain capital market equilibrium mechanisms are responsible for their performance results. In contrast, the relevant issue for loser funds, i. e. funds that recently underperformed, is whether the investment performance mean reverts and improves over time when certain governance mechanisms are executed. It is hypothesized that the two most important factors that may drive these equilibrium processes are fund flows and manager changes.

The empirical part of his study offers the reader a detailed analysis of the performance and performance persistence of mutual funds in the United States. The findings and conclusion that the superior past portfolio performance of mutual funds vanishes in the next period is very important and reinforce the empirical results documented in the literature. In addition, also recently underperforming funds return to average performance levels in the curse of the following year. Hence, the winner and loser funds seem to be exposed to some mean reverting processes that drive future fund performance to the average fund performance in the long run. This process is especially strong if the two equilibrium mechanisms, fund flows and manager changes, are intact. In the case that these mechanisms are absent, previous winner funds continue to significantly outperform recent loser funds while in the case that both mechanisms are prevalent the performance difference between these two groups of funds is virtually zero. Thus, fund flows and manger changes significantly reduce the persistence of mutual fund performance. These are extremely important empirical findings and insights from an academic as well as a practical perspective.

Overall, the theoretical analysis and the empirical results offer a number of interesting and important results and insights of the performance and performance persistence of mutual funds. Peter Lückoff provides with this research monograph a major contribution to the current academic research on mutual fund performance. I am convinced that these findings are of great interest to researchers and the international academic community and will have a significant impact on the future research of mutual fund performance. The insights of his study are also relevant also for investors, asset managers and portfolio management companies.

Prof. Dr. Wolfgang Bessler

Preface

The present study has been accepted as a dissertation at Justus-Liebig-University Gießen. This research was conducted while I was a research associate at the Center for Finance and Banking at Justus-Liebig-University Gießen, a junior research fellow at the Pensions Institute of Cass Business School, London, and a visiting research fellow at Exeter University Business School.

After five years of academic work, I would like to thank those who supported and accompanied me. Special thanks go to my dissertation supervisor Professor Wolfgang Bessler. He assisted and encouraged me on my way and improved the quality of my research by challenging my ideas and my thinking. I would also like to thank the second member of my dissertation committee Professor Volbert Alexander, who supported my academic path already as a graduate student.

Special thanks also go to Professor Ian Tonks (now University of Bath) who invited me as a Visiting Research Fellow to Exeter University Business School in 2008 and to Professor David Blake who appointed me as a Junior Research Fellow at the Pensions Institute of Cass Business School, London. My academic development has greatly benefited from our joint research project. Financial support from the German Academic Exchange Service (DAAD) is also gratefully acknowledged.

This work has also greatly benefited from discussions and interactions with several other people. I would like to thank all of those who have contributed to this work with their ideas and suggestions, their personal support and advice, and the time they invested. Specifically, I would like to thank: Christoph Becker, Dr. Claudia Bittelmeyer, James P. Clark, M. E., Lars Hermann, Julian Holler, Yan (Bonnie) Huang, Philipp Kurmann, Dr. Dorothea Reimer, André Scherres, Martin Seim, Dr. Jian (Jane) Shen, Dr. Matthias Stanzel, Alexander Stern, Dr. Rajesh Tharyan, Vladimir Vladimirov, Daniil Wagner, Stephanie Waskönig, who did a fantastic job editing this volume, and Jan Zimmermann. Lastly, very special thanks go to my parents Ute and Klaus-Peter Lückoff and to my wonderful wife Sara-Lisa Hennicken. This book is dedicated to her.

Peter Lückoff

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Introduction

Motivation and Relevance

> "It is very hard, if not impossible to justify active management for most individual, taxable investors, if their goal is to grow wealth" (Mark Kritzman, MIT Sloan School of Management).[1]

This quotation is supported by an array of academic studies providing empirical evidence that active mutual funds underperform the market on average, that the majority of individual funds underperform the market and that those few funds outperforming, if at all, are not identifiable ex ante.[2] Still, the dominant share of professionally managed assets follow an active investment strategy, despite the strong growth of passive products in recent years.[3] This apparent contradiction makes active mutual funds an interesting field of academic research on the behavior of market participants and its implications for the value of active management.

In recent years, mutual funds have become a dominant player in the capital market. Global assets under management by mutual funds peaked at 26.2 trillion USD in the last quarter of 2007, before dropping off to 18.2 trillion USD in the first quarter of 2009 in the course of the financial crisis (IFSL International Financial Services London, Fund Management 2009). Including other types of professionally managed investments[4] global wealth increased to 111.5 trillion USD in 2009, according to The Boston Consulting Group, corresponding to 160 percent of global GDP. Around one quarter of U. S. equities was held by mutual funds at the end of 2001 (Khorana, Servaes, and Tufano, 2005) and direct ownership of U. S. equities has declined from 47.9 percent in 1980 to 21.5 percent in 2007 (French, 2008).

[1] As quoted in Richard Stott, Twisting the facts on active management, Financial Times, 09 May 2010.

[2] See Jensen (1968), Malkiel (1995), Gruber (1996), Carhart (1997), Pástor and Stambaugh (2002b), Fama and French (2010) and Barras, Scaillet, and Wermers (2010).

[3] Indeed, according to State Street Global Investors only about one fifth of U. S. mutual fund assets were managed passively at the end of 2008 (SPDR University, Passive and Active Management: A Balanced Perspective, September 2009).

[4] Such as pension and insurance funds, sovereign wealth funds, hedge funds, private equity funds, exchange-traded funds and the funds of wealthy individuals.

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DOI 10.1007/ 978-3-8349-6527-1_1,

Thus, including other types of professionally managed assets, the dominant share of U. S. equities is managed by professional portfolio managers on behalf of their clients.

The delegation of investment decisions to professional portfolio managers adds a second layer of decision making to the process of channeling surplus funds to firms with profitable investment projects and financing needs. This has important implications from several aspects. From a macroeconomic perspective, it seems important to understand how the delegation of investment decisions affects security prices and the efficient allocation of resources in the economy. For example, turnover of stocks has increased from 20 percent in 1975 to an impressive 215 percent in 2007 (French, 2008). This implies significant changes in the way money is managed. Additionally, as delegated asset management affects the security prices observed in the markets, this has important implications for other areas of finance research. Moreover, companies that want to raise capital do not only have to consider the objectives of private investors but also the incentives faced by professional portfolio managers in their financing decisions. Most importantly, the rise of mutual funds in recent years has significantly affected how private investors' money is managed. This study analyzes mutual funds from the investors' perspective.

At the end of 2009, 21 percent of the financial assets of U. S. households were managed by mutual funds (ICI Investment Company Factbook 2010). The median household owned financial assets worth 150,000 USD, 80,000 USD of which were managed by mutual funds. Only 42 percent of these households owned stocks directly in addition to their mutual fund investments. Thus, the delegation of investment decisions to professional portfolio managers has become the dominant form of financial investments. Most investors mention retirement savings as the primary reason for their mutual fund investments.[5]

Among other services, one of the major objectives of mutual funds is to generate "outperformance". This refers to an investment return which is higher compared to that of a benchmark, adjusted for differences in risk levels between the fund and its benchmark. However, both academic and non-academic research reveals that mutual funds on average as well as the majority of individual funds fail

[5] In fact, 76 percent of U. S. households mentioned retirement saving followed by 6 percent for education (ICI Investment Company Factbook 2010).

to beat their benchmark based on net returns earned by investors.[6] Still, U. S. investors were willing to pay on average 0.67 percent of their assets more for active management in equities as compared to passive investments over the last 26 years (French, 2008). In 2006 this was equivalent to 101.8 billion USD or 0.77 percent of the U. S. GDP. The share of mutual funds in these costs rose from 0.11 percent in 1980 to 0.32 percent in 2006, due to an increase in assets under management. Thus, French (2008) suggests that investors could earn higher net returns by switching to a passive strategy. The observation that investors are willing to consistently pay significant sums for a service that has not yet been demonstrated to add value in the long run seems to qualify as an economic puzzle.

However, even if only a few funds outperform their benchmark, active management might still add value to some smart investors who are able to identify those outperforming funds ex ante. Yet, the phrase "past performance is not an indicator of future performance" is commonly found in the fine print of mutual fund prospectuses. Academic research on the persistence of mutual fund performance supports this statement (Hendricks, Patel, and Zeckhauser, 1993; Carhart, 1997). Neither the last year's winner funds continue to outperform, nor do the last year's loser funds continue to underperform in the subsequent year. Rather, the relationship between past and future performance is weak and dominated by a strong tendency for mean reversion. This is usually interpreted as an indication against the existence of managerial skill among active mutual fund managers.

However, some caveats have to be made. First of all, the methodological issues of how to measure performance are not yet settled, especially with respect to an appropriate risk adjustment. Performance evaluation studies mainly draw on the asset pricing literature to compute "fair" expected returns for each fund based on its investment strategy. However, misspecification of the benchmark model and estimation error might bias the performance measure and lead to misleading conclusions. Moreover, Wermers (2000) documents that active managers possess superior information based on an analysis of individual trades of fund managers gross of any transaction costs or fees. Bollen and Busse (2005) and Huij and Verbeek (2007) report that superior performance persists in the short term. Thus, the relevant questions are (1) why the superior information of fund managers does

[6] For academic research see, for example, Jensen (1968), Malkiel (1995) and Pástor and Stambaugh (2002b). For non-academic research see Standard & Poor's Index Versus Active (SPIVA) Scorecard, which is available online under http://www.standardandpoors.com/indices/spiva.

not translate into superior net returns and (2) why superior investment skills, if present in the short term, vanish over the long term.

Therefore, a comprehensive analysis of mutual fund performance and the value of active management needs to take real-world frictions into account. With respect to the first question, agency conflicts can help to explain this observation. Fund managers might maximize their own wealth rather than maximizing investors' returns. Moreover, the effects of fund flows and associated transaction costs have been put forward in the literature as a potential explanation for average underperformance (Edelen, 1999; Alexander, Cici, and Gibson, 2007). Berk and Green (2004) even offer a theoretical argument for the lack of performance persistence based on fund flows, which might contribute to an understanding of the second question. In their model, decreasing returns to scale in active management and a positive relationship between past performance and current fund flows explain why performance does not persist even if true investment skills exist. Thus, the open-end structure of mutual funds seems to be its own enemy. On the one hand, it ensures an efficient product market. Skilled fund managers can increase their assets under management, and by doing so increase their compensation, while investors can withdraw money from underperforming managers as a means of external or market-based governance. This mechanism is especially relevant in light of the existing agency conflicts due to the two-layered agency relationship, between the investor, the investment management company and the portfolio manager. On the other hand, investment performance strongly suffers from an increased asset base according to the arguments of Berk and Green (2004). The response of investors to past performance is responsible for abnormal (positive or negative) mutual fund performance to revert to the mean.

Related to the second question raised above, manager replacements might also contribute to performance reversals over time and help to explain the lack of long-term persistence. In the case of positive abnormal returns, skilled fund managers might decide to pursue other opportunities at a larger fund or even a hedge fund in order to maximize personal wealth.[7] Some of them might even be lured away by competing investment management companies. If the leaving fund manager had above average skills it is highly likely that fund performance deteriorates under a newly appointed manager. On the contrary, the investment management company

[7] Throughout this thesis it is assumed that the fund manager can be female or male even though it is referred to the fund manager as "he".

has strong incentives to fire an underperforming manager in an attempt to stop the losing streak. Appointing a new manager should, in this case, restore investment performance to average levels. Based on these arguments, the response of fund managers and of the investment management company to past performance might partially be responsible for mean reversion of mutual fund performance. Thus, it seems important to acknowledge that fund managers might change over time and that this might affect investment performance.[8]

Objective and Structure

The objective of this study is to provide a comprehensive and in depth analysis, both theoretically and empirically, of the two "equilibrium mechanisms" fund flows and manager changes and their roles in explaining the lack of long-term performance persistence. Thus, the behavior and interaction of fund investors, investment management companies and portfolio managers is investigated.[9] Most importantly, this study contributes to the existing literature by analyzing both equilibrium mechanisms simultaneously. This is especially important because both mechanisms depend on past performance and might affect each other. For example, the incentives for a winner-fund manager to leave might depend on the volume of new inflows he can attract at the existing fund. Moreover, outflows from an underperforming fund, which can be interpreted as external governance, might trigger the investment management company to replace the fund manager, which is a form of internal governance, in order to stop money flowing out of that fund. Hence, this analysis also contributes to the understanding of the existence of true investment skills among professional portfolio managers and the value of active management. It conditions fund performance on certain events or situations and investigates how these events affect conclusions on fund performance. Specifically, this provides empirical evidence on whether a lack of managerial skill or external factors explain the unsatisfactory investment results of most mutual funds. To put this study into a broader context, a detailed understanding of

[8] Note that most previous studies do not explicitly consider that performance outcomes of fund managers and funds can only be observed in conjunction with each other and treat one fund as the same entity over its whole lifetime even if the fund manager changes. One notable exception is Baks (2003).

[9] This study does not analyze how corporate managers respond to the incentives from delegated asset management even though this is also an important and interesting research topic.

the institutional setting and regulatory framework of mutual funds and especially of their open-end structure, which strongly determines the agency conflicts and behavior of investors, as well as of methodological issues related to performance evaluation and performance persistence is required.

Chapter 1 presents the institutional framework and the regulatory setting under which mutual funds offer their services. Viewed from the demand side, this chapter presents the role of mutual funds as intermediaries for the economy as a whole as well as the objectives of individual investors. Certain frictions such as transaction costs, minimum lot sizes, the benefits from holding a diversified portfolio and the insurance against personal liquidity shocks can explain why investors pool their assets in the form of mutual funds. Moreover, asymmetric information in capital markets and economies of scale in information production are the reasons for delegating investment decisions when investors decide to apply an active investment strategy instead of passively following an index. From the perspective of the supply side, this chapter discusses the two important characteristics of existing investment products: the investment strategy and the organizational design. Because return predictability is a necessary precondition for successful active management, theoretical and empirical studies that analyze whether future stock returns are predictable at all are reviewed. Next, this chapter defines active management and introduces a classification of different existing investment strategies. Lastly, different organizational forms of mutual funds and other investment products are presented and their advantages and disadvantages are related to different investment strategies. In fact, today's asset managers merely offer their services of investment advice in a variety of "wrappings" depending on the legal structure and investors' preferences. Thus, it is important to understand alternative structures of investment products and their relation to feasible investment strategies when analyzing mutual funds.

Following the review of potential benefits from delegating investment decisions to mutual funds in the first chapter, chapter 2 goes on to analyze the flip side of this coin. Specifically, potential conflicts of interest between the parties involved are analyzed. These conflicts might reduce the value of pooling assets and delegating investment decisions. First of all, portfolio managers might aim to maximize their personal wealth and follow certain career concerns that are not in line with performance maximization for investors. Second, the investment management company and its management board might follow their own interests to maximize fees, which in most cases corresponds to maximizing assets under management. These strategies might also involve third parties such as brokers. Thus, average mutual fund underperformance might be a result of poorly aligned interests in the asset management industry rather than a lack of managerial skill. Several potential solutions exist to reduce the detrimental impact of agency conflicts on net returns. These include restrictions with respect to the investment strategy and the use of certain instruments, external and internal governance mechanisms as well as incentive contracts and the ownership structure of funds. This chapter reveals the importance of the open-end structure of mutual funds to reduce agency conflicts.

Chapter 3 focuses on methodological issues and derives how to select an appropriate performance measure depending on a specific situation. A comprehensive review of different approaches to performance evaluation used in academia and in the industry is presented and these concepts are critically discussed. Moreover, a classification framework for different performance measures is developed. It becomes evident that no single measure can serve all applications. Rather, the characteristics of the investment strategy to be evaluated, the characteristics of the investor's portfolio and the temporal focus determine the choice of the theoretically correct performance measure. Moreover, new developments in the field of asset pricing are presented, which have an important impact on the benchmark factors used in the context of multifactor performance models. Additionally, not only new model specifications but also innovative estimation methodologies are reviewed. However, it remains especially problematic to distinguish reliably between skill and luck. After this methodological part empirical studies on the performance of mutual funds and cross-sectional performance determinants are reviewed. The interpretation of these studies is discussed critically, taking into account the methodological problems still present.

Chapter 4 moves on from an analysis of average fund performance to an analysis of the performance of individual funds or groups of funds and the dynamics of performance over time. Specifically, it starts with a critical discussion of the literature on performance persistence. These studies investigate whether future outperformers (and underperformers) can be identified based on an observation of past performance. This chapter also analyzes how investors respond to past performance in order to link this response to future performance in the next step. Specifically, past performance might determine current fund flows which in turn affect the actions of the mutual fund manager and, thus, performance. A comprehensive framework is developed on how portfolio managers can respond to the inflows and outflows of money they are exposed to. This framework helps to understand the role of fund flows as equilibrium mechanism and how subsequent performance is affected by past fund flows. Next, the role of manager changes as an additional equilibrium mechanism is discussed. Lastly, several measures to mitigate the detrimental impact of the equilibrium mechanisms on fund performance are presented. Some of these measures aim to reduce the costs from fund flows as, for example, the use of derivatives or the organizational structure of the fund's management. Other suggestions focus on a reduction of fund flows at the fund level including redemption restrictions or a secondary market for fund shares. Moreover, exchange-traded funds are proposed as an alternative investment product to conventional open-end funds in this context.

The theoretical part of this volume is followed by an empirical analysis of performance persistence and fund flows and manager changes as equilibrium mechanisms. Chapter 5 starts with a presentation of the research objective, data and methodology. A recent mutual fund sample is used which includes all active U. S. equity funds that existed at any time between 1992 and 2007. Importantly, all share classes of the same fund are aggregated to one entity based on a matching algorithm in contrast to the separate treatment of individual share classes in many earlier studies. From the methodological perspective, this study applies an innovative Bayesian approach for ranking mutual funds into decile portfolios based on their previous year performance. Moreover, the conventional four-factor model used as performance benchmark is augmented by additional factors controlling for liquidity risk and stock-return mean reversion based on recent developments in asset pricing research.

Performance persistence is analyzed in chapter 6. Updated evidence on the performance persistence debate is provided based on the innovations in the data and methodology mentioned above. The major focus of this chapter, however, is to analyze whether methodological aspects can explain why previous studies have documented that performance persists in the short term but not over longer periods. Specifically, these studies do not only differ with respect to the time horizon analyzed but also with respect to the performance measures used for portfolio formation and the estimation methodologies used for performance evaluation. Therefore, performance persistence is analyzed using different methodologies over identical time horizons but also using identical methodologies over different time horizons. This allows conclusions on the determinants of performance persistence and whether performance persistence decays over time. An important contribution in this respect is that performance persistence is analyzed for individual funds, instead of analyzing decile portfolios, which allows factor loadings to vary over time and across funds in the same decile. As a byproduct of this analysis, it is investigated whether investors can benefit from improved ranking measures of holding periods that are realistic given that switching funds is associated with certain transaction costs. In the last step, the migration of funds between different performance deciles and their survival in the top and bottom deciles is explored.

After chapter 6 has analyzed whether methodological issues explain why some studies document short-term performance persistence but fail to document long-term performance persistence, chapter 7 goes on to investigate potential economic explanations for this finding. The theoretical arguments of chapter 4 are put under a stringent empirical test. The research questions addressed in this chapter are whether the performance of recent winner funds suffers subsequently to excessive inflows and a manager replacement and how these two mechanisms interact. Among loser funds, the relevant research questions are whether subsequent performance benefits from outflows and a manager replacement and whether these external and internal governance mechanisms are complements or substitutes. Additionally, an alternative perspective provides insights into the implications of the equilibrium mechanisms for the performance spread between winner and loser funds. This chapter also includes several robustness tests with respect to the impact of fees and other variables on this relationship.

Chapter 8 provides further, more detailed, analyses of the equilibrium mechanisms. First, the "reaction time" of fund performance on fund flows and manager changes is determined. The question is how long it takes for both mechanisms to set in. Second, the question of whether a stronger response of investors to past performance results in a stronger performance reversal among both winner and loser funds, is investigated. This allows an analysis of whether steady flows over a longer time period have the same impact on performance as an identical amount of fund flows occurring over a shorter period of time. For example, slow moving flows might be easier to digest for funds as compared to more extreme fund flow events. In the last step, the results of the fund-flow mechanisms are contrasted with a sorting on past fund size. Underlying the fund-flow argument from above are capacity constraints in active management, which refer to changes in fund size. Thus, the fund-size analysis provides more fundamental insights into the underlying mechanisms. This also allows an investigation of whether large and small funds are differently affected by fund flows.

This thesis closes with concluding remarks and an outlook on future developments in the asset management industry and related research. Some modifications to the current structure of mutual funds are proposed to enhance the value of investors.

Part I Delegated Portfolio Management

1 Institutional Setting

In order to understand the performance determinants of active mutual funds in the cross-section and over time it is important to analyze their institutional setting in an integrated framework (Figure 1.1). Fund performance not only depends on the skills of the fund manager, but it is also related to the efforts of the fund manager and the actions of the investment management company and investors. First of all, frictions in the economy result in transaction costs and asymmetric information. On the one hand, this offers the opportunity to generate abnormal returns based on superior investment skills. On the other hand, a need for delegation follows from these frictions, especially for small retail investors.[10] In large part, this stems from economies of scale in information production and the reduction of transaction costs, both of which reduces the costs from market frictions for small investors. Thus, investors should theoretically benefit from delegated active management.

However, delegation always involves agency costs because it is not obvious if the mutual fund manager acts in the best interest of investors, i. e. exerts the highest effort.[11] Apart from that, different skill levels exist across managers. The open-end structure of mutual funds is an important feature in this context because it allows investors to withdraw money if they are not satisfied with the investment performance of their funds. It provides an efficient market-based governance mechanism which reduces agency conflicts and assures product-market efficiency because the asset base of unskilled managers is reduced over time and these managers eventually disappear from the market.[12]

However, the open-end structure also imposes certain costs on the fund.[13] In the short-term, the fund faces the risk of unexpected inflows or outflows through creations or redemptions from investors. In the long run, especially formerly

[10] In addition, transaction costs are a drag on the average performance of all investors.
[11] This is discussed in more detail in chapter 2.
[12] However, despite its importance in investor protection it is not clear whether an efficient product market alone assures a good governance: "While we agree that product market competition is probably the most powerful force toward economic efficiency in the world, we are skeptical that it alone can solve the problem of corporate governance" (Shleifer and Vishny, 1997, p. 738).
[13] This is discussed in more detail in chapter 4.

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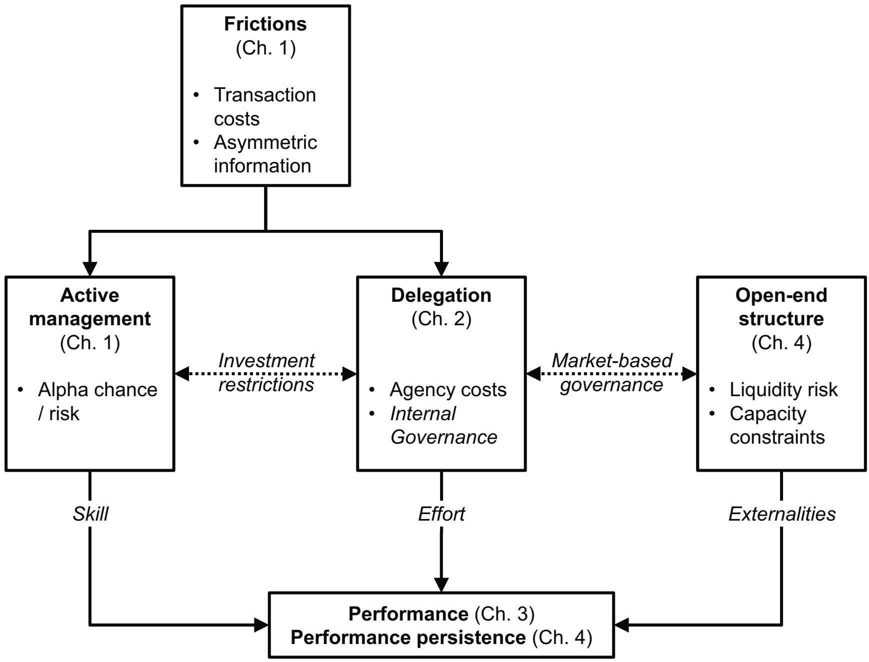
DOI 10.1007/ 978-3-8349-6527-1_2,

Figure 1.1: Integrated framework of active mutual fund management

This figure presents the integrated framework developed in this work. First, market frictions are a prerequisite for the successful generation of abnormal returns through active management. Second, market frictions explain the existence of mutual funds as one type of financial intermediary and are an important reason for why investors delegate their investment decisions to professional portfolio managers. However, delegation always involves conflicts of interest and agency costs. Important mechanisms to reduce agency costs are: (1) investment restrictions, which in turn affect the potential to generate abnormal returns; (2) internal governance mechanisms; (3) external or market-based governance mechanisms. The latter, however, entails negative externalities in the form of liquidity risk and capacity constraints.



successful funds face the risk of excessive asset growth because of new money invested in the fund. Both of these effects reduce average fund performance. Consequently, open-end mutual funds are in the tension field between effective external governance as a means of reducing agency costs and performance-reducing liquidity risk due to excessive fund flows.

Alternative approaches to the open-end structure for reducing agency costs are restrictions with respect to the investment strategy. Investment restrictions, however, also reduce the chance of generating abnormal returns because fund managers are no longer allowed to deviate from the benchmark. The extreme case of which are passive investment products that usually provide only market exposure but no abnormal returns. Consequently, the interplay between managerial skills, agency conflicts, and managerial effort, as well as externalities from the open-end structure has to be considered when analyzing investment performance and performance persistence of active mutual funds. In essence, performance is a function of skill, effort and externalities.

The role of mutual funds for the economy as a whole is discussed in section 1.1 and for individual investors in section 1.2. The following two sections present an overview of the supply side, namely the different investment products that are available to investors. Section 1.3 defines active management and presents different investment strategies in greater detail while section 1.4 focuses on the organizational design of the investment products.

1.1 Role of Mutual Funds

This section analyzes the role of mutual funds for the economy and relates it to the functions of banks and capital markets. The fundamental objective in finance is an efficient allocation of financial resources in the economy. On the one hand, economic units with funding needs (borrowers or firms) compete with each other for capital in order to pursue their investment projects (investment). Their aim is to minimize the costs of capital. On the other hand, economic units with surplus funds (savers or investors) offer their financial capital and try to maximize returns (saving).[14] In a perfect market without frictions firms' costs of capital and investors' returns were equal and no intermediary, neither banks

[14] Note that in a broader definition according to Walter (1999) agents from the household sector, the business sector and the government sector can act as both, units with funding needs and units with surplus funds.

nor mutual funds, would exist, i. e. investors would enter into a direct face-to-face relationship with firms (Bessler, 2007). However, in reality, market frictions prevent a direct contracting between borrowers and surplus units. These frictions include:

- Local divergence: Borrowers and surplus units appear at different locations.
- Divergent lot sizes: Usually, a firm's financing demand arises in larger lot sizes than one single surplus unit can provide. Furthermore, large lot sizes combined with non-divisibility of securities prevent in particular smaller investors from holding a diversified portfolio.
- Divergent risks: The risk characteristics of financial titles offered by firms do not correspond to the risk preferences of investors.
- Divergent maturities: The maturity of financial titles offered by firms does not correspond to the maturity preferences of investors.[15]
- Divergent liquidity: The liquidity[16] of financial titles offered by firms does not correspond to the liquidity preferences of investors.
- Asymmetric information: Usually, firms offering financial titles have better knowledge of the future prospects of their projects than investors. This results in a large degree of uncertainty for investors regarding future returns of different financial titles.

Broadly speaking, the difference between investors' returns and the costs of capital for firms are the sum of all transaction costs resulting from these frictions (van Horne, 1985; Schmidt and Schleef, 2001b; Bogle, 2005). An optimization of resource allocation is equivalent to a minimization of total transaction costs. Thus, the existence of intermediaries can be explained by the services they offer in order to reduce these costs (Benston and Smith, Jr., 1976; Leland and Pyle, 1977):

[15] Sometimes the period for which the interest rate and other terms are fixed differs from the maturity of the financial title. In this case, additional divergences might arise.

[16] Liquidity is defined here by the ease of converting an asset into cash (or cash into an asset), i. e. trading small and large quantities immediately and quickly with low direct (e. g. commissions) and indirect (e. g. price impact) costs.

> "One could argue that, if there were a friction that led to large costs for agents, then there would be an institutional response that would profit by alleviating this friction. According to this view, there cannot be any (important) frictions left in equilibrium. Alleviating frictions is costly, however, and the institutions which alleviate frictions may be able to earn rents. [...] Grossman and Stiglitz (1980) use a similar argument to rule out informationally efficient markets: market prices cannot fully reveal all relevant information since, if they did, no one would have an incentive to spend resources gathering information in the first place" (Amihud, Mendelson, and Pedersen, 2005, p. 6 f.).

Total transaction costs can be subdivided into individual components and classified into three categories, namely information production, trade execution and custody (Schmidt, 1980). First, resulting from asymmetric information, there is a need to reduce information barriers. Companies provide information such as financial statements to the capital market and investors and analysts gather, process and condense these information, all of which induces costs. Second, the trade execution itself involves costs such as brokerage fees, market impact costs and costs for the protection against execution risks. The third area covers costs for clearing and settlement and costs related to the custody of securities. The sum of these costs determines procedural efficiency which is a necessary condition for informational efficiency. All components of transaction costs must be considered simultaneously for a minimization of total transaction costs as a reduction of one component might increase another component.[17]

Organized capital markets as well as banks, mutual funds and other intermediaries have emerged as institutions which offer services related to a minimization of transaction costs (Figure 1.2).[18] With respect to the services offered by intermediaries, Bhattacharya and Thakor (1993) distinguish between brokerage services and qualitative asset transformation. Brokerage services basically include activities such as providing advice and transaction services that generate fee income. This also includes delegated portfolio management. Qualitative asset transformation instead refers to a transformation of risks. Consequently, the liabilities of an intermediary involved in qualitative asset transformation have different risk and

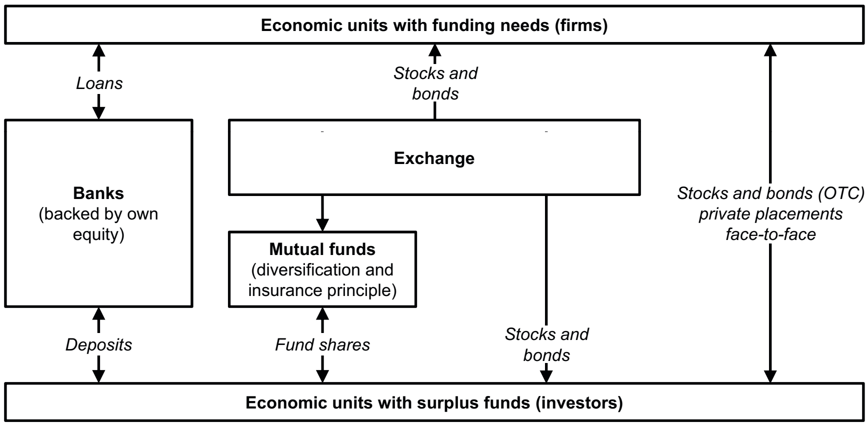
[17] For example, stricter disclosure and publication requirements might increase the information costs for firms but at the same time reduce investors' and analysts' costs (Schmidt, 1977).

[18] Other intermediaries include wealth advisors, insurance companies and pension plans.

return characteristics than the assets it holds. Usually, this involves the assumption of market risk by the intermediary and the backing of these risks with its own equity (Bessler, 2007). In this case, an indirect financing relation exists between firms and investors.

Figure 1.2: Allocation of financial resources in the economy

This figure presents the different financing channels of economic units with funding needs (firms), one the one hand, and the investment opportunities of economic units with surplus funds (savers), on the other hand. Based on Bessler (2007, p. 13).



Organized capital markets mainly offer brokerage services by providing a secondary market for securities and offering a liquidity pool.[19] This reduces local divergences and allows investors to sell securities before maturity (Table 1.1). Incongruities with respect to maturity are reduced but investors assume the price risk, i. e. the risk of selling a security before maturity at a lower market price, and the reinvestment risk, i. e. the risk of investing cash-flows paid during the life of the security at lower yields. Because investors might not be willing to hold these risks, firms with financing needs might have to deviate from the optimal maturity of issued securities and take on the risk of follow-up financing themselves. In this context, exchange operators and other institutions that make a market such as multilateral trading facilities (MTF) offer a low cost mechanism for trading secu-

[19] Organized capital markets also provide a primary market for the issuance of securities.

rities which provides investors and issuers with an efficient way to manage risks by buying or selling different securities. But in this context these institutions do not assume any market risks. Furthermore, asymmetric information is reduced through trading facilities that provide an efficient price discovery. However, as the information is revealed by the price of the securities a free-rider problem exists.[20]

Table 1.1: Frictions reduced by different financing and investment channels

This table presents the frictions reduced by different financing and investment channels under the assumption of non-divisibility of securities combined with a budget constraint for small investors.

Friction	Banks	Mutual funds	Direct	
			Exchange	No exch.
Local divergences	•	•	•	
Divergent lot sizes	•	•		
Divergent risks	•	•		
Divergent maturities	•	•		
Divergent liquidity	•	•	•	
Asymmetric information	•	•	(•)	

Banks transform risky long-term loans into risk-free short-term deposits and, by doing so, reduce the frictions and divergences described above (Bessler, 2007). Moreover, banks reduce the problems arising from asymmetric information (Gorton and Penacchi, 1990). They maintain a long-term relationship with their loan customers and accumulate information over time. By keeping this information private, banks avoid a free-rider problem. Based on this informational advantage, banks can strip cash flows and offer risk-free deposits to investors. In this process, which is usually referred to as indirect financing, banks take on market risks such as liquidity risk, default risk and interest rate risk by providing their own equity. Even though banks mainly provide indirect financing via intermediation they are also a major player in direct financing via the capital market, sometimes referred to as substitution of intermediation (Schmidt, 1979). In their role as a player in the capital market, banks provide advice with respect to the issuance of securities and the trading of these securities in a secondary market. Financial analysts, usually employed by banks, reduce asymmetric information if they publish

[20] See also the discussion regarding information efficiency in section 1.3.1.

unbiased and fair research reports. Thus, banks clearly perform both services of intermediaries, brokerage and qualitative asset transformation. In general, direct and indirect financing are both competing and complementing each other at the same time (Bhattacharya and Thakor, 1993; Merton and Bodie, 1995).

In recent years, a shift from intermediation to fee-producing services has been observed among banks (Allen and Santomero, 2001). Part of this shift involves the increasing role of mutual funds offered by investment management companies, some of which belong to a financial conglomerate with a commercial banking arm.[21] The competition that banks face from capital markets led to the development of mutual funds, which was especially pronounced in countries with mature capital markets such as the U. S. and the U. K. (Allen and Santomero, 2001).[22] Today, mutual funds successfully compete with bank deposits for the money of investors. Mutual funds invest this money, on behalf of their investors, directly via the capital market in bonds or equities issued by companies, making them one of the largest capital provider as a group.[23] Consequently, mutual funds can be characterized as a collective investment vehicle providing intermediated direct financing.

Mutual funds are almost perfect pass through vehicles as investor's claims are contractually linked to the underlying assets and marked to market (Khorana, Servaes, and Tufano, 2005).[24] In contrast to banks, mutual funds do not assume any risks by providing own equity. The two primary functions of mutual funds are, first, providing liquid access to a diversified basket of securities and, second, gathering and processing information at a cost lower than that of individual investors. The first function reduces divergences with respect to the lot size as well as the risk, maturity and liquidity of securities while the second function reduces costs resulting from asymmetric information. Moreover, as mutual funds bring together investors and borrowers, they reduce local divergences. Mutual funds offer retail investors the possibility of generating income additional to their la-

[21] The assets held by mutual funds rose from 2.8 trillion USD in 1995 to 11.1 trillion USD in 2009 while the share of households' financial assets held in mutual funds rose from 2 percent in 1979 to over 12 percent in 1995 and to 21 percent in 2009 in the U. S. (ICI Investment Company Factbook 2010).

[22] An interesting question, however, is whether the role of intermediaries declines once the frictions mentioned above are reduced (Allen and Santomero, 2001).

[23] The share of U. S. equities held by mutual funds rose from 4 to 24 percent during the period from 1959 to 2009 (ICI Investment Company Factbook 2010).

[24] Only the payment of management fees leads to a small deviation of the cash flows received by the fund and the cash flows passed on to its investors.

bor income by providing financial capital directly to the economy (Laux, 2007). This function becomes increasingly important as many pay-as-you-go financing schemes for personal pensions are transformed into the funding principle.

Arnold (1976) proposes that one of the fundamental mechanisms in risk management is to strip down cash flows into different parts and to combine these stripped cash flows into new securities. Stripping down into homogeneous parts only reduces divergences with respect to the lot size, while stripping down into heterogeneous parts also helps to reduce the costs of asymmetric information and allows the creation of securities with different risk profiles that better meet the preferences of investors (Gorton and Penacchi, 1990). The process of stripping and combining is usually performed in multiple layers beginning with the separation of the cash flows to the firm into a cash flow to equity and a cash flow to debt. The production function of mutual funds is in the first step to pool different securities into one portfolio and, in the second step, to offer investors homogeneous shares of this portfolio in small lot sizes with daily liquidity. Mutual fund shares are an efficient tool for investors to manage risks.

First of all, investors face the risk of unexpected liquidity shocks. The pooling of assets of a large number of investors by a financial intermediary provides insurance against liquidity risk if liquidity shocks are more or less uncorrelated among investors (Gorton and Penacchi, 1990; Diamond and Dybvig, 1983).[25] Open-end funds can offer this insurance as they are obliged to redeem fund shares on a daily basis. Investors can transfer their fund assets into cash without trading in the underlying market. Thus, fund shares are qualitatively different from their underlying securities in that they offer a higher degree of liquidity; mutual funds transform liquidity (Chordia, 1996; Nanda, Narayanan, and Warther, 2000; Cherkes, Sagi, and Stanton, 2009). Moreover, due to the obligation to redeem fund shares daily, the maturity of assets is reduced. German open-end real estate funds, which offer participation in a portfolio of real estate assets with a daily redemption of fund shares, can serve as an example. In the context of liquidity and asset pricing, mutual funds might even offer investors the possibility of earning risk premia on illiquid securities while, at the same time, offering a high degree of liquidity.

However, mutual funds do not transform liquidity by assuming liquidity risk themselves backed by own equity but rely on a different mechanism. Specifically,

[25] Note that a systematic liquidity need by investors might result in a run that prevents the financial intermediary from satisfying the liquidity demand of all investors.

mutual funds offer a pooling mechanism based on the insurance principle. The costs for this liquidity service are shared equally by all fund investors independent of their actual liquidity demand (Johnson, 2004). First, mutual funds hold a certain proportion of their portfolio in cash which leads to a cash drag on performance as the risky assets offer higher average returns than the risk-free asset. Second, if the fund has to trade the underlying securities as a result of redemptions the transaction costs and a potential liquidity discount resulting from fire sales are shared equally by all fund investors. Thus, a wealth transfer takes place from investors who have low liquidity demands to investors with high liquidity demands (Greene and Hodges, 2002; Zitzewitz, 2003).[26] Note, however, that mutual funds were unable to offer this liquidity transformation without the existence of relatively liquid secondary markets for the underlying securities.

Moreover, investors might not be able to hold a diversified portfolio of risky assets because of the non-divisibility of securities and budget constraints faced by retail investors. Small investors are usually unable to duplicate the portfolio of a mutual fund and cannot attain the same risk-return tradeoff. Mutual funds reduce the risks assumed by small investors by reducing the lot sizes of diversified security positions which allows a more even distribution of risks in the economy. Under the assumption of non-divisibility of securities combined with a budget constraint for small investors, mutual fund shares are qualitatively different from all securities or portfolios of securities, which are available to small investors without the existence of mutual funds. Thus, mutual funds offer qualitative asset transformation. However, they do not rely on own equity as risk buffer but rather make use of the diversification principle.

A second important function of mutual funds is the reduction of asymmetric information to the benefit of their investors. In general, investors have an incentive to generate a competitive advantage with respect to the extent or speed of information processing. The gathering and processing of financial information, however, involves a high degree of economies of scale. Potential sources of cost benefits in information production are the development of special skills and the cross-sectional and temporal reusability of information (Bhattacharya and Thakor, 1993). As a result, investors tend to delegate this task to finance professionals

[26] Note that this argument does not apply to exchange-traded funds because according to the creation and redemption in kind mechanism liquidity costs are paid only by investors who demand liquidity (Guedj and Huang, 2008). See also the discussion in section 4.5.4.

such as analysts or fund managers. Only the existence of asymmetric information in the market justifies the ambition to generate additional value by active portfolio management which is still the dominating investment approach in the fund industry.[27] Active funds promise their investors participation in their superior information by generating, on average, higher risk-adjusted returns than the market. Passive funds, in contrast, focus on a reduction of divergences with respect to the lot size and liquidity and, thus, only offer cheap access to a liquid and diversified portfolio. However, both active and passive funds are basket securities that reduce adverse selection costs in trading (Subrahmanyam, 1991; Gorton and Penacchi, 1993).[28]

Active management is more relevant in markets with a lower degree of market efficiency and a higher degree of asymmetric information as, for example, in international equities or small cap stocks. However, investors can only profit from their private information if security prices reflect this information in due course. This depends on the behavior of other investors with respect to information acquisition and trading. According to Grossman and Stiglitz (1980), the more information is already reflected in the price of a security the lower the gain to be made from acquiring additional information regarding this company. However, Barlevi and Veronesi (2000) argue that if the impact of noise on security prices is relatively high, for example induced by a high degree of liquidity-induced trading, the incentive to gather information individually might even increase in the level of aggregate information processing. Prices are less revealing in this context and it becomes more important to distinguish between liquidity-induced and information-induced trading. Active mutual funds exploit information asymmetries and, through their professional management and processing of large amounts of information, contribute to a high level of market efficiency. As information efficiency is a precondition for allocation efficiency, active funds also improve the efficient allocation of financial resources in the economy.

[27] However, the share of passive retail mutual funds rose sharply in recent years from 1.0 percent in 1984 to 12.6 percent in 2006 and for institutional funds from between 2.8 and 25.8 percent in 1986 to between 28.7 and 52.7 percent in 2006 depending on the type of institutional fund (French, 2008).

[28] Adverse selection costs refer to the risk of trading against a market participant with private information. This risk is significantly reduced in diversified security baskets because private information usually refers to the idiosyncratic component of a stock's return.

Without market frictions, mutual funds were redundant securities[29] and would only offer brokerage services according to the definition of Bhattacharya and Thakor (1993). However, in the presence of market frictions mutual funds also qualify for providing qualitative asset transformation services, though to a lesser degree than banks (Koppenhaver and Sapp, 2005). They enter the traditional dichotomy between indirect financing via banks and direct financing via capital markets. Mutual funds primarily reduce divergences with respect to liquidity and the lot size by providing access to a diversified portfolio of primary securities with preferred risk-return characteristics. However, they do so by making use of the insurance principle and the diversification principle instead of providing own equity, as banks do. Therefore, mutual funds offer direct financing. The services of mutual funds could be interpreted as an efficient trading mechanism focused on the needs of retail investors.[30] For the economy as a whole, mutual funds play an important role in the reduction of the costs of capital through a reduction of transaction costs (in a broad definition). However, as investors delegate the management of their portfolio, agency conflicts arise between the investment management company, the portfolio manager, and the investor (see chapter 2). Resulting agency costs are an important determinant of fund performance, and might be even an impediment to efficient resource allocation.

1.2 Objectives of Investors

Professional Management

Investors aim to maximize utility derived from consumption and to smooth the level of utility over time.[31] They invest their financial wealth accordingly and in this context mutual funds are a popular instrument used. Consequently, the fundamental objective of mutual fund investors is cheap and liquid access to a professionally managed and diversified portfolio (Gruber, 1996). In practice, the objective of most investors is reduced to earning high returns, as summarized by

[29] The return of a redundant security is a linear combination of the returns of other securities. The put-call parity is one prominent example.

[30] This becomes even more obvious in the case of exchange-traded funds. Their major characteristic is the in-kind creation and redemption process which offers efficient trading in security baskets.

[31] The aim to smooth utility results from marginal utility being a decreasing function of the level of utility. Specifically, the utility gain made by higher consumption in one period is more than offset by the loss in utility by lower consumption in another period.

William J. Mikus, the founder of Mikus Capital: "Investors just care whether they made money or not."[32] However, on a theoretical basis the risk of the investment has to be considered as well. Thus, Gruber (1996) and Bessler and Lückoff (2007b) argue that performance, i. e. risk-adjusted return, is the primary goal of investors. Performance is determined on different levels by the overall asset allocation, short-term variations in the asset allocation, usually referred to as tactical asset allocation or timing, and security selection.[33] Some of these decisions are usually delegated by the investor to a professional portfolio manager.

The performance of investors ultimately depends on, first, the level of delegation exercised by investors and, second, the investment strategy and skills of the professional portfolio manager.[34] The higher the degree of delegation, i. e. the fewer investment decisions are made by the investor, the higher is the contribution of the fund manager to overall portfolio performance of the investor. Consequently, depending on their own financial education, investors choose different levels of delegation with the most sophisticated investors delegating least.[35] However, even though a high degree of delegation seems most beneficial for unsophisticated investors, because they face the highest costs when making own investment decisions, a higher degree of delegation is usually also associated with higher agency costs.[36] Thus, the optimal level of delegation is not trivial to determine.

Different investment products offer different degrees of delegation, being lowest for focused index funds and highest for active multi-asset funds. Investors of passive index funds only delegate the implementation of their investment strategy to the fund manager but face the asset allocation and, in the case of indices focused on certain sectors or regions, timing decision on their own. Security selection is not applicable to index funds. Active fund managers, in contrast, pick individual securities based on their analysis on a discretionary basis on behalf of the investors. The level of delegation is rather low for active sector funds, such as technology funds. The flexibility of the fund manager is restricted to choosing individual

[32] Suzanne McGee, Morgan Stanley Pitches System To Measure Mutual Fund Risk, Wall Street Journal, 10 February 1997.

[33] See section 1.3.2 for a more detailed discussion.

[34] Note that investor returns are not necessarily equal to the returns of the investment products due to investors trading in and out of these products over time. The lower the degree of delegation the higher the difference between fund returns and investor return can become.

[35] Goriaev, Nijman, and Werker (2008), Keswani and Stolin (2008b) and Kempf, Rünzi, and Thiele (2009) all emphasize cross-sectional differences in sophistication between fund investors.

[36] For a discussion of potential agency conflicts see chapter 2.

securities from the universe of all technology stocks while the investors make decisions about their asset allocation and, to a certain degree, timing decisions on their own. On the other hand, investors who choose a flexible multi asset fund exert the highest level of delegation. The fund manager can freely change the allocation between different asset classes such as stocks and bonds, overweight or underweight different sectors within these classes and pick individual securities. In this case, the investor not only delegates the security selection but also the tactical and strategic asset allocation decision.

However, multi-asset funds still play only a minor role based on their assets under management.[37] Thus, investors almost exclusively delegate the timing and selection decisions but not the asset allocation decision. Consequently, the overall risk exposure of investors over time is determined primarily by their own investment decisions, for example through reallocation between equity funds on the one hand and bond or money market funds on the other hand. This results in mutual fund managers focusing on the objective of return maximization, but not so much on the avoidance of losses in bad periods which would help to smooth utility over time. This might be seen as one of the fundamental institutional shortcomings in the context of delegated asset management through mutual funds.

Diversification

Many investors face a budget constraint which prevents them from holding a diversified position in securities because of the relatively high number of stocks required to attain the desired level of diversification. Thus, another important objective of investors is access to a diversified portfolio of securities which minimizes idiosyncratic risk. Mutual funds can, by reducing the divergences with respect to the lot size, satisfy this demand. However, the degree of diversification depends on the specific fund type. Passive funds offer access to a certain index which is usually not constructed based on portfolio optimization. Active funds, in contrast, can incorporate diversification considerations into their portfolio composition.

Closely related to the access to a diversified portfolio in small lot sizes is the objective of investors to gain access to new asset classes which are otherwise not investable for them. This objective became more important in recent years as the benefits from including alternative asset classes such as real estate, private equity, commodities or timber gained publicity.

[37] According to the ICI, multi-asset funds made up only less than 6 percent of total assets at the end of 2009 (ICI Investment Company Factbook 2010).

Liquidity

Besides the performance and diversification objectives investors prefer liquid investments over illiquid investments. Because their investment horizon is uncertain the ability to transform their invested money immediately into cash at any time and without incurring a large discount is a valuable service for mutual fund investors (Schmidt and Iversen, 1991). Providing this service requires a management of the liquidity of the fund's assets by the portfolio manager (Yan, 2006). This involves choosing an appropriate cash position as well as the determination of the liquidity of the securities held by the fund. The liquidity level of mutual fund shares is equal among all funds: they offer daily redemption at the net asset value (NAV). Thus, an evaluation of the liquidity service of different funds involves the estimation of the costs implied by this service rather than measuring the liquidity of the fund shares. In this context, funds that are traded on an exchange in an attempt to offer even higher liquidity to their investors play a special role.[38]

Additional Services

Gruber (1996) additionally mentions customer services such as position management, record keeping, check writing and a reduction of transaction costs as objectives of investors. Furthermore, depending on the legislation mutual funds can improve the tax management of investors in different countries. For example, Germany introduced a flat rate tax (Abgeltungsteuer) on income and gains from capital investments as part of the German Corporate Tax Reform 2008 (Unternehmensteuerreform 2008). Investors pay a 25 percent tax on all capital gains once they sell a security which has a large impact on the compound interest over several years if they manage their portfolio actively. However, if investors buy a mutual fund instead the fund manager can rebalance the portfolio without paying taxes. Tax liabilities are only generated when the investors sell the mutual fund shares which allows them to earn a substantially higher interest on interest over time as compared to a direct investment into stocks or bonds. However, please note that the tax laws in the U. S., for example, are different. The only tax advantage from holding mutual funds in the U. S. arises with exchange-traded funds. These funds offer a unique creation and redemption in kind mechanism which helps to reduce the unrealized capital gains significantly (Poterba and Shoven, 2002).

[38] These relatively new developments are discussed in section 4.5.4.

1.3 Investment Strategies

1.3.1 Return Predictability and Equilibrium Considerations

Successful active investing requires superior information compared to that of other investors, i. e. asset returns need to be forecasted with a higher precision than the market's expectation implies. If returns are not predictable, an active variation of portfolio weights does not translate into higher returns but only into higher transaction costs and, thus, lower performance. Successful active investors might possess more information than the market (extent of information) or possess the same information as the market but ahead of time (speed of information).[39] The information advance can be achieved by better information acquisition or faster information processing.[40] Better information acquisition usually refers to "soft information" such as personal meetings (one-on-ones) with the CEO of a company while faster information processing is important for "hard information" such as fundamental firm data or macroeconomic figures as access to this information is usually not restricted and can be obtained at a low cost (e. g. through the purchase of an information terminal such as Reuters or Bloomberg). The superior intelligence can apply to firm-specific information (micro level) or to a more aggregate level such as industries or the macroeconomic situation as a whole (macro level). Micro level information is more important for security selection while macro level information is used in factor timing. In other words, micro-level forecasting refers to forecasting relative returns of individual assets while macro-level forecasting refers to forecasting the general market return.

According to the efficient market hypothesis, information advances are not possible as "prices at any time fully reflect all available information" (Fama, 1970, p. 383). It is often claimed that active management is not a valid strategy in efficient markets. However, Grossman and Stiglitz (1980) argue that the market for information cannot always be in equilibrium, i. e. informationally efficient markets

[39] Note, however, that active investors can, in a strict sense, only benefit from their information advance if the market as a whole learns about this information and draws the same conclusions from it which is then transmitted into prices by the transactions of other market participants. In fact, there are limits to the ability of the market to arbitrage away potential mispricings because it might be too costly for informed investors to borrow enough to bet against noise traders, i. e. individuals trading for reasons other than information (Stein, 2005). Once it is admitted that prices can stay away from fundamentals for a longer period, it may be rational for informed investors to follow the trend rather than to oppose it (Brunnermeier and Nagel, 2004).

[40] This includes the faster transmission of orders to exchanges which is an important success factor for algorithmic traders.

cannot always exist, if information acquisition is costly. Rather, an "equilibrium degree of disequilibrium" (Grossman and Stiglitz, 1980, p. 393) exists. The more agents acquire information, the more prices become informative such that individual learning and aggregate learning become substitutes. If prices become fully revealing, i. e. reveal all private information of informed investors, uninformed investors can free-ride on the information of others. The higher the fraction of informed investors the smaller the incentive to learn individually. In equilibrium, the gain from obtaining information equals the costs such that informed investors are compensated for the resources spent. Consequently, superior information does not translate into superior net returns. Rather, active and passive investing yield the same net returns.

However, if prices are affected by a sufficient amount of noise they might not be fully revealing. For example, Barlevi and Veronesi (2000) argue that noise traders, i. e. market participants trading due to liquidity shocks, might also affect prices if their liquidity shocks are large enough such that uninformed investors can no longer distinguish whether low asset prices result from bad information or from a large degree of noise trading. Thus, in the presence of a sufficiently large number of traders who do not exclusively trade based on private information prices are not fully revealing and it might pay for investors to acquire information. Moreover, the results of Grossman and Stiglitz (1980) are based on an auction as trading mechanism. Thus, informed investors have to reveal their information before the transaction takes place. Today's trading mechanisms, however, allow trading without revealing the private information to all other market participants before the transaction is executed. Attempts to hide the actual order flow are dark pools or iceberg orders (Schwartz, Davis, and Pagano, 2006). Another important aspect is that the same level of efficiency applies neither to all markets nor to all market participants (Bessler, 1989). For example, the stock prices of blue-chip companies with an extensive analyst coverage might be relatively informative while prices of small-cap stocks are not. Furthermore, in the presence of asymmetric information, the information content of prices depends on the capital that informed investors have to exploit their information. Consequently, certain profit opportunities might exist even if markets have become highly efficient in recent years.

The degree to which returns are predictable in reality remains an empirical question. A vast amount of the academic literature is concerned with the prediction of returns. Most of these studies focus on return prediction at an aggregate level (portfolio or index returns) which can be used for market timing strategies, but not on the prediction of cross-sectional differences between individual assets in the future. Early studies have focused on predicting asset returns based on historical return data of the same asset basically relying on autocorrelation patterns.[41] More recent works include information from other company-related or macroeconomic variables into the forecasting model. Table 1.2 provides a summary of these studies and the employed predictor variables.

The results of these studies can be summarized as follows:

1. Stock returns seem to be predictable based on fundamental data: "There is much evidence that stock returns are predictable" (Fama and French, 1988, p. 3). However, in most studies this conclusion is only drawn based on in-sample prediction.

2. The coefficient of determination R^2 of the regressions increases with the forecast horizon. However, this result cannot be interpreted as evidence for the claim that long-run returns can be forecasted more precisely than short-term returns (Kaul, 1996; Cochrane, 1999a).

3. A high degree of model uncertainty exists, i. e. the individual studies identify different variables as good predictors. Overall, the dividend yield and interest-rate variables seem to be good predictors when comparing the results of all studies (Kaul, 1996; Cremers, 2002). Campbell, Lo, and MacKinlay (1997, p. 269 f.) suggest that interest-rate variables have an advantage at short horizons whereas the dividend yield performs better at longer horizons.

However, several potential statistical problems render the empirical results regarding the predictability of returns at least questionable (Figure 1.3). The error term in most of the regressions is not well behaved resulting in an overestimation of the t-statistics (Lanne, 2002). Furthermore, inferences are biased in finite samples due to the use of lagged endogenous explanatory variables (Stambaugh, 1999). If the dependent variable and at least one of the explanatory variables is not stationary, both the t- and F-statistics are biased and the predictive relationship might indeed be spurious (Ferson, Sarkissian, and Simin, 2003). Furthermore, inferences are biased if the choice of the predictive variables is determined by the results of other authors using similar data sets or when not all predictors that have been

[41] For a review of these studies see Bessler and Lückoff (2008).

Table 1.2: Predictive return regressions

This table presents an overview of different regression specifications used in return prediction studies. Variables are defined as follows: 1 – lagged return (eventually filtered); 2 – dividend yield; 3 – P/E ratio; 4 – dividend-earnings ratio (payout ratio); 5 – trading volume; 6 – default spread; 7 – short-term interest rate (t-bill); 8 – change in short-term interest rate; 9 – term spread; 10 – spread between overnight rate and short-term government bonds; 11 – January dummy; 12 – (excess-) return of a portfolio of small-cap stocks; 13 – detrended (growth of) industrial production; 14 – (change in) inflation rate or inflation surprise. Based on Cremers (2002, p. 1226).

Authors	Variables													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Chen, Roll, and Ross (1986)	•					•	•	•	•	•			•	•
Keim and Stambaugh (1986)	•								•			•		
Campbell (1987)	•						•	•		•				
Fama and French (1989)		•				•			•					
Harvey (1989)	•	•				•	•		•	•	•			
Balvers, Cosimano, and McDonald (1990)	•	•											•	
Fama (1990)		•				•			•				•	
Ferson (1990)	•						•	•		•				
Schwert (1990)		•				•			•				•	
Ferson and Harvey (1991)	•	•				•	•		•	•				•
Hodrick (1992)	•	•				•	•		•					
Ferson and Harvey (1993)	•						•						•	•
Nelson and Kim (1993)		•											•	
Goetzmann and Jorion (1993)	•	•												
Whitelaw (1994)		•				•	•			•				
Pesaran and Timmermann (1995)		•	•				•	•		•			•	•
Kothari and Shanken (1997)		•				•	•			•				
Pontiff and Schall (1998)		•				•	•		•					
Ferson and Harvey (1999)		•				•	•		•	•				
Bossaerts and Hillion (1999)	•	•	•	•			•		•		•			•
Avramov (2002)		•	•			•	•		•		•	•		•
Cremers (2002)	•	•	•		•	•	•	•	•	•	•		•	•
Wetherilt and Wells (2004)	•	•	•	•			•							

searched for are incorporated into the test statistics, which is usually referred to as data snooping or data mining (Lo and MacKinlay, 1990; Ferson, Sarkissian, and Simin, 2003). Consequently, Cooper and Gulen (2006) report that most of the previous results in favor of return predictability indeed seem to be a result of data snooping. Data snooping is a severe problem because, first, there is little theoretical guidance on which predictor variables to choose, second, new studies are conditional on the findings of previous studies and, third, the academic literature is biased toward a publication of significant results while variables that have been analyzed but did not work as predictor are usually not published (Cooper and Gulen, 2006).

Boudoukh, Richardson, and Whitelaw (2008) question the earlier conclusion that returns are more predictable over longer horizons. In particular, the sampling error inherent in small samples can explain why the coefficient estimated and R^2 increase with the forecasting horizon. They conclude that long-horizon return predictability might be a “myth”. In addition, Simin (2008) documents that asset pricing models, which are frequently used in practice to generate expected returns, cannot beat static benchmarks based on one-step ahead forecast errors. This result holds for size and book-to-market sorted portfolios as well as for individual firms. Even conditional asset pricing models do not perform significantly better in forecasting returns, though recent studies such as Lewellen and Nagel (2006) and Ang and Chen (2007) suggest that they are superior in explaining returns compared to unconditional versions. This more sceptical view on the predictability seems to be more in line with empirical evidence on the investment performance of professional investors (Cooper and Gulen, 2006).

However, Cochrane (2008) strictly argues in favor of return predictability. In fact, he shows that dividends are clearly not predictable at all. If both dividends and returns were unpredictable then, according to present value logic, the dividend-price ratio should be a constant. Thus, the correct question is not whether returns are predictable, but rather which of dividend growth or returns is predictable. Analyzing both variables jointly, his results suggest that returns are much more predictable than dividends. The question about return predictability does not yet seem to be settled. However, even Cochrane (2008) warns that return predictability might not be successfully applied in long-term market timing strategies due to the short horizons of available data sets. Moreover, long-horizon predictability of asset returns might only reflect a risk premium for holding macroeco-

Figure 1.3: Potential statistical problems of predictive return regressions

This figure presents the statistical problems associated with predictive return regressions.

Problem:
Autocorrelation and heteroscedasticity of the error term.

Result:
Overestimation of the t-statictic.

Potential solution:
– GLS / GMM
– Newey and West (1987)
– White (1980)
– Hansen and Hodrick (1980)
– Hodrick (1992)
– non-overlapping observations

Problem:
Small sample bias due to lagged endogenous explanatory variable.

Result:
Biased coefficients and inferences.

Potential solution:
– VAR (Nelson and Kim, 1993)
– Bayesian approach
– monte carlo / bootstrapping
– overlapping observations
– larger sample
– short-term returns

Problem:
Data mining due to reliance on previous studies using a similar data set.

Result:
Biased inferences as the total number of "searched" predictors is not considered.

Potential solution:
– Bayesian approach
– adjustment of inferences
– new data set

Problem:
Spurious regression due to non-stationarity in dependent and at least one explanatory variable.

Result:
Biased t- and F-statistics.

Potential solution:
– inclusion of lagged values
– taking first differences
– Cochrane-Orchutt approach

nomic risk over the business cycle (Cochrane, 1999b). This premium compensates for holding assets that do relatively poorly in downturns and provide high returns in upturns because investors usually aim to smooth their consumption over the business cycle.

In addition to the broad literature on return predictability, a similarly extensive amount of literature exists for return anomalies. These anomalies also constitute predictable patterns in the cross-section or time series of returns that are not in line with existing asset pricing models.[42] Anomalies present either an abnormal profit opportunity, i. e. a market inefficiency, or are a result of a misspecified asset pricing model to determine the "normal" or "fair" returns (Schwert, 2003). In fact, specific anomalies might be interpreted as proxies for unknown risk factors rather than inefficiencies (Malkiel, 2003). Furthermore, transaction costs might prevent market participants from fully exploiting these anomalies even though they appear statistically significant (Keim, 2008). In an efficient market with a rational response of investors no profit opportunities should remain after the anomaly has been documented in the literature. However, even though some of the anomalies became weaker after their documentation, or can be explained by more sophisticated asset pricing models, others such as the January effect or the momentum effect remain relatively robust even in recent studies (Schwert, 2003; Avramov and Chordia, 2006).

Even under the assumption that the relevant parameters such as expected returns and covariances were predictable in a statistical sense, a certain degree of estimation error would remain. This estimation error might severely negatively affect the portfolio choice. DeMiguel, Garlappi, and Uppal (2009) perform an extensive simulation study comparing the performance of 14 different asset allocation-models including the classical approach that ignores estimation error, Bayesian extensions, models using moment restrictions and constraints on the portfolio weights, as well as asset allocation-models based on the optimal combination of portfolios. Their results suggest that none of these sophisticated models can significantly beat a naive $1/N$ allocation to the risky assets. Thus, the gain from portfolio optimization is more than offset by the estimation error resulting from a prediction of the parameters. Ignoring parameter uncertainty can lead to severe mistakes in the asset allocation decision (Barberis, 2000).[43] Additionally,

[42] For a review of anomalies see Schwert (2003) and Keim (2008).
[43] For example, the results of Barberis (2000) even indicate that the optimal allocation to

Avramov (2002) suggests that model uncertainty, i. e. the uncertainty of choosing the correct variables for the prediction model, has an even larger impact on the utility of portfolio optimizing investors than parameter uncertainty. Overall, these empirical results leave a doubt on the claim that active management can successfully provide superior risk-return characteristics. In the first step, returns do not seem to be reliably predictable based on, first, macroeconomic or fundamental information or, second, derived from market anomalies. Even if they were, the second step of optimizing a portfolio based on these predictions cannot be easily operationalized. However, most of these results are not based on single stocks, so the potential for successful stock picking cannot completely be ruled out.

1.3.2 Active versus Passive Investing

Because the empirical literature does not provide a consistent conclusion on the predictability of asset returns, both an active and a passive approach to investing have emerged. Theoretically, all investors value higher returns but dislike risk. Under usual assumptions and no predictability of asset returns, the corresponding investment strategy is to choose a portfolio on the efficient frontier. When the risk-free asset is available, this boils down to a combination of the market portfolio and the risk-free asset with the relative weights depending on the personal risk preferences, i. e. to take a position on the capital market line in the μ-σ-diagram. The market portfolio contains all risky assets according to their market weight. However, in reality this position cannot be attained as the market portfolio consists not only of traded securities but also of non-traded assets such as real estate or even human capital.[44] Consequently, this strategy can only be approximated by investing in a value-weighted broad market index of traded securities. If only a subset of all assets is available for investing, then it is no longer obvious that value-weighting is necessarily optimal. However, recent studies point out that even if the market portfolio is not investable, the use of market proxies does not alter the conclusions of empirical studies to a large degree (Low and Nayak, 2009; Levy and Roll, 2010).

stocks might indeed decrease with the investment horizon after taking parameter uncertainty into account. A result which is opposite to the conventional view that the allocation to stocks increases with the investment horizon due to long-term reversals.

[44] Human capital in this case can be interpreted as the discounted value of all future labor income generated from personal skills. As the working life is limited this position has similar characteristics as a bond even though investors have certain flexibility in determining the maturity date by retiring earlier or later.

Proponents of active management, in contrast, argue in favor of a deviation from a passive portfolio in an attempt to systematically end up above the capital market line ex post. Thus, they believe in the existence of superior investment skills that generate higher returns at the same risk level as a passive position on the capital market line.[45] Active investing requires an active alteration of the portfolio weights over time.[46] This, in turn, requires successful forecasting abilities of asset returns by the manager.[47] A positive correlation between active changes in portfolio weights and subsequent asset returns is an appropriate measure of active investment (Lo, 2008). Specifically, the expected return $E(r_{it})$ of portfolio i in t is the expected weighted average of the returns of the m individual securities:

$$E(r_{it}) = \sum_{j=1}^{m} E(w_{ijt} r_{jt}) \ , \tag{1.1}$$

where r_{jt} is the return of asset j in t and w_{ijt} is the corresponding weight in portfolio i. This can be broken down into:

$$E(r_{it}) = \underbrace{\sum_{j=1}^{m} Cov(w_{ijt}, r_{jt})}_{\text{active component}} + \underbrace{\sum_{j=1}^{m} E(w_{ijt}) E(r_{jt})}_{\text{passive component}} \ . \tag{1.2}$$

The first term in equation (1.2) (active component) refers to the contribution of active changes of the portfolio weights over time to the portfolio return while the second term (passive component) refers to the expected return of the portfolio keeping portfolio weights fixed. Thus, the contribution of active management to the portfolio returns ex post can be measured as the portfolio return minus its expected return based on the expected portfolio weights and the expected returns of the individual securities.[48]

However, if stocks move in trends or the momentum effect is apparent, then simple indexing strategies as defined above show a positive correlation between

[45] Equivalently, active management might reduce the risk at a constant level of average returns.
[46] Note that indexing also implies time-varying portfolio weights due to price movements of individual securities.
[47] For a discussion of the predictability of asset returns see section 1.3.1.
[48] See the discussion in section 3.5 on how expected weights and expected returns can be determined in a performance evaluation context.

portfolio weights and subsequent asset returns which is interpreted as active management according to the definition of Lo (2008). Thus, passive investing can be defined either by not actively changing the portfolio weights, i. e. indexing, according to e. g. Malkiel (2003) or by constant portfolio weights according to Lo (2008).[49] The first definition accepts that weights change passively over time and minimizes the trading volume (changing weights, no trading). The advantage of this view of passive management is that any deviation from the index is interpreted as active management which can be measured by a comparison of the index returns and the returns of the active investment product. The required data is usually obtainable from public sources. According to the second definition, a passive manager keeps portfolio weights constant by active rebalancing which might result in significant portfolio turnover depending on the cross-sectional differences in asset volatilities (constant weights, trading). This distinction between active and passive management has more theoretical appeal than the first one. The important advantage is that it does not rely on the specification of a benchmark, which can often result in misleading conclusions if the benchmark is not properly specified. However, it is important to note that the second approach relies on portfolio data which is often unavailable. Both definitions, however, have in common that portfolio weights of active strategies vary over time with the aim to achieve an improved risk-return tradeoff.[50]

This concept of measuring active management can easily be translated into a multi factor world. If asset returns are assumed to follow a k-factor model, such as the one-factor CAPM or the three-factor model of Fama and French (1993), the returns of asset j can be described by the following equation:

$$r_{jt} = \alpha_j + \beta_{j1} f_{1t} + \ldots + \beta_{jK} f_{Kt} + \epsilon_{jt} \ , \tag{1.3}$$

where f_{kt} is the k-th factor's return.[51] In combination with equation (1.3), equation (1.2) can be rewritten as:

[49] Note that in the case of non-autocorrelated asset returns indexing is also passive investing according to the definition of Lo (2008).
[50] Throughout this work the differences between the two definitions are pointed out whenever they are relevant.
[51] Note that for simplicity, the rate on the risk-free asset is omitted; r_{jt} and f_{kt} can alternatively be interpreted as returns in excess of the return on the risk-free asset.

$$E(r_{it}) = \underbrace{\underbrace{\sum_{j=1}^{m} \alpha_j E(w_{ijt})}_{\text{security selection}} + \underbrace{\sum_{k=1}^{K} Cov(\beta_{ikt}, f_{kt})}_{\text{factor timing}}}_{\text{active component}} + \underbrace{\underbrace{\sum_{k=1}^{K} E(\beta_{ikt}) E(f_{kt})}_{\text{risk premia}}}_{\text{passive component}} , \qquad (1.4)$$

where $\beta_{ikt} = \sum_{j=1}^{m} w_{ijt}\beta_{jk}$. The portfolio return can be broken down into security selection, factor timing and risk premia (Lo, 2008).[52] The latter component is a purely passive reward for bearing market risk while the former two constitute the active part of the portfolio return. For a successful security selection, or positive alpha, managers need to put positive weights in securities with positive idiosyncratic risks during the holding period. Successful factor timing refers to a variation of the factor exposure in accordance with the realized factor returns. In its simplest form, managers increase their market exposure when the expected market return is high, and vice versa. The third component, risk premia, denotes the return contribution of the average exposure of the portfolio to certain risk factors. This component constitutes a reward for bearing risk and cannot be attributed to the investment skills of the manager. It is rather a "fair" compensation for risk.

In addition to selection and timing, the portfolio composition is determined by long-term asset allocation. This refers to the choice of different asset classes and their weights in the portfolio. An asset class is characterized by its specific loading on the different risk factors.[53] Thus, asset allocation determines the average risk exposures in equation (1.4) as denoted by $E(\beta_{ikt})$, some of which might even be zero depending on which asset classes are chosen. Generic asset classes include, for example, equity, fixed income, real estate, and commodities. In some cases, asset classes are defined on a more disaggregated level: individual industrial sectors for equities (e. g. financial, industrial, health care), individual issuer groups for fixed income (e. g. developed governments, emerging market governments, corporates), individual commodities (e. g. oil, precious metals, energy), and different types of real estate (e. g. commercial property, residential property). Sometimes, new

[52] Note that short-sale constraints might impose a limit on the potential of factor timing especially during periods of negative risk premia.

[53] Note that this definition strongly depends on the choice of the number and types of risk factors used to characterize different asset classes.

assets such as hedge funds, private equity, or even stakes in timber or ships, are perceived as a new asset class because they offer new risk-return profiles. The long-term asset allocation usually remains fixed over time while short-term variations are sometimes called tactical asset allocation by practitioners. However, according to the definition above, a variation in the weights between different asset classes should be interpreted as factor timing.

Based on Brinson, Hood, and Beebower (1986) and Brinson, Singer, and Beebower (1991) many authors claim that more than 90 percent of a funds return can be explained by its asset allocation, and that active security selection plays only a minor role. However, this is only valid for the explanatory power for the variation in returns over time (time series). Usually, it is more interesting to understand the return contributions of security selection and asset allocation across different funds (cross section). In this case, about 35 to 40 percent of cross-sectional return differentials can be explained by asset allocation for U. S. mutual funds (Ibbotson and Kaplan, 2000) and about 65 percent for Swiss and German mutual funds (Drobetz and Köhler, 2002). According to Xiong, Ibbotson, Idzorek, and Chen (2010), active security selection and asset allocation are equally important in explaining cross-sectional return differentials once controlling for the impact of the market.

Several attempts have been made to measure the degree of active management and to classify investment strategies. These approaches usually provide insights into a fund's investment strategy based on an easily comprehensible metric by aggregating portfolio information data or without relying on detailed portfolio information at all. One of the most popular measures is the tracking error (or tracking error volatility) which can be easily computed to analyze the degree of active management. Tracking error of fund i is usually defined as the time-series standard deviation of the difference between the funds' return and the benchmark return:[54]

$$x_{it} = r_{it} - r_{mt} \tag{1.5}$$

$$\mathrm{TE}_{it} = \sigma_x \ . \tag{1.6}$$

[54] Note that r_{mt} is sometimes replaced by the expected return of a factor model. In this case, tracking error reduces to the standard deviation of the error term in a regression of the funds' return on the factors.

Thus, the tracking error is a measure for the additional standard deviation of the portfolio return due to active deviations from the benchmark. It is often used in institutional mandates to restrict the portfolio manager. An alternative to the tracking error is a simple correlation measure between the fund and its benchmark. The higher the correlation between both time series, the less active the fund is perceived to be (Alexander and Dimitriu, 2004). However, individually both approaches, tracking error and the correlation with the benchmark, are only very rough measures of activity.

Portfolio turnover is sometimes used to indicate how active a manager is. It requires information on portfolio holdings for computation. Turnover is usually defined as the fraction of the portfolio that has been traded over a certain period. For example, an annual turnover of 100 percent implies that on average each position in the portfolio has been exchanged in the course of the year. In fact, in this case the trading volume is 200 percent of total assets. Wermers (2000) documents that annual turnover levels of equity funds have more than doubled from 32.7 percent in 1975 to 72.8 percent in 1994. However, turnover is only a rough measure of active management as fund flows also affect the trading volume. Edelen (1999) estimates that about 70 percent of fund flows translate into transactions. Thus, funds with volatile fund flows have high levels of portfolio turnover, though they are not an indication of active trading.[55] Furthermore, turnover only measures how "busy" the portfolio manager is, but not how far he deviates from the benchmark (Cremers and Petajisto, 2009).

The active share by Cremers and Petajisto (2009) is another approach for measuring active management. It is defined as the deviation of the fund i's portfolio weights from the benchmark weights:

$$\mathrm{AS}_i = \frac{1}{2}\sum_{j=1}^{m} \left| w_{ij} - w_{mj} \right| , \tag{1.7}$$

where m is the number of assets in the universe of all assets available to the fund manager and w_{ij} (w_{mj}) is the weight of fund i (the benchmark index) in asset j. The active share measures the fraction of the portfolio that deviates from the

[55] Note that CRSP reports the turnover ratio defined as the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month total net assets of the fund. This definition excludes at least part of the liquidity-induced trading volume.

benchmark. An active share of 30 percent implies that 70 percent of the holdings correspond to the benchmark weights. Thus, the active share measure can never be larger than 100 percent. Cremers and Petajisto (2009) report that while in 1980 98.5 percent of all assets (or 97.9 percent of all funds) had an active share of more than 60 percent, these numbers decreased to 55.2 percent of all assets (or 76 percent of all funds) in 2003, partly because of the emergence of index funds but also partly because active funds became less active.

Kacperczyk, Sialm, and Zheng (2008) define the return gap as the difference between the funds' actual return and its hypothetical return based on the portfolio holdings of its last disclosure date. This measure specifically focuses on the short-term activities of fund managers. The higher the absolute value of the return gap, the more active the portfolio manager seems to be in the short run, irrespective of whether this is good or bad for investors. The empirical results show that the overall average of the return gap does not appear to be significantly different from zero. However, it has a high cross-sectional dispersion ranging from −11.3 basis points per month for the lowest decile to 15.4 basis points for the highest decile, significantly different from zero in both cases. Furthermore, it appears to be highly persistent. Some fund managers seem to persistently add value through short time trading while others pursue activities that persistently destroy value.

1.3.3 Specific Investment Strategies

Actual investment strategies are quite diverse across and even within different categories. The more active and complex the investment strategy, the less individual strategies within this category have in common. For example, Bookstaber (2003) argues that hedge fund strategies are more easily defined by what differentiates them from other strategies, rather than by what different hedge fund strategies have in common, i. e. hedge fund strategies are all strategies that do not fit into one of the other categories. Figure 1.4 classifies existing investment strategies along their degree of activeness.[56]

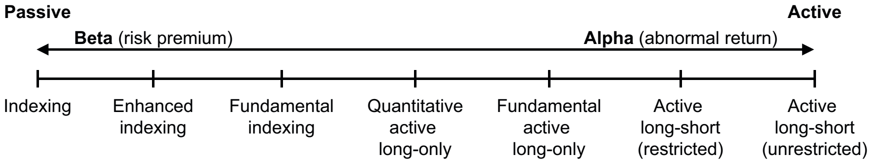
1.3.3.1 Indexing and Enhanced Indexing

As the most passive of all products, index funds are shown on the left hand side of Figure 1.4. By definition, they should have the lowest tracking errors, the

[56] It is not possible to draw clear distinctions lines between the different categories as they smoothly flow into one another.

Figure 1.4: Active-passive continuum

This figure presents the continuum of investment strategies ranging from purely passive to highly active.



lowest turnover and the lowest active share because their investment objective is to replicate as closely as possible the performance of a prespecified market index at a low cost. Therefore, this strategy is not passive in the sense of constant portfolio weights but accepts variations in the relative weight of portfolio assets over time.[57] Moreover, some authors argue that a purely passive strategy does not exist in the real world because changes in the relative weights due to stock price movements are not the only active component of indexing (e. g. Ranaldo and Häberle, 2007).[58] Indeed, value-weighted indices can be interpreted as trend chasing in disguise as they imply a momentum strategy for winners and a stop-loss strategy for losers if they eventually drop out of the index. Moreover, tracking a passive index involves an active strategy that follows the index rules. As most indices only contain a subset of the market based on relative size companies with decreasing market capitalization will eventually be replaced by companies that have grown recently.[59] In addition, IPOs have to be considered and eventually added to the index.[60] In addition to disclosed index rules, the index committee, in most cases, has discretionary flexibility in their decision making. Additionally, cap-weighted indices are influenced by financing decisions of companies and the

[57] Compare the discussion about the two alternative definitions of passive investing in section 1.3.2.

[58] Note that if all investors were passive investors, in the sense of holding portfolio weights, constant this would be at odds with market equilibrium. In contrast, all investors can be indexers in equilibrium, holding all assets according to their market weight.

[59] For example, MLP, a financial advisor, was removed from the German DAX index and replaced by Continental in September 2003 after only two years of membership in the index following a period of strong underperformance. Other recent examples include the replacement of Deutsche Postbank and Infineon by Fresenius and Hannover Rück, respectively.

[60] For example, Deutsche Postbank, the financial services arm of Deutsche Post, became member of the DAX index in September 2006 after its IPO in June 2004.

resulting changes in the capital structure. If, for example, a company decides to buy back its own shares this might be a positive signal and subsequent prices tend to increase (Bessler, Drobetz, and Seim, 2009). However, this company will have a lower weight in the index due to its lower free-float market capitalization. Furthermore, following index constituent changes involves high indirect transaction costs as many other market participants want to trade in the same direction (Mase, 2007). All of these alterations in the portfolio weights can be interpreted as active management.

If the tracked index has a relatively small number of rather liquid constituents, a full replication strategy might be appropriate, i. e. the index fund buys all constituents according to their index weight. However, this practice involves transaction costs resulting in a gap between the fund's performance and the index performance. Thus, especially in the case of illiquid underlyings, index funds try to replicate the index without actually buying all constituents. Rather, they rely on enhanced indexing strategies, known as representative sampling, that trade-off transaction costs against tracking error relying, for example, on cointegration analysis or principal component analysis (Alexander and Dimitriu, 2004). In practice, several exchange-traded funds aim to minimize the tracking error by the use of index swap contracts.[61] However, this only transfers the index tracking risk to the swap seller who receives a premium for taking the risk. Furthermore, as passive funds usually hold a relatively constant portfolio of assets over time, they can earn extra returns by lending their securities for the purpose of short selling (Elton, Gruber, Comer, and Li, 2002).[62]

Keim (1999) presents a clinical study of Dimensional's $9-10$ Fund. The aim of this index fund is to track the performance of the two smallest deciles of NYSE market capitalization. However as these stocks are fairly illiquid, the fund applies a special approach to index tracking. Specifically, it excludes very illiquid and low-priced stocks, trades very patiently and uses upstairs markets for block trades. Furthermore, the fund acts as a liquidity provider (market maker) rather than as a liquidity demander in these markets. These tactics lead to an average 2.2 percent annual premium of the fund over the index, yet with a high volatility of

[61] In a swap agreement, the buyer of an index swap receives exactly the index return while the seller receives a fixed payment. In Germany, the exposure of exchange-traded funds to swaps is restricted to 10 percent of total assets to limit the counterparty risk.

[62] However, ETF providers pass on only between 50 and 99.5 percent of the lending fees to investors (John Jannarone, Getting a Fair Share from ETFs, Wall Street Journal, 08 January 2010).

spreads between -6.98 and 6.47 percent. This example again shows that passive investing, in reality, might not be passive at all.

Several alternative approaches to index construction have emerged in recent years (Figure 1.5). With respect to the selection of constituents, there is an important difference between diversified broad-market indices and concentrated indices which apply alternative selection methodologies and contain only a subset of stocks. Broad-market indices are an efficient tool for generating beta exposure and to proxy for the market portfolio. The initial objective of index products was to provide investors with a way to invest passively at a low cost, i. e. to earn risk premia according to equation (1.4). However, more concentrated and selective indices focus on certain sectors, regions or investment topics such as new energy. Also, special indices select stocks based on fundamental variables like dividends. The use of concentrated indices in active investment applications is increasing even though the products themselves remain passive. A concentrated index usually contains only little company-specific idiosyncratic risk, because it combines several stocks in one portfolio, but still provides exposure to industry-specific idiosyncratic risk.[63] Moreover, different concentrated indices tend to have distinct exposures to the relevant risk factors in equation (1.3). Thus, these products can be used for factor-timing strategies according to equation (1.4) without trading a large number of individual securities.

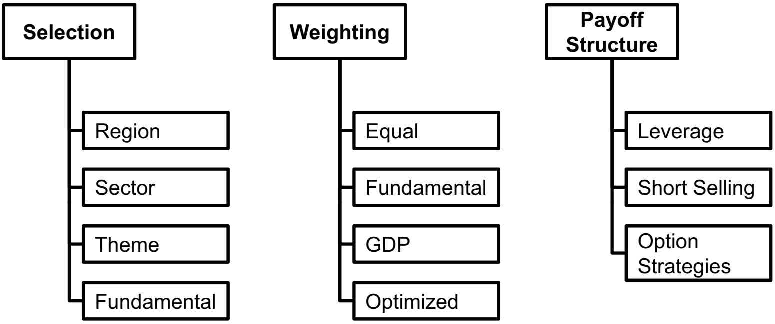
Indices with alternative weighting schemes are offered in addition to alternative selection methodologies. Some indices apply equal weighting instead of value weighting, giving more weight to small stocks which have been documented to earn higher returns compared to large stocks (Banz, 1981).[64] Amenc, Goltz, and Le Sourd (2009) provide empirical evidence that the performance of equal-weighted indices is superior compared to value-weighted indices. Also, fundamental variables have been proposed as alternative weights (see discussion below). To account for differences in the propensity for an exchange listing across industries or regions, a weighting according to the contribution to GDP could be used. A GDP-weighted index should come closer to the risk-return profile of the theoretical market portfolio, which consists of traded and non-traded assets. Another promising approach would be to develop indices which are weighted according to

[63] However, the smaller the investment universe the lower the degree of diversification of company-specific risks. For example, Nestlé S. A. made up almost 40 percent of the Dow Jones Stoxx 600 Food and Beverage Index at the end of November 2008.

[64] For example, an equal-weighted version of the S & P 500 exists.

Figure 1.5: Alternative investment strategies

This figure presents alternative investment strategies.



a portfolio optimization. However, this would require an estimation of future expected returns and covariances, which seems infeasible in practice. Moreover, the optimization procedure is very sensitive to estimation error and often produces corner solutions, which are not balanced. Thus, empirical results suggest that problems associated with the implementation render this approach inferior compared to equal weighting DeMiguel, Garlappi, and Uppal (2009). Deutsche Börse offers two indices with optimized weights, which aim to minimize the portfolio variance (DAXplus Minimum Variance) or to maximize the Sharpe ratio (DAXplus Maximum Sharpe Ratio) based on a portfolio of the 30 DAX constituents.

The use of derivatives even allows index providers to construct indices with alternative payoff structures. Derivatives can be used to lever the investment, multiplying the market return with a certain factor. Short indices use derivatives to reverse the market exposure. If the underlying index appreciates by one percent, the short index falls by the same amount. Lastly, option-based indices offer nonlinear payoff structure by duplicating strategies such as covered-call writing or protective-put strategies. Consequently, modern indexes involve a high degree of trading and the gap between indexing and active investing narrows.

1.3.3.2 Fundamental Indexing

Market indices are usually not constructed based on optimal portfolio considerations, but rather as an indicator of the direction of the market. Thus, some authors argue that most of the existing market indices are not appropriate underlyings of investment products (e. g. Arnott, Hsu, and Moore, 2005). Arnott, Hsu, and Moore (2005) propose instead fundamental indexing which weights stocks according to economic variables such as book values, sales figures or the like rather than their market capitalization.[65] According to the authors, this avoids an overweighting of recent winners and underweighting of recent losers and value stocks which is inherent in capitalization-based indices.[66] Furthermore, if asset prices fluctuate around their "fair values" then capitalization-based indices overweight overvalued and underweight undervalued stocks, exactly opposite of what active managers should be doing.[67]

In contrast, Perold (2007) argues that "fair values" are not known. Thus, a higher price for a security does not necessarily reflect a higher probability of being overvalued. Random mispricing does not automatically lead to systematic reversals. Accordingly, capitalization-weighted indices are equally likely to overweight or underweight stocks that turn out to have been overvalued (or undervalued) ex post.[68] Moreover, fundamental indexing is more active than pure indexing because it involves active though rules-based adjustments of the portfolio weights. Consequently, the tracking error, the turnover and the active share are higher compared to pure indexing. Perold (2007) points out that transaction costs can put a significant drag on the performance of fundamental indexation while capitalization-weighted indices usually require only low portfolio turnover. Consequently, Blitz and Swinkels (2008) argue that fundamental indexation is merely an active value strategy tilting the portfolio toward "undervalued" stocks as measured by fundamental ratios. However, because it does not rely on more sophisticated quantitative methods, Blitz and Swinkels (2008) argue that funda-

[65] Note that fundamental indexation is only an active weighting strategy but does not involve an active selection in the sense of setting the weight of some stocks to zero.
[66] These approaches are sometimes referred to as market-valuation-indifferent indexing (Treynor, 2005).
[67] This aspect was put forward by Jeremy J. Siegel in "The 'Noisy Market' Hypothesis", Wall Street Journal, 14 June 2006.
[68] Indeed, the fundamental value also fluctuates randomly. Thus, even if the stock price increased by 3 percent over the previous period, the fundamental value might have increased by 5 percent and the stock is now "undervalued".

mental indexing is an inferior proposition to active value investing. The empirical results of Jun and Malkiel (2007) and Amenc, Goltz, and Le Sourd (2009) support a rather sceptical view. Jun and Malkiel (2007) focus on the Research Affiliates Fundamental Index (RAFI) which contains 1000 stocks weighted according to fundamental ratios. This index outperforms conventional indices such as the S & P 500 or the Russell 1000 by more than 3 percent per year in the period from 2000 to 2007. Walkshäusl and Lobe (2010) complement these results and report that fundamentally constructed indices outperform their capitalization-weighted counterparts based on a global portfolio and based on 44 out of 50 major stock markets around the world. Amenc, Goltz, and Le Sourd (2009), in contrast, suggest that fundamentally-weighted indices cannot outperform value-weighted or equal-weighted indices in the long-run. Moreover, accounting for the size and value tilt of the fundamentally weighted index by the three-factor model of Fama and French (1993) renders the alphas in the study of Jun and Malkiel (2007) insignificant. Similarly, Walkshäusl and Lobe (2010) report for only nine out of their 50 countries significantly positive four-factor alphas based on the model of Carhart (1997) when they adjust the benchmark factors for fundamental weighting. Thus, the benefits of alternative weighting schemes remain rather low according to empirical results and they are merely an instrument that offers efficient access to a value tilted portfolio.

1.3.3.3 Active Long-Only Strategies

Active long-only strategies can be divided into quantitative and fundamental strategies. Quantitative investment funds usually apply a similar strategy as fundamental indexing funds. However, both groups are different because quantitative funds usually rely on more sophisticated models. These models screen a large universe of potential stocks based on fundamental data and historical return characteristics and select a subset of stocks in which the portfolio manager invests. This approach relies on a large database of fundamental data on investable stocks and requires high computer power. However, as the selection algorithms are usually developed and tested based on historical data the fundamental idea of quantitative investing is that return patterns observed in the past repeat in the future. An advantage of quantitative investing and its unambiguous reliance on computer models is to discipline the manager in order to avoid behavioral biases. Because mutual funds are not required to disclose their investment strategy most databases do not explicitly differentiate between traditionally managed and purely quantitatively managed funds and no empirical results exist on the benefits of the one approach compared to the other. The turnover, tracking error, active share and return gap of quantitative funds should be on similar levels as those of conventional active funds but might have a large cross-sectional variation within the group of quantitative funds.

In contrast to quantitative active strategies, fundamental active strategies focus more on qualitative research methods. Technical analysis and chartism, i. e. the prediction of future stock price movements based on a mostly visual analysis of historical price data, belong to this category. Fundamental analysis, which relies to a large degree on determining the "fair" value of a company by comparing multiples such as the price-to-earnings ratio (P/E ratio) or the enterprize-value-to-EBIT ratio relative to competing companies of the same industry, also belongs to this category. Fundamental analysis is based on a broader set of available information compared to technical analysis. In this context, soft information from one-on-one meetings with the management of a company becomes more important than the strict reliance on hard data in quantitative management. However, qualitative research methods are subject to a certain degree of subjectivity, which is especially problematic if portfolio managers are affected by behavioral biases.

Based on their construction, active mutual funds should have high tracking errors, and a significant active share and return gap. However, for many active funds these numbers are relatively low. In fact, 30 percent of all active U. S. equity funds deviate from the benchmark only by 20 to 60 percent of their holdings (Cremers and Petajisto, 2009). As a result their market exposure as measured by beta is usually close to one (or slightly below one because of their cash position) and their abnormal performance as measured by alpha close to zero. A combination of tracking error and active share can be used to categorize funds into four groups (Cremers and Petajisto, 2009):

1. "Closet indexers": low active share and low tracking error. These funds are managed close to the benchmark but are marketed as active funds. They still offer a high degree of diversification.

2. "Factor bets": low active share and high tracking error. These funds overweight or underweight certain sectors while keeping the weight within these

sectors close to the benchmark weight. According to equation (1.4) this strategy is defined as factor timing. Idiosyncratic risk is still diversified while industry risk is concentrated in these funds.

3. "Diversified stock picks": high active share and low tracking error. These funds do not alter the sector allocation compared to the benchmark but pick only certain stocks from each sector. Industry risk is still diversified but idiosyncratic risk might be concentrated in these funds.

4. "Concentrated stock picks": high active share and high tracking error. These funds pick certain stocks from only a subset of available industries and can be perceived as the most active group. The degree of diversification is usually relatively low.

1.3.3.4 Active Long-Short Strategies

Active long-short basically refers to investment strategies followed by hedge funds. These funds are explicitly organized as private vehicles in order to circumvent the strict regulation of mutual funds. Therefore, their investment strategies are merely unrestricted allowing short selling, the use of derivatives, leverage as well as investments in illiquid assets. Hedge funds aim to deliver absolute returns that are independent of the general market movement. Technically speaking, they produce alpha and try to keep beta as low as possible. Thus, in contrast to mutual funds, their investment performance cannot be evaluated relative to a benchmark. Bookstaber (2003) even argues that due to the diverse strategies followed by hedge funds no common definition can be formulated for what hedge funds are doing.

Hedge fund strategies can be classified into the following three groups: (1) relative value; (2) event driven; (3) opportunistic (Bessler, Drobetz, and Henn, 2005; Bessler, Drobetz, and Holler, 2007). Relative value refers to strategies that involve a long position in a presumably undervalued security while at the same time shorting a similar security in order to minimize the systematic risk. Examples are equity market neutral, convertible arbitrage and fixed income arbitrage. Event driven funds invest in distressed securities or try to profit from mergers and acquisitions by going long the target and short the bidder in anticipation of a successful deal.[69] Opportunistic strategies such as global macro, short selling, long-short equity or emerging markets are based on superior private information in narrow market segments. The systematic risk exposure is lowest for relative value strategies, increases for event driven strategies and is highest for opportunistic strategies.

Because hedge funds usually provide access to relatively concentrated portfolios, their active share is expected to be high as is their return gap. Furthermore, without any benchmark orientation, tracking errors are also rather high while the portfolio turnover can be relatively low for some hedge fund strategies and at the same time extremely high for others. An example for the latter are hedge funds following algorithmic trading strategies. A potential problem when evaluating the investment performance of hedge funds is that investments in new asset classes not considered in the performance evaluation model can show up as alpha even if they constitute in fact beta risk and the relevant risk factor is missing in specification of equation (1.4). A potential solution is to include additional risk factors that account for non-linearities into the benchmark (Fung and Hsieh, 2004; Bessler and Lückoff, 2007b).

1.3.3.5 Activist Investors

Some investors choose not to actively manage the portfolio weights in order to vary their risk exposure over time but rather try to more directly influence the risk and return characteristics of their portfolio assets. These investors actively engage in interaction with the management of their portfolio companies with respect to operational and financing decisions which have an influence on the idiosyncratic and systematic return components. As investors care about total return, i. e. the sum of capital appreciations and payouts, a common means of maximizing short-term returns is to force the management to increase the payout to investors. Two kinds of such activist investors can be distinguished. The first group are investors that are basically too large to trade their portfolio stocks efficiently, such as large pension funds or sovereign wealth funds. These funds do not have the option to exercise market-based corporate governance through voting-by-feet. Rather, they have to rely on conversations with the top management. The second group are activist hedge funds which pursue a more aggressive approach in changing the

[69] The position might be reversed in certain scenarios such as in anticipation of a failure of the deal.

current strategy of their target companies. For example, many hedge funds aim to replace the current management or to significantly alter the capital structure after they invest in a company. Commonly, hedge funds do not acquire large stakes but rather rely on other investors supporting their strategy at shareholders' meetings (Brav, Jiang, Thomas, and Partnoy, 2008; Klein and Zur, 2009).

Empirical results for pension funds suggest that the positive influence of large activist shareholders such as CalPERS on the financial performance of the target firms vanished over time (Nelson, 2006). Specifically, the positive results of earlier studies seem to be driven by the inclusion of only a few extreme targets in the period from 1992 to 1993 and a failure of these studies to control for contaminating events.[70] These results are consistent with recent findings for targets of sovereign wealth funds. Bortolotti, Fotak, Megginson, and Miracky (2009) report a positive announcement return but a significant underperformance of sovereign wealth fund targets over the following twelve months. However, these results might be partly explained by significant investments in the financial sector which were entered too early in the course of the current financial crisis. Indeed, over half of the value of the investments in their database is targeted toward financial service providers. In contrast to these results hedge fund targets are followed by positive abnormal returns even though the stakes they acquire are usually relatively small compared to sovereign wealth funds. Klein and Zur (2009) provide empirical evidence for an increase in shareholder value following hedge fund investments which is basically explained by an increase in leverage and dividend payouts. Brav, Jiang, Thomas, and Partnoy (2008) confirm the outperformance of activist hedge fund targets but explain this effect by changes in the operational strategy of the target companies. Based on a sample of German hedge fund targets Bessler, Drobetz, and Holler (2008) also confirm an increase in shareholder value which varies in the cross-section with respect to certain hedge fund characteristics. However, the potential to generate long-term value added might be questioned as it appears that financial performance is transferred to current periods at the expense of long-term prospects. Moreover, Bessler, Drobetz, and Holler (2010) demonstrate that in bad times, the targets of activist hedge funds generate negative abnormal returns and underperform their control group. This evidence suggests that part of the positive abnormal returns in good times can be explained by enthusiasm of other investors rather than the true skills of hedge fund managers. Rather, a positively biased

[70] For a summary of empirical studies on the "CalPERS effect" see Table 1 of Nelson (2006).

reaction of investors to financial measures such as dividend increases, share buybacks or an increase in the leverage results in exaggerated growth forecasts during good times. This cannot be duplicated in bad times.

These studies suggest that the risk-return profile of companies is not exogenously given for large investors but rather that some investors are able to influence the management of the companies in a favorable way. Thus, in a broad sense active investing is not restricted to the successful selection of stocks but can in some cases also involve consulting and business advice. However, the focus of the remainder of this study is on conventional active investment strategies that take the return distribution of potential investment targets as exogenously given.

1.4 Organizational Design

There are different investment products which are marketed and sold to investors. Mutual funds were probably the first and are still the most popular of these products. However, over time other alternative organizational structures have emerged. The investment strategy is an important determinant of the optimal organizational design or "wrapping". The value chain of asset management companies not only contains the provision of investment management services but also the wrapping of different strategies into products.[71] Existing investment products can be characterized along these two dimensions: (1) the investment style; (2) the organizational fund design with respect to their maturity and the number of outstanding shares (Figure 1.6). Along the first dimension, the investment strategy ranges from active to passive.[72] Along the second dimension, the investment product can be closed-end with a fixed number of outstanding shares and a fixed maturity. Alternatively, the investment product might be open-end with unlimited maturity and a variable number of outstanding shares which adjusts according to the supply and demand from investors.

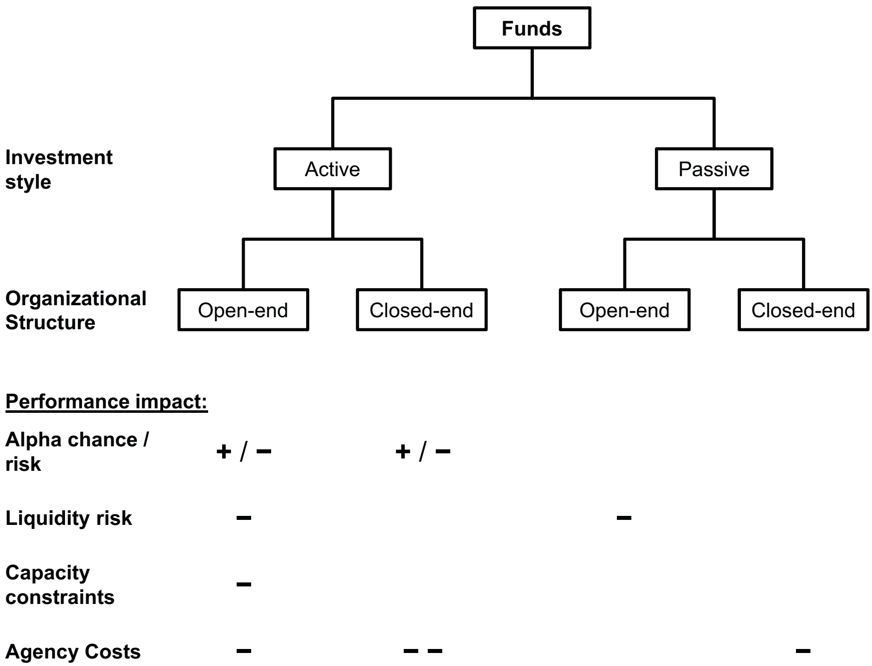
The combination of investment strategy and organizational fund design has important implications for performance. First of all, an active strategy offers the chance to earn positive abnormal returns, yet it also contains the risk of lower returns compared to a passive benchmark. Moreover, portfolio turnover is higher

[71] For example, DWS, the asset management arm of Deutsche Bank, describes itself as "Multi-Wrapper-Asset Manager" because it offers open-end funds, closed-end funds, warrants, structured products and insurance products.

[72] See also the discussion in section 1.3.3.

Figure 1.6: Classification of investment products

This figure presents a possible classification of investment products along two dimensions. The first dimension refers to the investment style and the second dimension refers to the organizational fund design with respect to the maturity and the number of outstanding shares. Below, plus (+) or minus (−) signs indicate whether investment performance is affected positively or negatively, respectively.



for active products compared to passive products, which directly translates into higher transaction costs. Consequently, the gross performance of active investment products must exceed the performance of passive products in order to achieve the same level of net performance.

In addition, open-end products face liquidity risks because investors can freely withdraw money whenever they need or can invest more money into the investment product without any limits. This results in a higher portfolio turnover compared to closed-end products through liquidity-induced trading. The costs resulting from liquidity service can be severe in market turmoil (Coval and Stafford, 2007). Active open-end products face an additional risk from capacity constraints which arise when investors heavily allocate money to recent outperformers.[73] These products then grow in size and suffer from decreasing returns to scale in active management (Berk and Green, 2004). Closed-end products are completely sheltered from inflows and passive investment strategies usually do not suffer from decreasing returns to scale and can therefore be scaled up more easily.[74]

Agency costs are another important determinant of fund performance.[75] Investors (principals) usually delegate their investment decisions to professional portfolio managers (agents). The latter might follow their own interests which are usually not perfectly in line with those of investors. For example, recent underperformers might take on higher risk, i. e. gamble, in an attempt to close their performance gap (Brown, Harlow, and Starks, 1996). Moreover, the investment management company also follows its own interests, for example by strategically transferring performance from one investment product to another product offered by the same family (Gaspar, Massa, and Matos, 2006). The two major regulatory mechanisms of mutual funds that aim to reduce these agency costs are the obligation to redeem fund shares on a daily basis, which facilitates market-based governance, and restrictions with respect to the investment strategy, which should avoid, for example, excessive risk taking. Consequently, passive open-end products provide the highest level of investor protection and the lowest agency costs. First, money can be withdrawn on a daily basis and, second, the investment strategy is heavily restricted and the portfolio composition is usually very transparent. On the other hand, active closed-end products are exposed to the highest level of

[73] Liquidity risk and capacity constraints are discussed in greater detail in section 4.3.
[74] If the weight of certain index constituents exceeds a level which allows liquid trading alternative indexing strategies can be applied as discussed in section 1.3.3.
[75] Potential agency conflicts are discussed in greater detail in section 2.1.

agency costs. It becomes clear from Figure 1.6 that active open-end products face severe impediments when it comes to generating positive abnormal returns.

Specific investment products offered for sale do not in reality follow this basic bimodal specification. Rather, the two dimensions outlined above represent a continuum of concrete specifications. Funds might use different measures to restrict redemptions such as loads, lock-up periods or redemption notice periods. Furthermore, the fund trading mechanism itself can be classified into creation and redemption in cash or creation and redemption in kind. Additionally, fund shares might be listed at an exchange offering an alternative way to trade fund shares. Moreover, investment strategies include a wide variety as discussed in section 1.3.3. Hence, not every fund design is appropriate for every investment strategy but certain optimal combinations exist (Table 1.3). This section presents the most important organizational structures and discusses their advantages and disadvantages as related to different investment strategies. The focus is on economic differences rather than providing a detailed discussion of legal characteristics.[76]

1.4.1 Open-End Funds

Open-end funds, or mutual funds, were probably the first investment product for retail investors and can serve as a forerunner of all other investment products.[77] Already in 1868 the prospectus of the Foreign and Colonial Government Trust in Scotland stated that the aim of the trust was to offer investors of "moderate means" the benefits of a diversified investment in foreign and colonial government stocks (Laux, 2007). The first so-called open-end mutual fund, the Massachusetts Investors Trust, was introduced in 1924. Since then, mutual funds have become an important player in the capital markets and a fundamental element of private retirement savings.

Assets under management of mutual funds amounted to 18 trillion USD at the end of 2005 (Ramos, 2009).[78] Afterwards, they peaked at 26.2 trillion USD in the last quarter of 2007 before dropping off to slightly more than 18 trillion USD in

[76] Due to different legislations mutual funds and other investment products domiciled or registered for sale in different countries differ from each other. Interested readers are referred to Pozen (1999, p. 110 ff.) and the website of the Investment Company Institute (ICI) at http://www.ici.org.

[77] For a detailed discussion of mutual funds see Pozen (1999).

[78] The 20 most important countries together made up about 11.5 trillion USD according to Ramos (2009). Khorana, Servaes, and Tufano (2005) estimate that the 62 largest mutual fund markets together managed total assets of 11.7 trillion USD at the end of 2001.

Table 1.3: Investment strategies and asset classes

This table presents in panel (a) the wrapping of different investment strategies and in panel (b) the wrapping of different asset classes.

	OEF	ETF	Structured Products	CEF	Hedge Funds
(a) Investment Strategies					
Indexing	•	•	•	•	–
Enhanced indexing	•	•	•	•	–
Fundamental indexing	–	•	•	–	–
Quantitative active	•	–	–	–	•
Fundamental active	•	–	–	•	•
Long-Short (restr.)	•	•	•	–	–
Long-Short (unrestr.)	–	–	•	–	•
Activist	–	–	–	–	•
(b) Asset Classes					
Equity	•	•	•	•	•
-Sector	•	•	•	•	(•)
-Region	•	•	•	•	(•)
Fixed income	•	•	•	•	•
Foreign exchange	–	•	•	–	•
Real estate	(•)	–	–	•	•
REITS	(•)	•	•	•	•
Private equity	–	•[a]	•[a]	–	•
Commodities	–	•[a]	•[a]	–	•
Electricity	–	•[a]	•[a]	–	•
Shipping	–	•[a]	•[a]	–	•
Timber	–	•[a]	•[a]	–	•
Volatility	–	•[a]	•[a]	–	•

[a] Via Indices.

the first quarter of 2009 in the course of the financial crisis (IFSL International Financial Services London, Fund Management 2009). These assets were managed by a total of 52,286 funds as of the end of 2005, though only 33,182 of these funds are primary share classes while the others are different share classes of the same underlying portfolio with different fee structures (Table 1.4).[79] The U. S. market is by far the largest mutual fund market in the world with more than 20 percent of all funds by number and more than 60 percent of all assets under management (Table 1.5).[80] On average, the mutual fund industry has grown by 7.87 percent per year from 1996 to 2001 in the 62 major mutual fund markets analyzed by Khorana, Servaes, and Tufano (2005). According to The Boston Consulting Group, the total value of professionally managed assets, including other forms of delegated asset management, rose globally to 111.5 trillion USD in 2009.[81]

Mutual funds are an important part of the economy in developed countries. Total assets under management make up almost one quarter of domestic GDP on average. The net assets of U. S. funds comprised of even 60.4 percent of the local GDP in 2005. In the U. K. this number amounted to 30.3 percent while in Germany it was only 14.0 percent. Per capita wealth invested in mutual funds was 3,969 USD for Germany, 9,226 USD for the U. K. and 21,773 USD for the U. S. in 2005. Equity funds (including balanced funds) in the median country held 11 percent of the domestic equity market capitalization in the major markets.[82] In the U. S., this number was as high as 25 percent. For the bond market, all bond funds in the median country held 6 percent of all outstanding bonds. Considering all primary securities such as equity, bonds and loans, mutual funds held 4 percent in the median country. This number varies significantly in the cross section and is, for example, around 20 percent for the U. S and France.

In general demand side and supply side factors have contributed to the tremendous growth of the mutual fund industry in recent years. Stronger laws, stricter

[79] Consistent with these numbers, Khorana, Servaes, and Tufano (2005) report a number of 55,160 funds at the end of 2001.

[80] Excluding markets not considered in Ramos (2009). The ICI estimates that U. S. mutual funds account for 12 percent of the number of funds and 48 percent of total assets globally in 2010, down from 15 percent of the number of funds and 60 percent of the assets in the year 2000 because other markets developed faster over that period (ICI Mutual Fund Fact Book 2001 and 2010).

[81] Walter (1999) reports a slightly more conservative estimate of total assets under management of close to 30 trillion USD at the end of 1997 for the asset management industry as a whole.

[82] The average amounts to 56 percent but is biased by the two off-shore fund locations Luxembourg and Ireland.

Table 1.4: Key Statistics of Global Mutual Fund Market

This table presents key statistics for the global market for mutual funds. The numbers are based on Khorana, Servaes, and Tufano (2005) (rows denoted by [a]), who analyzed 62 markets at the end of 2001, and Ramos (2009), who analyzed 20 markets at the end of 2005.

	Total	Mean	Median	SD	Min.	Max.
# funds (primary share classes)	33,182	1,659		1,875		
# share classes	52,286	2,614		4,062		
# inv. man. comp. (IMC)		102	50	139	16	642
Total assets (AUM) (bn USD)	11,545.85	577.29		1,664.99		
Av. fund size (m USD)	347.96					
Av. market share of IMC (%)		2.20	2.00	1.70	0.20	6.30
Market share of top5 IMC (%)		57.40	57.10	16.70	28.50	89.40
# new funds / # funds		0.10	0.10	0.02	0.05	0.14
AUM / GDP		0.23	0.25	0.16	0.02	0.60
AUM / capita		6,114	4,886	5,984	29	21,773
AUM / primary assets[a]		0.17	0.04	0.65	0.00	4.85
Equity AUM / market cap[a]		0.56	0.11	2.43	0.00	14.67
Bond AUM / credit market[a]		0.17	0.06	0.54	0.00	3.17
Annual fee (%)		1.12	1.11	0.25	0.54	1.77
Initial fee (%)		1.43	0.89	1.46	0.01	3.91
Redemption fee (%)		0.18	0.05	0.34	0.00	1.39
Total fee (%)		1.44	1.45	0.32	0.86	1.95

Table 1.5: Key Statistics of Domestic Mutual Fund Markets

This table presents key statistics for the most important mutual fund markets around the world. The numbers are based on Khorana, Servaes, and Tufano (2005) (rows denoted by [a]), who analyzed 62 markets at the end of 2001, and Ramos (2009), who analyzed 20 markets at the end of 2005. Countries are denoted as follows: D – Germany; ES – Spain; F – France; I – Italy; JP – Japan; UK – The United Kingdom; US – The United States. Numbers for Australia, Canada and Luxembourg are not available in these studies.

	D	ES	F	I	JP	UK	US
# funds (primary share classes)	1,190	2,691	4,916	1,028	2,635	2,089	6,791
# share classes	1,211	2,692	5,750	1,087	2,635	4,168	18,444
# inv. man. comp. (IMC)	134	101	198	64	64	215	642
Total assets (AUM) (bn USD)	388.35	309.01	986.63	453.76	371.82	649.01	7,567.57
Av. fund size (m USD)	326.34	114.83	200.70	441.40	141.11	310.68	1114.35
Av. market share of IMC (%)	0.70	1.00	0.50	1.60	1.60	0.50	0.20
Market share of top5 IMC (%)	69.90	57.30	54.50	54.00	59.90	28.50	34.30
# new funds / # funds	0.08	0.08	0.09	0.08	0.10	0.07	0.05
AUM / GDP	0.14	0.29	0.48	0.27	0.08	0.30	0.60
AUM / capita	3,969	6,320	13,888	6,656	2,458	9,226	21,773
AUM / primary assets[a]	0.04	0.10	0.21	0.13	0.03	0.06	0.19
Equity AUM / market cap[a]	0.11	0.12	0.27	0.25	0.03	0.13	0.25
Bond AUM / credit market[a]	0.02	0.10	0.22	0.10	0.02	0.01	0.14
Annual fee (%)	1.02	1.36	1.26	1.43	1.15	1.13	0.54
Initial fee (%)	3.52	0.01	1.29	0.57	0.34	3.34	3.91
Redemption fee (%)	0.00	0.02	0.07	0.00	0.17	0.13	1.39
Total fee (%)	1.72	1.36	1.53	1.54	1.25	1.82	1.60

regulation and better investor protection improve the growth of assets under management. Furthermore, assets grow faster in countries with wealthier and more educated populations with lower transaction costs and a higher popularity of defined contribution pension plans (Khorana, Servaes, and Tufano, 2005). Fewer barriers of entry into the asset management industry lead to a larger size of the industry in a country which, in turn, comes along with a higher efficiency in terms of product sophistication, investment performance and fees (Ramos, 2009). Thus, the U. S. market is the most developed mutual fund market. This is also evidenced in the lowest market share of the top-5 investment management companies. Lesser developed markets are usually more innovative by launching more funds per existing fund than more saturated markets.

For their services, investment management companies receive an annual fee which is a fixed percentage of total net assets as compensation for their investment advice and administration. The SEC requires that all funds report the total expense ratio (TER) in their prospectus, which includes all costs that are deducted from the fund's asset on an annual basis such as management fees, 12b-1 fees for marketing and distribution and fees related to legal services, accounting and other administrative services. Usually, an additional one-time sales load or commission is charged by the investment management company at the purchase or sale of the fund.[83] In most markets, mutual funds are either managed and marketed by a full-service provider or managed by an independent investment management company and sold through affiliated or unaffiliated brokers. A significant fraction of the 12b-1 fee and the sales load is usually passed on to the distribution channel as a compensation for marketing efforts.[84]

The fee structure varies considerably across funds and across different countries (Khorana, Servaes, and Tufano, 2009). More complex products tend to charge higher fees. Moreover, mutual fund fees are lower in countries with better investor protection. Some countries rely more on initial and redemption fees than others, primarily as a result of different distribution structures. The annual fees in 2001 were lowest in the U. S. compared to other countries at 0.54 percent, most likely as a result of a large fraction of passive funds and the highest competition among

[83] A front-end load applies when the fund is purchased and a back-end load when the fund is sold.
[84] According to the ICI, 63 percent of 12-b1 fees have been paid to brokers in February 2003 (http://www.ici.org/funds/abt/ref_12b1_fees.html).

investment management companies (Khorana, Servaes, and Tufano, 2005).[85] Indeed, Mahoney (2004) reports an average total expense ratio of all U. S. funds of 1.37 percent in 2003 if all funds were equal-weighted and 0.76 percent if all funds were weighted by their total net assets. Worldwide, the asset-weighted figure was 1.29 percent in 2002 (Khorana, Servaes, and Tufano, 2009). In contrast, average fees of passive index funds were 0.42 percent in 2003, varying between 0.08 and 0.85 percent (Mahoney, 2004). Boldin and Cici (2010) report a slightly higher number of 0.69 percent, 0.32 for institutional index funds and 0.80 for retail index funds. The rise in low-cost index funds or exchange-traded funds in recent years led to a decrease in average fees in the U. S. (Ramos, 2009).[86]

With respect to distribution and marketing costs, Mahoney (2004) documents that 56.1 percent of all U. S. mutual funds charge sales loads and 65,8 percent charge 12b-1 fees (September 2003). Only 31.1 percent of all funds are classified as pure no-load funds charging neither a sales load nor 12b-1 fees. In total, investors paid approximately 2.8 billion USD for loads and 9.5 billion USD for 12-b1 fees in 2003 in the U. S. (Mahoney, 2004). For Australian funds, Parwada (2003) reports average relative spreads between purchase and redemption prices of equity funds of 1.65 percent. However, in many cases investors pay less than the maximum load stated in the prospectus, thus the above figures may be slightly misleading (Christoffersen, Evans, and Musto, 2007).

In the U. S., open-end funds are a special type of a management company which is one of the three major types of investment companies according to the Investment Company Act of 1940 (ICA).[87] An investment company is a company whose main business objective is holding securities of other companies purely for investment purposes. Investment companies have their own board of mainly independent directors. These directors approve an advisory contract with an investment advisor that is legally independent of the fund itself and oversee the investment advisor. Thus, in the U. S. the SEC delegates this task to the board

[85] For earlier periods, Gruber (1996) and Carhart (1997) report average management fees of 1.1 percent for U. S. equity mutual funds.

[86] For a more detailed discussion of mutual fund fees in different countries see also Khorana, Servaes, and Tufano (2009).

[87] The three major types of investment companies are face-amount certificate companies, unit investment trusts and management companies according to ICA § 4. The latter can further be subdivided into open-end companies or closed-end companies according to ICA § 5 (a) and into diversified companies and non-diversified companies according to ICA § 5 (b).

of directors (Haslem, 2010).[88] The assets of the fund are held by a custodian in a segregated account in order to shelter them from a potential bankruptcy of the investment advisor. The investment advisor manages the assets of the fund on behalf of its shareholders who in turn share the profits and losses and pay expenses on a proportional basis.[89] Open-end management investment companies are required to report a daily net asset value, i. e. the sum of the market value of all assets held by the fund, at which fund shares can be bought or sold directly from the investment management company.[90] Accounting statements are disclosed on a semi-annual basis and externally audited, though many U. S. funds voluntarily disclose their portfolio holdings at a quarterly frequency.

In the U. S., management companies, i. e. open-end funds and closed-end funds, are further subdivided into diversified and non-diversified funds. According to ICA § 5 (b) (1) at least 75 percent of the value of the total assets of a diversified fund may not be invested into securities of any one issuer to more than 5 percent of the fund's assets and may not make up more than 10 percent of the voting securities of any one issuer. Consequently, a diversified fund holds at least 16 different securities in its portfolio in the U. S. (15 · 5 percent plus 1 · 25 percent). However, even though funds can choose not to be classified as diversified fund in the U. S. most funds do so because of a preferential tax treatment of diversified funds compared to non-diversified funds. In other countries, such as Germany, funds are legally required to be diversified.[91] Note that this definition of diversification

[88] With respect to the oversight of the fund manager and the investment management company other countries follow a different approach. For example, in Germany, both the custodian bank and the German capital market supervision agency (Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin) oversee the investment management company.

[89] Other countries have similar legal structures. For example, in Germany, the so-called "investment triangle" (Investment-Dreieck) dictates the separation of the investment advisor (Kapitalanlagegesellschaft, KAG, Investmentgesetz (InvG) § 6 (1), § 2 (4) and § 30 (1,3)), the custodian bank (Depotbank, InvG § 20) and the separate assets (Sondervermögen, InvG § 30). Similar to the U. S., the investment advisor manages the fund's assets on behalf of its investors. The regulation governed by the investment triangle has been watered down recently in § 2 (5) InvG in that it allows an investment corporation (Investmentaktiengesellschaft). In this case, the investment management company and the assets are the same entity. The company objective of the investment corporation is the management of the corporation's assets according to the diversification principle.

[90] If a fund charges a front-end load or back-end load the ask price of fund shares is above or the bid price below the net asset value, respectively.

[91] Specifically, a maximum of 49 percent of total asset may be held in cash. Furthermore, a maximum of 10 percent of total assets may be invested into securities of any one issuer and the combined share of total assets that exceeds a maximum of 5 percent of the total assets invested into securities of any one issuer may not exceed 40 percent of total assets (InvG § 60). This can be interpreted as an exception for 40 percent of a fund's total assets that allows the fund manager to expand the 5 percent limit up to 10 percent. Consequently, a German fund holds at least 16 securities (4 · 10 percent plus 12 · 5 percent). Exceptions

does not rule out that a fund invests all of its assets entirely into one industry or geographical area. Diversification is defined based on single securities which might not universally correspond to the economic meaning of diversification.

With respect to taxes, U. S. mutual funds qualify under fairly general conditions for a pass-through tax treatment according to § 851 (b) (4) of the Internal Revenue Code (IRS) if certain requirements with respect to distribution and diversification are met. In this case, investors are treated as if they invested directly into the shares held by the fund.[92] Capital gains, dividends and interest are then distributed to the fund's investors and the fund itself does not have to pay any corporate taxes.

The investment strategy of mutual funds is restricted through their organizational design and regulatory environment with respect to the use of derivatives. The daily redemption feature imposes certain liquidity requirements on the investable securities.[93] Thus, the possibility of open-end funds to provide liquidity transformation, i. e. make illiquid asset classes more liquid, is restricted because they face the risk of large capital outflows. Moreover, the open-end structure of mutual funds prevents fund managers from pursuing long-term investment strategies because they face the risk of outflows when convergence to fundamentals is unlikely to be smooth or rapid (Stein, 2005). Combined with regular performance assessments, this results in mutual funds focusing on short-term strategies with the risk of earning only low abnormal returns. Furthermore, arbitrage of large long-term mispricings such as the technology bubble is almost infeasible for open-end fund managers.[94] Closed-end funds could more easily follow long-term strategies (Bers and Madura, 2000).

apply to index funds (InvG § 63).

[92] Note that this might be different in other legislations. For example, after the German Corporate Tax Reform in 2008 (Unternehmensteuerreform 2008) mutual fund investments are treated favorably compared to a direct investment because portfolio rebalancing on the fund level does not generate a tax liability.

[93] For example, the German InvG does not impose any specific liquidity requirements. However, InvG § 46 ff., specifying securities that are permitted to be held by mutual funds, indirectly demands a certain degree of liquidity. According to InvG § 60 (5) only 20 percent of total asset may be invested in derivatives and the market risk of the funds may no more than double as a result of this investment (InG § 51). Furthermore, InvG § 59 rules out short sales. For a more detailed discussion see section 2.2.1 and Walter (1999, p. 27 ff.).

[94] Stein (2005) even argues that it is riskier for a mutual fund or hedge fund to bet against overvaluation during a bubble as compared to a manager of an overpriced firm by issuing equity. If the market would rise even further, the fund manager faces the risk of liquidation while the corporate manager only has a large amount of cash and the opportunity costs of not timing the equity issuance better.

In general, mutual funds can be classified into different groups according to their investment universe. The major groups are equity funds, bond funds and money market funds. The latter invest primarily in short-term fixed income securities issued by governmental organizations. However, some money market funds also include commercial papers of banks and companies with high credit ratings or asset-backed securities in their portfolios. Open-end real estate funds, which are very common in Germany, invest the money of their investors in commercial property and the returns mainly stem from rental income and appreciation in the price of the properties owned by the fund (Sebastian and Tyrell, 2006; Bannier, Fecht, and Tyrell, 2008). Funds of funds are investment vehicles that invest in other funds. The objective might be to identify skilled managers who produce alpha or to increase the diversification. However, as investors have to pay fees on both levels the advantage of these products remains questionable. Another more recent product innovation popular in the U. S. are 130/30 funds or hedged mutual funds (Agarwal, Boyson, and Naik, 2009). These funds are conventional mutual funds that allow a more extensive use of derivatives in order to follow hedge fund style investment strategies. In Europe, the European Union proposed the Undertakings for Collective Investment in Tradable Securities (UCITS) directive which in its third release also relaxes the use of derivatives.[95]

1.4.2 Exchange-Traded Funds

Exchange-traded funds are usually governed by the same legal rules as mutual funds.[96] U. S. exchange-traded funds were introduced in 1993 and are usually organized as management companies even though some are organized as unit investment trusts. Unit investment trusts offer participation in a fixed portfolio of securities, i. e. the composition of the portfolio does not change significantly over time.[97] The major differences between exchange-traded funds and mutual funds refer to the trading mechanism and to the investment style.

Conventional mutual fund shares are traded in a cash transaction directly with the mutual fund itself. The price of this transaction equals the net asset value

[95] UCITS allows the marketing of mutual funds across national boundaries within the European Union if the fund and the fund manager are registered within a country of the European Union. In 2005 about 77 percent of the assets of all funds in countries of the European Union comply with these rules and qualify as UCITS (Ramos, 2009).

[96] For a more detailed discussion see Gastineau (2001), Elton, Gruber, Comer, and Li (2002), Kostovetsky (2003) and Bessler and Lückoff (2007a).

[97] Note that the definition of unit trusts in the U. K. is different.

of the fund which is determined once per trading day at a specific time (forward pricing rule). In contrast, exchange-traded funds have an innovative market model and are continuously traded in a secondary market such as the XTF segment of Deutsche Börse. If excess demand or excess supply for a specific exchange-traded fund exceeds a certain level the price of the exchange-traded funds deviates from the indicative net asset value (iNAV), i. e. the continuously calculated net asset value of the exchange-traded fund based on its underlying securities. Next, fund shares are created or redeemed, respectively, by the designated sponsor or market maker through an in-kind transaction (rather than a cash transaction as with conventional open-end funds). In the case of excess demand for exchange-traded fund shares, i. e. the price of the exchange-traded funds exceeds its iNAV (premium), the designated sponsor acquires the securities held by the exchange-traded fund in the exact composition of the tracked index (creation basket). The creation basket plus a cash position is then delivered to the investment advisor (or more precisely to the custodian) in return for the corresponding number of exchange-traded fund shares (in-kind creation). The gap between the price of the exchange-traded fund and its iNAV closes as a response to the higher supply of exchange-traded fund shares. In the case of excess supply of exchange-traded fund shares, i. e. the price of the exchange-traded fund is below its iNAV (discount), the transaction is reversed (in-kind redemption).

This arbitrage mechanism reduces deviations of the exchange-traded fund price from its iNAV and brings supply and demand back to the equilibrium. Additionally, the costs for the liquidity service are allocated to investors with liquidity demand rather than shared by all fund investors (Guedj and Huang, 2008). However, the ability of exchange-traded funds to transform illiquid assets into liquid securities is limited because the creation and redemption in kind process requires a high level of liquidity for an efficient functioning.[98] For U. S. exchange-traded funds the creation and redemption in kind mechanism additionally offers the possibility to significantly reduce unrealized capital gains of the fund (Poterba and Shoven, 2002). Specifically, the exchange-traded fund manager first hands over the securities with the lowest purchasing price in redemption transaction. This reduces the taxes paid by fund investors. In other jurisdictions, as, for example, in Germany, this tax advantage does not apply due to different tax rules.

[98] Indeed, Engle and Sarkar (2006) provide empirical evidence that the premium or discount of exchange-traded funds is negatively related to the liquidity of their underlyings.

The second important difference between exchange-traded funds and conventional mutual funds is the fact that exchange-traded funds usually follow passive or rules-based investment strategies. Originally, exchange-traded funds replicated the performance of broad market indices such as the S & P 500 in the U. S. or the DAX in Germany. More recent products differ from this approach and apply alternative investment strategies.[99] For example, many exchange-traded funds track relatively concentrated indices which focus only on a certain region or sector. This allows investors to effectively use passive products for active factor-timing strategies according to equation (1.4). Thus, concentrated exchange-traded funds are an efficient tool for trading sector- or country-specific systematic risks. Moreover, some exchange-traded funds have moved toward semi active rules-based investment strategies. Specifically, dividend-strategy based exchange-traded funds choose only the constituents of a specific index with higher than median dividend yields. Fundamental index exchange-traded funds choose securities based on a combination of P/E ratios, cash flows, revenues, sales or other fundamental information (Arnott, Hsu, and Moore, 2005). Short exchange-traded funds offer the participation in the negative performance of an index. Completely active funds with discretionary strategies based on fundamental research still have yet to be established.

Consequently, exchange-traded funds offer the same services as conventional mutual funds but no active management, resulting in significantly lower fees for exchange-traded funds.[100] Technically, they provide cheap beta exposure but do not aim to produce alpha.

1.4.3 Retail Structured Products

In recent years, especially in European markets such as Germany and Italy, conventional mutual funds face strong competition from retail structured products (also warrants or certificates). For example, in Germany 285,584 retail structured products existed at the end of 2009 according to Deutscher Derivate Verband (DDV), the German association of the 14 largest issuers of retail structured

[99] See also the discussion of alternative index strategies in section 1.3.3.

[100] Specifically, equity exchange-traded funds on average charge fees of 37 basis points while bond exchange-traded funds charge 16 basis points. Open-end funds, in contrast, charge between 84 and 175 basis point for equity investments and between 47 and 101 basis points for bond investments according to Morningstar and Barclays Global Investors (Barclays ETF Landscape May 2009).

products, compared to only 6,477 retail mutual funds, according to BVI Bundesverband Investment und Asset Management e. V., the German association of investment management companies. Retail structured products are legally constructed as bonds issued by banks with a final payoff that depends on the price(s) of its underlying(s). These underlyings might be single stocks, baskets of stocks, interest rates, commodities or market indices. Thus, retail structured products have a limited maturity and are traded at an exchange during their lifetime. The much lower regulation of retail derivatives as compared to mutual funds especially in Germany has probably contributed much to the tremendous growth of these products. Investment banks as issuers of these products can respond much more quickly to recent market trends, such as the popularity of BRIC (Brazil, Russia, India, China) investments, than investment management companies because the launch of a new mutual fund requires a lot more paperwork and time due to stricter regulations. Furthermore, the administration of retail structured products is much leaner compared to mutual funds.

A major difference between retail structured products and mutual funds is the non-linear payoff structure of these products. On the one hand, this offers the advantage to construct derivatives that correspond closely with the risk preferences of investors. Especially after the burst of the technology bubble in March 2000 investors were in search of presumably save investments which largely contributed to the growth of investment products with build in capital guarantees. Certain retail structured products, such as Garantiezertifikate (guarantee certificates), offer a full capital guarantee and other structures, such as Diskountzertifikate (discount certificates) or Bonus-Barriere-Zertifikate (bonus-barrier certificates), at least reduce potential losses up to a certain point. However, leverage products also exist and can be used by retail investors to increase their market exposure as long and short positions. On the other hand, these complex payoff structures make the pricing of retail derivatives very complicated. Most retail investors are probably unable to completely understand and anticipate price movements of these products. The payoffs of retail structured products can be duplicated by option strategies. Thus, the service these products provide to retail investors mainly refers to the packaging of different options into one product. As banks, in contrast to retail investors, can use over-the-counter (OTC) options they can offer access to certain markets or positions which could not be replicated by retail investors on their own. This offer some scope for liquidity transformation through retail structured products. As long as the issuer can hedge his exposure, even illiquid assets can be used as underlying. However, the issuer does not have the obligation to buy back the derivatives whenever the investors want to sell. Thus, when the liquidity of the underlyings is low, the investors can only sell their derivatives on the secondary market and eventually have to bear a significant liquidity discount.

Surprisingly, sellers of retail structured products usually do not charge a management fee for their products. However, they do not offer their service for free either. In many cases the underlyings of retail structured products are price indices or the payoff only depends on the price of the underlying stock but not on the dividends paid over the lifetime of the derivative. Thus, the issuers of retail derivatives collect the dividends of their hedge position but do not pass these on to the investors. Furthermore, sellers of retail derivatives can earn profits in secondary market trading of their products. Even though all retail structured products are listed at an exchange this does not guarantee fair prices. Due to the large number of retail derivatives the liquidity is very low and in many cases the issuer of the derivative is the counterparty in transactions. Recent research has documented a life cycle of derivative prices (Stoimenov and Willkens, 2005; Willkens and Stoimenov, 2007). Specifically, prices of retail structured products on the issuance day in the primary market are on average 2.13 (for the DAX index as underlying) to 3.89 (for DAX stocks as underlying) percent higher than the fair value based on a duplication with exchange traded options (Stoimenov and Willkens, 2005). This price gap acts like a hidden front-end load. Furthermore, shortly after the derivative has been issued investors largely buy the derivative via the exchange while the issuer sells. This reverses over the life cycle and investors tend to sell shortly before the product matures while the issuer buys back remaining outstanding shares of the derivative. Stoimenov and Willkens (2005) and Willkens and Stoimenov (2007) show that the price of the derivative is initially above its fair price derived from a duplication of the derivative based on exchange-traded options and falls below its fair price over the life cycle. Thus, the issuers sell at a premium in the beginning and buy back at a discount to fair value shortly before the maturity of the derivative. The gains made by these transactions allow the issuers of the retail structured products to offer these products without an "official" management fee.

In summary, even though retail structured products offer tailor made payoff structures the pricing and implicit costs of these products remain opaque. Furthermore, in contrast to mutual funds investors of retail structured products bear the default risk of the issuer. This fact had long been neglected by investors, but they became aware of it when Lehman Brothers, one large issuer of warrants and retail structured products, collapsed in September 2008. Since then, some efforts have been started to reduce the opaqueness of the products and to improve the transparency of the market. Some issuers even construct products that do not face the default risk of the issuer because they use the hedge position as collateral. However, it remains a question of whether or not retail structured products can be a serious competition for mutual funds in the long run. In the U. S., with much stricter investor protection and eventually more sophisticated retail investors, no significant market for retail structured products has emerged so far.[101]

1.4.4 Closed-End Funds

A closed-end management investment company (closed-end fund, CEF) is another type of management company according to the Investment Company Act of 1940. The total net assets managed by closed-end funds declined to 188 billion USD in 2008 after 313 billion USD in 2007 but reached again 228 billion USD in 2009 (ICI Investment Company Factbook 2009 and 2010). This corresponds to less than 2 percent of total assets managed by mutual funds. The largest fraction of closed-end fund assets is invested in rather illiquid securities such as municipal bonds. In total, 60 percent are invested in bonds and 40 percent in equity. The major difference between open-end and closed-end funds is that the maturity of closed-end funds and the number of outstanding fund shares is fixed at the initial offering of the fund. Thus, fund shares cannot be created or redeemed as with open-end funds. However, as closed-end fund shares are usually traded at a secondary market they still offer a certain degree of liquidity.[102] The mechanism that brings supply and demand for closed-end fund shares back into equilibrium is the price of closed-end fund shares while the number of outstanding closed-end fund shares remains fixed. As a result, the market price of closed-end funds fluctuates around

[101] Only a lesser-known type of investment company under the Investment Company Act of 1940, a face-amount certificate company, exists. This type of investment company is comparable from its organizational design to retail structured products even though it does not offer non-linear payoff structures. However, after tax law changes have eliminated the tax advantage of face-amount certificate companies only a few of them are still in operation today.

[102] Even though closed-end funds differ from retail structured products in their legal structure their economic characteristics are very similar.

its net asset value according to supply and demand (Lee, Shleifer, and Thaler, 1991; Pontiff, 1996). In contrast, the equilibrium mechanism for open-end funds is an adjustment of the number of outstanding shares while the price of open-end funds always equals its net asset value. Anderson, Coleman, Gropper, and Sunquist (1996) argue that the closed-end structure results in a lack of external governance because managers of these funds do not face the risk of withdrawals.

Most of the academic research on closed-end funds has concentrated on explaining why closed-end fund shares tend to trade at a discount on average after the fund usually has been issued at a price above its net asset value.[103] Closed-end fund discounts are subject to a large cross-sectional variation and tend to revert to the mean over time (Lee, Shleifer, and Thaler, 1990). Potential explanations range from behavioral factors such as investor sentiment (Lee, Shleifer, and Thaler, 1990, 1991; Doukas and Milonas, 2004), miscalculation of the net asset value due to restricted holdings (Lee, Shleifer, and Thaler, 1990), market segmentation (Chan, Jain, and Xia, 2008) and over tax issues to managerial skills (Lee, Shleifer, and Thaler, 1990; Wermers, Wu, and Zechner, 2007; Berk and Stanton, 2007). However, no agreement has been reached so far and, consequently, the discount of closed-end funds remains a puzzle in finance. In practice, some closed-end funds have been converted into exchange-traded funds in order to remove the discount.

1.4.5 Hedge Funds

Hedge funds are alternative investment vehicles which have grown in importance during recent years. The total assets of hedge funds peaked at 1.93 trillion USD in the second quarter of 2008 and declined to 1.43 trillion USD by June 2009 (Hedge Fund Research). Hedge funds differ from mutual funds with respect to their investment strategy and the incentive contract between the investors and the hedge fund manager. In contrast to mutual funds, hedge funds are usually organized as private vehicles such as partnerships in order to circumvent the regulatory pressure which is faced by mutual funds.[104] The investment strategies and

[103] For a comprehensive survey see Dimson and Minio-Kozerski (1999).

[104] Under the Investment Advisor Act, the SEC proposed the following regulation for hedge funds since February 2006: registration with SEC, designation of a Chief Compliance Officer, implementation of certain policies and a code of ethics to ensure that action is taken in the best interest of clients. The investment strategy is not directly addressed in this regulation. However, this rule is currently not being enforced as a federal appeals court decision recently invalidated the rule.

compensation contracts of hedge funds are not allowed for mutual funds. Thus, choosing another wrapping is the only way to offer these services, at least to a subset of qualified investors.

As hedge funds do not follow any known benchmark the correlation of their returns with other asset classes is usually very low, though the correlation increases in recent periods, especially during market distress (Bessler and Holler, 2009). Thus, if judged in a conventional μ-σ-framework they improve the risk-return profile of investors' portfolios. However, this does not appropriately account for the different risk characteristics of hedge fund investments. Specifically, hedge fund returns are not normally distributed, but usually display negative skewness and excess kurtosis (fat tails) (Bessler, Drobetz, and Holler, 2007). Furthermore, extreme events might happen with a higher probability than implied by conventional value-at-risk considerations based on the normal distribution. This has to be considered when hedge fund performance is evaluated (Bessler and Lückoff, 2007b). Fung and Hsieh (2004) suggest extending conventional factor models for performance evaluation by factors that explicitly account for non-linearities in hedge fund returns. Indeed, recent studies on hedge fund performance conclude that on average these products offer alphas of around five to seven percent annually (Kosowski, Naik, and Teo, 2007; Agarwal, Boyson, and Naik, 2009). Agarwal, Boyson, and Naik (2009) argue that this can be partly explained by higher manager skills as well as by lower regulation. Naik, Ramadorai, and Stromqvist (2007) suggest that capacity constraints exist in certain hedge fund styles. In particular, strategies relying heavily on the liquidity of the underlying markets, such as relative value, fixed income and emerging markets, suffer from the tremendous growth of hedge funds in recent years. Consequently, some hedge funds impose redemption restrictions, such as lock-up and redemption notice periods. This allows them to invest in illiquid strategies and to gain 4 to 7 percent higher returns than hedge funds without redemption restrictions (Aragon, 2007).

Another important difference between hedge funds and mutual funds refers to the incentive contract. While mutual funds charge a volume-based fee proportional to their assets under management, hedge funds add a performance fee. For example, the management receives 20 percent of the return that exceeds a certain threshold (hurdle rate). To avoid that managers benefit from high returns that only compensate earlier losses of the fund these contracts usually contain a high watermark below which no performance fee is paid. This asymmetric fee contract induces an option-like payoff structure as managers benefit from high returns but do not suffer to the same degree from low returns (Fung and Hsieh, 1999). In order to reduce the incentive to pursue risky bets hedge fund managers are usually expected to hold a significant share of the fund themselves. However, this might lead to a risk averse investment behavior which has to be weighted against the incentives to increase risk due to the option-like payoff structure. Kouwenberg and Ziemba (2007) argue that around one third of the hedge fund asset should be held by the managers.

1.4.6 Comparison of Different Structures

The differences between the organizational structures are summarized in Table 1.6. All investment products organized as mutual funds, including exchange-traded funds and closed-end funds, underly restrictive regulation and, consequently, offer a high degree of investor protection. This also includes a protection of the assets against a default of one of the involved parties. Hedge funds are subject to less regulation and therefore bear higher risks for investors. Depending on their investment strategy they might be exposed to significant counterparty risk in OTC derivative contracts. Retail structured products do not protect the assets of the investors against a default of the issuer. This is especially relevant as the issuer is usually a bank that operates in several other business lines. Thus, losses completely unrelated to the retail structured products business might lead to a default which affects all outstanding structured products.

With respect to the investment strategy hedge funds are the most active investors facing the lowest investment restrictions. These are followed by active mutual funds and active closed-end funds. However, even within the group of active funds some are more active, such as 130/30 funds (Agarwal, Boyson, and Naik, 2009), while other active funds in fact follow their benchmark very closely. Cremers and Petajisto (2009) refer to the latter group of funds as closet indexers. Passive mutual funds, passive closed-end funds, exchange-traded funds and retail structured products usually follow passive strategies. However, also within this group some products are more active than others. For example, some exchange-traded funds implement rules-based investment strategies that aim to outperform passive market indices while others just try to track these indices as closely as possible. The latter are the least active products even if tracking an index

Table 1.6: Characteristics of different investment products

	Open-end funds		Exchange-	Structured	Closed-end	Hedge funds
	active	passive	traded funds	products	funds	
(a) Construction						
Legal status	investment company		investment comp.	bond	investment comp.	limited partners.
Regulation	high		high	low	high	low
Default risk	no		no	yes	no	yes
Number of issued shares	variable		variable	constant	constant	variable[a]
Maturity	open-end		open-end	limited	limited	open-end
(b) Investment Strategy						
Investment style	active	passive	passive	passive	active[b]	active
Degree of diversification	high	high	medium – high	medium – high	medium – high	low
Portfolio transparency	low	high	high	high	low[c]	low
Derivatives use	restricted		restricted	unrestr.	restricted	unrestr.
Return source	beta and alpha	beta	beta	NA[d]	beta and alpha	alpha
(c) Costs						
Management fees	medium – high	low	low	low	medium	high
Indirect costs	medium	low	low	high	low	medium
Tax efficiency	medium	low	high[e]	low	medium	low
(d) Liquidity						
Continuous trading	no[f]		yes	yes	yes	no
Trading venue	direct (cash)		exchange / OTC[g]	exchange / OTC	exchange	NA[h]
Liquidity of underlyings	medium		high	medium	low	low
Short positions	no		yes	no[i]	no	no

[a] Sometimes restricted. [b] Sometimes passive. [c] High for passive closed-end funds. [d] Depends on underlying. [e] Only U.S. [f] Yes if listed at fund exchange. [g] Also in-kind transaction with market maker. [h] Sometimes exchange listed. [i] Products with short exposure available.

is interpreted as some kind of active management by some researchers because weights adjust procyclically (Arnott, Hsu, and Moore, 2005; Lo, 2008; Ranaldo and Häberle, 2007). The level of diversification is usually higher the higher the degree of delegation. For example, hedge funds usually follow only one certain strategy which results in a very focused exposure. In contrast, balanced mutual funds can even distribute their assets over many asset classes and, consequently, offer a diversified portfolio. As market indices are usually not constructed following considerations based on modern portfolio theory they are not perfectly diversified in reality. Portfolio transparency is usually reciprocal to the degree of activeness. For passive products the portfolio composition follows objective rules and, therefore, offers a high degree of transparency on a daily basis. Mutual funds are required to disclose their portfolio semi-annually. Hedge funds usually do not disclose their trades to investors even though large investors or funds of funds might be able to get more detailed information about the trades of hedge funds.

Management fees are usually reciprocal to the complexity of the investment strategy. However, management fees only cover the direct and obvious fees that are stated in the prospectus. Indirect costs consist of all other costs the investor has to bear but which are not obviously declared in the contracts. These include direct and indirect transaction costs on the portfolio level such as brokerage fees and market impact, respectively, which also increase with the illiquidity and complexity of the investment strategy. Retail structured products are a special case as they do not charge management fees. Rather, issuers of these products collect dividends from the underlyings without passing them on to investors and earn trading profits in the secondary market. Specifically, the trading in the secondary market is usually dominated by the issuer due to the extremely high number of offered products. It is questionable if this guarantees a fair price discovery. Indeed, several studies have documented a life cycle of prices of retail structured products (Stoimenov and Willkens, 2005; Willkens and Stoimenov, 2007). These studies suggest that at their issuance in the primary market, and shortly thereafter in the secondary market prices, are usually higher than the fair price implied by an option pricing model. This is the period when demand from investors is relatively high and the issuer is usually on the sell side of transactions. This reverses over the life of the structured product and shortly before expiration of the products prices tend to be lower than their fair value. During this period investors tend to sell their structured products and the issuer is more likely to buy back his previously issued structured products. Thus, it is hard for investors to take the total of all costs into consideration when they choose from different investment products. However, in general more transparent products with higher competition in less complex investment strategies tend to imply the lowest costs.

In addition to costs, taxes play an important role as investors care about after-tax returns (Dickson, Shoven, and Sialm, 2000; Bergstresser and Poterba, 2002; Fong, Gallagher, Lau, and Swan, 2009). The returns of different investment products are taxed differently and the managers of these products have different possibilities to efficiently manage the taxes.[105] For example, while rules-based or passive products usually do not consider tax implications the managers of active mutual funds have the possibility to take the tax effects of their trades into account and can optimize the after-tax returns to a certain degree. However, exchange-traded funds provide a higher degree of tax efficiency as they can reduce the unrealized capital gains to a minimum through the creation and redemption in kind process (Poterba and Shoven, 2002). Specifically, if exchange-traded fund shares are redeemed, the exchange-traded fund manager delivers those stocks with the highest unrealized capital gains as a transfer in kind does not induce a tax event for the investor. However, due to a different tax legislation in Germany this advantage does not apply to German exchange-traded funds. The tax advantages of retail structured products in Germany and face-amount certificate companies in the U. S. have been abolished.

Usually, exchange-traded funds, retail structured products and closed-end funds are listed and continuously traded at an exchange while mutual funds and hedge funds are not. However, some efforts have been made in Germany to set up fund exchanges where open-end funds can be traded in a secondary market. The investment strategy and the trading mechanism have a direct impact on the required liquidity of the underlyings. Underlying assets of open-end funds should provide a certain level of liquidity as daily fund flows might force the fund manager to sell off some of the assets. This might lead to severe problems if their liquidity is low and the discount that has to be realized following a forced sale is high.[106]

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[105] Hence, the tax implications of different investment products depend on the national legislation as well as on investor characteristics and, therefore, it is impossible to draw general conclusions.

[106] For example, German open-end real estate funds suffered from high outflows during the end of 2008 and, as a result, had to be closed in order to avoid fire sales of real estate assets. For a discussion see Sebastian and Tyrell (2006) and Bannier, Fecht, and Tyrell (2008).

Exchange-traded funds require a high degree of liquidity from their underlying portfolio as otherwise an efficient functioning of the creation and redemption in kind process cannot be guaranteed. However, some exchange-traded funds track illiquid or non-investable indices and do not offer creation or redemptions in kind. These exchange-traded funds do not satisfy the strict definition of exchange-traded funds and are more closely related to passive open-end funds or even retail structured products from their characteristics. Retail structured products usually do not demand a high degree of liquidity from the index they track by construction. However, as the issuer faces the need to hedge his exposure, the underlying index or the investment strategy should be hedgeable with low costs. As issuers of structured products usually have access to OTC markets this restriction is not overly binding. This is especially true as the issuer can hedge part of his exposure by netting it with other issued structured products (macro-hedging). Closed-end funds and hedge funds do not require a high degree of liquidity from their underlying assets because closed-end funds do not face any risk of redemptions and hedge funds usually have negotiated redemption restrictions with their investors. Moreover, both products can easily benefit from an investment in illiquid assets or strategies and earn an illiquidity premium in the sense of Amihud (2002).

1.5 Discussion

Based on the theoretical analysis in this chapter it is argued that market frictions lead to the existence of intermediaries such as banks and mutual funds. Due to asymmetric information in the capital market and economies of scale in information production many retail investors delegate their investment decisions to professional portfolio managers. Their aim is to earn abnormal returns relative to a passive benchmark based on these managers' superior investment skills. This delegation, however, at the same time gives rise to a two-layered agency problem, among the investors, the investment management company and the portfolio manager.

One important measure to reduce agency conflicts and to assure an efficient product market is the open-end structure of mutual funds. Thus, investment products can be broadly characterized by their investment style, active versus passive, and by their organizational structure, open-end versus closed-end. Active funds provide the chance to generate positive abnormal returns, i. e. positive alpha, but at the same time face higher agency conflicts compared to passive funds because the portfolio manager of an active fund is less restricted in the investment decisions. Open-end funds further reduce agency costs compared to closed-end funds because they facilitate efficient external governance, but at the same time open-end funds suffer from liquidity risk due to unexpected fund flows. Additionally active open-end funds suffer from potential capacity constraints stemming from decreasing returns to scale in active management: once the asset base increases, the potential to generate positive alpha is reduced. Thus, an analysis of the advantages and disadvantages of active versus passive funds needs to consider the performance impact of the open-end versus closed-end structure and the complex tension field between alpha potential, agency costs, liquidity risk and capacity constraints.

2 Agency Conflicts

In September 2003 the mutual fund industry was hit by its first big scandal in history (e. g. Zitzewitz, 2006). Several investment management companies were accused of improprieties regarding pricing calculations and trading deadlines. Favorable clients were allowed to trade on a high frequency in mutual fund shares generating profits at the expense of long-term fund investors. In return, these clients "parked" large amounts of assets into other funds from the same investment management company generating fee income. These actions were a violation of the fiduciary standards of the mutual funds and were in some cases illegal.[107] This scandal has spawned a discussion about conflicts of interest in delegated management. The efficiency of governance mechanisms, manager compensation as well as the appropriateness of the fee level in general have been addressed.

It is acknowledgeable that agency problems are inherent in delegated asset management. However, as a natural consequence of market forces, the interests of all service industries diverge from those of their clients. So what makes the mutual fund industry so special that it requires its own regulatory environment?[108] First of all, mutual funds pool the assets of a large number of investors and are wholly owned by these investors. However, unlike regular companies mutual funds do not have direct employees and do not generate profits by selling certain products or services to other businesses or consumers.[109] Outside companies, such as the investment management company, provide investment advice and other services based on a contractual agreement. However, it appears that many fund investors do not see themselves as owners of the fund but rather as customers purchasing investment advice from the investment management company (Tkac, 2004). Effectively, they are both. The fact that they are owners of the funds' assets entitles

[107] For a more detailed discussion see section 2.1.3.3.

[108] However, the regulation of the mutual fund industry still differs from other professions that also entail a high level of responsibility and might have severe consequences for their clients. For example, medical doctors, lawyers and architects all need a certain form of license to carry out their profession and are usually subject to a specific professional code of conduct, while this is not true for asset managers. Only in the case of wrongdoing, asset managers can be banned from the profession for a certain period of time.

[109] Instead, the investment management company generates profits by selling investment advice.

P. Lückoff, *Mutual Fund Performance and Performance Persistence,*
DOI 10.1007/ 978-3-8349-6527-1_3,

them to a higher degree of information disclosure, especially with respect to the portfolio holdings.

In the context of this study, agency conflicts in delegated asset management are highly important. First, they might be partly responsible for average underperformance of mutual funds because return maximization is not the common objective of investors, fund managers and the investment management company. Second, and even more important, the open-end fund structure is an important instrument for reducing agency conflicts but at the same time reduces the ability of fund managers to persistently outperform the market even if they possess true investment skills. Specifically, only if fund investors are free in moving their assets from poorly performing fund managers toward those with presumably higher skills and better aligned interests, agency conflicts can be reduced and investor performance improved. However, capacity constraints and equilibrium mechanisms, which will be discussed in chapter 4, explain why exactly this investor behavior, moving assets from poorly performing funds to presumably outperforming funds, reduces the ability of fund managers to provide persistent outperformance. Thus, the open-end fund structure is beneficial for a reduction of agency conflicts but at the same time adversely affects the persistent generation of outperformance. In order to balance these two aspects, a detailed understanding of agency problems in delegated asset management and potential alternative measures to reduce these problems is required.

Section 2.1 discusses potential conflicts of interest in delegated asset management between the investors, the fund manager and the investment management company. The following section 2.2 presents the regulatory response to agency conflicts and discusses implicit incentives that might help to align these interests.

2.1 Potential Conflicts of Interest

Market frictions and asymmetric information lead to the need for private investors to delegate their investment decisions to professional portfolio managers as discussed in chapter 1.[110] However, at the same time the delegation of tasks of a principal (investor) to an agent (portfolio manager) involves potential conflicts of interest (Jensen and Meckling, 1976).[111] This is especially relevant as the true

110 For a recent survey of theoretical models on delegated portfolio management see Stracca (2006).

111 For a review of the literature on agency conflicts see Eisenhardt (1989).

investment skill of the portfolio manager is unknown ex ante (hidden characteristics) and as the true effort cannot be observed (hidden action). The ex post observed performance of the portfolio manager is a result of his investment skills and luck (good or bad). As true skill is unobservable, learning over time plays an important role in the relationship between fund managers and investors (Berk and Green, 2004). The noise between the portfolio managers' actions and the observed outcome complicates the contracting between the investor and the portfolio manager (Ippolito, 1992).[112] In terms of a broad definition of transaction costs in the sense of Schmidt (1980) an efficient investment via mutual funds requires a reduction of overall transaction costs for the investor. Specifically, the cost reduction from delegation of the investment decision that stems from market frictions and asymmetric information should outweigh the additional agency costs.

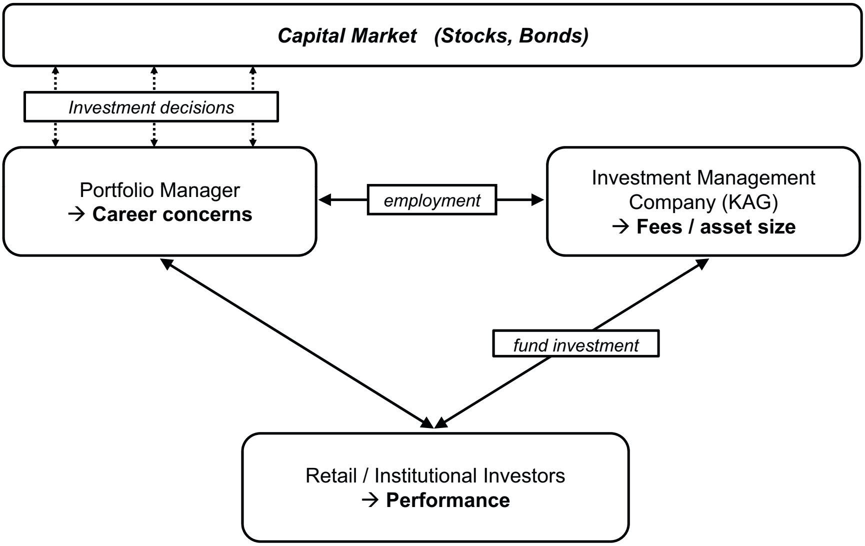
Investors try to maximize (risk-adjusted) returns net of all costs such as transaction costs and commissions. In contrast, the portfolio manager tries to maximize his life-time income and his behavior is driven by career concerns. In addition, the investment management company (or its corporate management) might follow interests different from those of the portfolio manager. First and foremost, it tries to maximize profits by maximizing fee-income, which in general is linearly related to total assets under management, or minimizing effort and own costs (Figure 2.1). Performance maximization is not the shared interest of all parties involved in delegated asset management and this might explain why average risk-adjusted returns of investors are around or even below zero as empirically documented by several studies (e. g. Jensen, 1968; Malkiel, 1995; Carhart, 1997).

However, in addition to these three main interest groups other parties are involved in the delegated investment management process. This includes brokers or other distribution channels for fund shares, the board of directors of the fund responsible for monitoring the investment management company, the custodian of the fund's securities, the broker that exercises the trades of the fund, and, in some cases, an external investment advisor who provides additional portfolio management expertise (Chen, Hong, and Kubik, 2007). All of these parties act in their own interest and might try to extract some of the returns generated by the fund. The following sections review the literature on distortions of mutual fund

[112] Note, however, that the performance and with it the relationship between skill / effort and outcome can be measured more precisely in the context of mutual funds than in the context of the firm.

Figure 2.1: Potential conflicts of interest

This figure presents the relationship between the conflicting interests between mutual fund investors, portfolio managers and the investment management company.



performance due to personal career concerns of fund managers (section 2.1.1), the divergence of investment management companies' interests from the performance objective of the investors (section 2.1.2) as well as on reducing their own effort, hiding costs and privileged treatment of (un-) affiliated third-parties (section 2.1.3).

2.1.1 Investors and Portfolio Managers

2.1.1.1 Career Concerns and Tournaments

Tournament Behavior

Fund managers face direct incentives in the form of compensation contracts (Elton, Gruber, and Blake, 2003) and indirect incentives to increase their compensation through asset maximization (Chevalier and Ellison, 1997) or to decrease their employment risk (Chevalier and Ellison, 1999b). In addition, these incentives vary over time depending on the previous performance rank (Brown, Harlow, and Starks, 1996) and the current market state (Kempf, Rünzi, and Thiele, 2009). As a result, the investment strategy of fund managers might not be driven solely by the desire to generate abnormal returns for their investors. Rather, they might choose a suboptimal portfolio composition from the investors' perspective in order to maximize their own interests.

Investors observe past performance and allocate their money toward recent winners.[113] However, the withdrawals from previously underperforming funds seem to be less performance-sensitive resulting in a positive and convex "performance-flow relationship".[114] Based on this important link between past performance and inflows strong incentives emerge for mutual fund managers (Brown, Harlow, and Starks, 1996). The compensation and prestige of portfolio managers usually increases in line with the size of the funds they manage. Money flows disproportionately into funds with the highest performance ranking which acts like an implicit incentive contract and heavily affects mutual fund managers' risk attitudes. Specifically, according to Brown, Harlow, and Starks (1996), mid-year loser funds tend to strongly increase the risk of their funds in an attempt to end up among the top funds at the end of the year when most of the fund investors are believed to reallocate their money. However, due to the convexity of the performance-flow relationship they do not face a symmetric risk of outflows if the increase in risk does not pay off or even results in losses. In contrast, mid-year winner funds, having a lead over their peers, face an incentive to lock-in their position by indexing.[115] This behavior, usually referred to as "segment tournament", is more pronounced among younger and less well known funds (Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997).[116] Moreover, managerial gaming has become more

[113] Note that in light of more recent evidence about a lack of performance persistence, i. e. no relationship between past and future fund performance, if measured adequately, this is not a rational performance-maximization strategy (e. g. Carhart, 1997).

[114] Several more recent studies support this result empirically (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lynch and Musto, 2003). For a more detailed discussion see section 4.2.

[115] Note that very similar incentives emerge from the direct use of performance incentives (Carpenter, 2000; Elton, Gruber, and Blake, 2003). However, due to the fact that performance-based compensation is still very rarely used in the mutual fund industry its relevance for the behavior of fund managers on aggregate is not comparable to that of the performance-flow relationship. Yet, the empirical results of Elton, Gruber, and Blake (2003) indicate that incentive fees can even intensify the relationship between past performance ranking and shifts in the risk level of the fund. Thus, both direct and indirect incentives have a marginal impact on risk shifting.

[116] "Tournament" refers to a situation where winners receive a large price while losers get virtually nothing (Kempf and Rünzi, 2008b).

relevant in recent years (Brown, Harlow, and Starks, 1996). Chevalier and Ellison (1997) support these results by applying mutual fund holdings data and comparing the portfolio composition between September and December. Using holdings data allows them to distinguish between random changes in the riskiness of the stocks in the portfolio as compared to active reallocations of the fund manager toward riskier stocks.

In fact, the risk shifting is not intended by the investors and might constitute real costs to them from an ex-ante perspective. The risk level may deviate, as a result of tournament behavior, from the level desired by investors and stated in the prospectus. However, ex post, if the strategy of the portfolio manager pays off, the investors might also be better off. Thus, the costs of such behavior are not too trivial to quantify.

Moreover, further aspects have been identified in the literature that complicate this relationship. First of all, the earlier studies analyze the impact of mid-year performance on risk changes without controlling for fund flows (Koski and Pontiff, 1999). Indeed, the risk levels of winner funds might decrease just because the manager is unable to immediately place the new money in stocks. The fraction of the portfolio held in cash or being indexed increases and, as a result, risk decreases. Similarly, loser funds first use their cash position to pay out redemptions before they eventually have to borrow additional money. This increases the leverage and the risk of the fund. However, the empirical results of Koski and Pontiff (1999) are not clear cut and do not unambiguously support this hypothesis. Managerial gaming still seems to have the major impact on fund risk.

The current state of the market also influences the fund managers' actions as they face not only compensation incentives but also employment risk (Kempf, Rünzi, and Thiele, 2009). Specifically, employment incentives and compensation incentives of losing fund managers might be diametrical. The relationship between the termination likelihood and risk-adjusted returns, termed "performance-termination relationship" is convex, especially for young managers (Chevalier and Ellison, 1999b).[117] Termination risk increases disproportionately at the lower end of the performance distribution. As a result, the tournament behavior reverses for mid-year loser funds in a market state where employment risk is relatively more important (Kempf, Rünzi, and Thiele, 2009). Employment incentives are

[117] Note that in order to be consistent with the previous terminology this term deviates slightly from the terms used by Chevalier and Ellison (1999b).

expected to be stronger in bear markets as more funds are closed and fewer new funds are opened during a bear market while compensation incentives dominate in bull markets. In a bear market, mid-year loser funds tend to index in order not to end up at the lowest tail of the cross-sectional performance distribution at the end of the year in an attempt to prevent a potential job loss.[118] This incentive is stronger the worse the employment opportunities in the industry and the younger the fund manager (Chevalier and Ellison, 1999b). The empirical results of Kempf, Rünzi, and Thiele (2009) support these hypotheses based on portfolio holdings data of U. S. equity mutual funds over the period from 1980 to 2003.

Employment risk becomes relatively less important in good market states because even if a fund manager is fired in one year due to a low performance ranking the likelihood of finding another job in the industry is still relatively high (Kempf, Rünzi, and Thiele, 2009). In this case, the traditional tournament behavior dominates; i. e. mid-year loser funds increase risk. Mid-year winners in general are not affected by employment risk in either market state. Thus, their tournament behavior does not significantly differ between bull or bear markets.

Strategic Interaction and Family Tournaments

So far, no strategic interactions between fund managers in the same peer group have been assumed. This case can be interpreted as using an exogenous benchmark such as a market index for the performance ranking, and the traditional tournament behavior emerges. However, in the case of an endogenous benchmark with strategic interactions, it turns out that the incentives reverse (Taylor, 2003). The action of fund managers strongly depends on the actions of other managers in the same peer group. Mid-year winners, trying to lock in their lead, need to take into account the risk increases of mid-year losers. As winner-fund managers expect loser-fund managers to buy riskier assets they need to mimic this strategy in order to retain their relative position. However, in this case loser funds cannot gain much from increasing risk but should instead follow the opposite strategy of winner funds by decreasing their risk. The smaller the number of players who interact, such as in specialized segments, the more pronounced the strategic interaction.

Building upon this intuition, Kempf and Rünzi (2008b) argue that fund managers not only enter a segment tournament in order to maximize inflows but at

[118] This behavior is similar to analysts issuing more conservative forecast when they face greater employment risk (Hong and Kubik, 2003).

the same time compete with other fund managers within the same fund family for promotion, advertising budgets, as well as other resources or cross-fund subsidization (Kempf and Rünzi, 2008b).[119] This "family tournament" is similar to the segment tournament unless the managers do not compete against other funds in the same investment objective but against managers of the same fund family but with different investment objectives. Different relative rankings are likely within the family and the segment. The incentives emerging from a high rank within the family but a low rank within the segment (or vice versa) are not unambiguous. Additionally, the incentives might reverse for extreme positions. Extreme loser-fund managers have an incentive to index while extreme winner-fund managers start to gamble (Chevalier and Ellison, 1997).

Further Empirical Evidence and Statistical Issues

In general, the results on tournaments have also received empirical support based on other data sets than U. S. mutual funds which the above studies relied on. For example, Hallahan and Faff (2009), applying a data set of Australian mutual funds and a non-parametric approach, confirm the conclusions of Taylor (2003) on strategic interaction. For the U. K., Acker and Duck (2006) support the notion that loser-fund managers adopt extreme portfolios with either high or low market exposure depending on their expected market movement. Furthermore, a similar relationship between past relative performance and changes in risk levels has been documented for hedge funds and commodity trading advisors (Brown, Goetzmann, and Park, 2001). This result implies that direct performance incentives, as commonly used in the hedge fund industry, have a similar impact on tournament behavior as indirect performance incentives through the performance-flow relationship. However, somewhat puzzling, absolute performance does not have a significant impact on hedge fund managers' risk taking despite the use of high water marks and the absolute return objective in the hedge fund area. Hedge fund managers who are below their high water mark in the middle of the year do not start gambling. This suggests that reputation costs also play an important role. The hedge fund industry seems to be small enough and managers' names are visible enough to investors to induce long-term reputation incentives.[120] The threat of termination motivates managers more than short-term performance gains.

[119] For cross-fund subsidization see section 2.1.2.2 and Gaspar, Massa, and Matos (2006).

[120] For the benefits of a disclosure of fund manager names see also Massa, Reuter, and Zitzewitz (2010).

However, in stark contrast to these studies, recent work challenges the statistical significance of the tournament behavior. For example, Busse (2001) suggests that the results of the earlier studies using monthly data to compute the shift in the funds' standard deviation were biased due to daily return autocorrelation in mutual fund returns. This correlation structure might result from an exposure to thinly traded small-cap stocks. Busse (2001) re-estimates the tournament models using daily data and documents that the shift in fund risk disappears. Goriaev, Nijman, and Werker (2005) argue that inferences based on daily data are even more exposed to the bias from autocorrelation than tests using monthly data. They document that a neglect of cross-sectional dependency between idiosyncratic fund returns affects the test statistics (which has already been noted by Busse (2001) as a potential additional source of biased results). However, Goriaev, Nijman, and Werker (2005) also support the results of Busse (2001) and conclude that "over the sample periods studied so far, there is little empirical evidence in favor of the tournament hypothesis for mutual fund managers". Also Brown, Gallagher, Steenbeek, and Swan (2005) question if investors indeed suffer greatly from "informationless" trading of mid-year loser-fund managers in an attempt to catch up with better performing funds. Chen and Pennacchi (2009) offer a partial solution to the opposing findings of the initial studies on tournament behavior and the conclusions of Busse (2001) and Goriaev, Nijman, and Werker (2005). In the model of Chen and Pennacchi (2009), managers of mid-year loser funds do not increase total fund volatility, as proposed by the early studies, but rather tracking error volatility; i. e. they actively deviate from the benchmark. Based on a large sample of more than 4,000 mutual funds this argument is supported empirically.

2.1.1.2 Herding

In addition to career concerns, fund managers have an incentive to herd in order to avoid a poor relative ranking and punishment after a series of bad returns.[121] These managers heavily invest in popular sectors and mimic the strategies of others ignoring their their own private information. In addition, instead of acquiring own information, fund managers might just follow the recommendations of sell-side analysts (Brown, Wei, and Wermers, 2007). In particular, young fund

[121] Scharfstein and Stein (1990), Wermers (1999), Sias (2004), Hong, Kubik, and Stein (2005), and Cohen, Polk, and Silli (2009). Herding behavior has also been documented for equity research analysts (Bernhardt, Campello, and Kutsoati, 2006).

managers have an incentive to avoid unsystematic risk and deviations from their style benchmark because they face a higher termination risk after a period of relative underperformance (Chevalier and Ellison, 1999b). Herding is consistent with the perception that managers who undertake similar actions as other managers appear to have higher investment skills (Scharfstein and Stein, 1990). A contrarian strategy, in contrast, can be more easily followed by older and more experienced fund managers because their performance-termination relationship is almost insensitive to performance (Chevalier and Ellison, 1999b). A deviation from the crowd seems to be beneficial for their career in the case of positive risk-adjusted returns. However, these incentives involve the risk of "churning", i. e. trading without any superior information in an attempt to signal non-existent skills. Consequently, depending on the tenure of the fund manager the trading activity might deviate from the optimal level given their real skill and information.

However, the empirical results on herding versus contrarian investing are inconsistent. The study of Wei, Wermers, and Yao (2008) suggests an outperformance of contrarian funds. Fund managers who trade against the herd generate value and outperform herding funds by around 2.6 percentage points per year which cannot solely be explained by liquidity provision of contrarian funds but is also related to superior information of contrarian fund managers (Wei, Wermers, and Yao, 2008). Moreover, stocks widely held by contrarian funds even outperform those least widely held by contrarian funds by more than 5.0 percentage points in the following year adjusted for stock characteristics.[122] A study of daily trades reveals that, in contrast, when many fund managers herd into the same direction in one stock, the subsequent returns are similar irrespective of whether the trade is a buy or a sell (Hu, Meng, and Potter, 2008). Thus, investing against the crowd is not successful. Moreover, when opinion divergence of fund managers is high, i. e. there is a similar amount of buying and selling, subsequent returns appear to be low, especially for stocks with short-sale constraints.

It has become evident from the discussion above that fund managers might follow their own interest, irrespective of conflicting empirical results on tournament behavior, which does not result in optimal portfolios from the investors' point of view. A clear agency conflict between investors and portfolio managers exists. In particular, portfolios of mutual funds tend to be too risky if investors chase past

[122] Characteristics-based benchmarks are based on Daniel, Grinblatt, Titman, and Wermers (1997).

performance (Bagnoli and Watts, 2000). In addition, changing the style and, more importantly, the risk of the investment strategy over the cycle of the year negatively affects investors and results in lower performance. This result is stronger the more investors concentrate only on a small fraction of the highest ranked funds. A potential solution to the negative impact of tournament behavior is to require the disclosure of risk-adjusted performance measure. If investors monitored the risk of their funds more closely and chose funds based on risk-adjusted performance rather than raw returns, this could mitigate the incentive for loser funds to gamble with investors' money.

2.1.2 Investors and Investment Management Companies

In addition to the conflicting interests between portfolio managers and investors as discussed above, investment management companies (or its management and shareholders) follow their own interests of profit maximization. Usually, management fee income is the dominant source of revenues for investment management companies. As performance-based fee contracts are still relatively rare, fee maximization is almost identical with a maximization of assets under management in the fund family (Elton, Gruber, and Blake, 2003). Assets under management grow as a result of positive investment returns (internal growth), which is in line with the interests of investors, and as a result of inflows (external growth). Thus, one strategy to maximize fees is to follow strategies that try to influence investors' buying and selling decisions directly. As already discussed above, past performance is one of the most important drivers of inflows into mutual funds.[123] Consequently, an alternative way to maximize fee income is to exploit known biases in investor behavior with respect to performance or to boost the performance of all or a subset of funds in the fund family in order to indirectly trigger inflows. Moreover, some investment management companies might even try to manipulate fund performance in order to maximize inflows.

2.1.2.1 Distribution Channels and Advertisement

Brokers and Financial Advisors

In 2004, 79 percent of all mutual fund share classes and slightly more than 50 percent of all assets under management in U. S. mutual funds were distributed by

[123] For a more detailed discussion of this relationship see section 4.2.

brokers (Bergstresser, Chalmers, and Tufano, 2009). In countries like Germany, where traditionally banks affiliated with the investment management company play the most important role in marketing mutual funds, this number is most likely even higher. Thus, from the perspective of profit maximizing investment management companies it seems reasonable to target these brokers. Kick-back payments are a common incentive scheme. Brokers that sell a fund of a specific investment management company are rewarded by receiving part or all of the sales load. Furthermore, brokers might receive an annual trailer fee for as long as the investors stay invested in the fund. Indirectly, brokers might be compensated for their selling efforts by fund management companies directing their trades to the trading desks of these brokers (Mahoney, 2004). In light of these incentive schemes, it remains questionable whether brokers add value to mutual fund investors by supporting the choice of funds with future superior performance or whether their advice is biased.[124]

Indeed, empirical evidence in favor of the selection abilities of brokers is rather weak. Bergstresser, Chalmers, and Tufano (2009) analyze the benefits of brokers and financial advisors selling mutual funds through intermediated channels. The results suggest that in general brokers fall short in delivering the service of choosing funds with relatively higher risk-adjusted performance, even before distribution costs. In a similar vein, Christoffersen, Evans, and Musto (2007) compare the benefits from load funds sold through affiliated or captive brokers, load funds marketed by unaffiliated brokers and from no-load funds both from the perspective of the investor and the fund family. It seems that captive brokers are better able to identify future outperformers while, at the same time, they seem to be reluctant to advise investors to pull out of underperforming funds. From the perspective of fund families, captive brokers cause a cannibalization within the fund family but are also better in recapturing redemptions from one fund of the affiliated family into another fund from the same family. Supporting these results, Chen, Yao, and Yu (2007) document an underperformance of funds that are managed and distributed by insurance companies of more than one percent per year. They explain this underperformance by agency conflicts resulting from insurers' cross selling efforts.

The advice of brokers does not seem to be independent of the level of sales charges: (1) brokers tend to channel investors into funds with higher sales loads

[124] For a theoretical analysis see Stoughton, Wu, and Zechner (2010).

and smaller fund size on average (Zhao, 2005c); (2) fund flows are sensitive to the size of distribution charges (Bergstresser, Chalmers, and Tufano, 2009); (3) funds sold by brokers exhibit a higher performance-flow sensitivity than no-load funds (Zhao, 2005c). Even in the case of index funds, where fee differentials predict future performance, financial advisors and brokers seem to systematically channel index fund investors into those funds that pay higher distribution fees (Boldin and Cici, 2010). Several legal actions have been brought against brokers that advised their clients to buy disadvantageous share classes with respect to their fee structure and the amount invested (Sarkar, 2006). This behavior is not in line with the fiduciary standards of the mutual fund industry (Bergstresser, Chalmers, and Tufano, 2009). However, even in light of these empirical results it cannot be ruled out that brokers offer other services that are valuable to the investors and compensate for the lower performance (Bergstresser, Chalmers, and Tufano, 2009). Potential services include advice for the optimal saving rate, overall asset allocation, the determination of the optimal risk budget, tax counseling as well as time saving. Furthermore, Stoughton, Wu, and Zechner (2010) suggest that brokers can improve social welfare by facilitating the participation of small investors in actively managed mutual funds. However, given that equity funds generate higher fees for both, the investment management company and the broker, it is likely that investors are advised to hold more expensive equity funds as compared to lower costs funds such as bond and money market funds.

Advertising Performance

As another means to increase inflows, fund families target high rankings in fund lists of important media outlets such as the Wall Street Journal (SmartMoney Fund Screen), Barron's or Money Magazine (Jain and Wu, 2000; Comer, Larrymore, and Rodriguez, 2008). These advertisements can be interpreted as a costly signal of fund quality because, first of all, the advertisement itself is costly and, second, the implicit promise of superior performance might result in significant outflows if subsequent performance cannot meet the expectations (Jain and Wu, 2000). However, the empirical results of Jain and Wu (2000) suggest that post-advertisement performance is significantly negative based on one- and four-factor alphas even though pre-advertisement performance was superior compared to the four-factor benchmark. Despite this observation, fund flows are significantly higher for funds included in the lists compared to other funds controlling for several fund characteristics, prior-period performance and fund flows. Using daily return data and a greater variety of investment styles Comer, Larrymore, and Rodriguez (2008) confirm these results. Only funds with very flexible investment objectives (international equity and hybrid funds) are able to outperform their benchmark in the post-advertisement period.

Changing Names and Pretending Innovation

Another possibility to increase net inflows is to strategically change fund names according to current “hot” investment styles. Cooper, Gulen, and Rau (2005) report that these name changes in many cases do not necessarily go along with an actual change in the investment strategy. As a result, performance is unaffected on average. However, funds that change their name can in general attract abnormal cumulative inflows of 20 percent in the subsequent year, equivalent to 60 million USD per fund on average. Changing names toward a hot style (or away from a cold style) leads to an increase in abnormal fund flows by 28 percent.

Similarly, fund families that start more new funds compared to competing fund families or offer a greater variety of investment styles are perceived to be more innovative and can attract more fund flows from investors (Khorana and Servaes, 2007; Zhao, 2008). This is especially true if the new funds differ from existing funds in their investment strategy. On the one hand, tilting the range of fund offerings toward more extreme styles at the same time increases the risk of significant underperformance. On the other hand, it also improves the chance for superior performance.[125] However, if the reason for starting new funds is only to attract inflows and not a signal of true innovation in investment strategies, investors might be mislead and their fund choices systematically biased toward fund families pretending to be innovative. Unfortunately, Khorana and Servaes (2007) do not compare the subsequent performance of these new and allegedly innovative funds with existing funds. Thus, no definite conclusions on the impact of investors' welfare can be drawn.

[125] See also the discussion on the creation of “star” fund managers in the following section 2.1.2.2.

2.1.2.2 Fund Families and "Star" Managers

Strategically Boosting Fund Performance

Over 90 percent of all U. S. equity mutual funds are part of a fund family and 98 percent of all assets under management are managed by these funds (Gaspar, Massa, and Matos, 2006). Anecdotal evidence suggests that fund families exploit the patterns in investor behavior and fund flows to increase their assets under management. Specifically, investment management companies try to create "star" funds with stellar outperformance because investor flows respond strongly to past superior performance in a convex fashion.[126] Even the other funds from the same fund family benefit from the creation of a star fund manager by positive spill-over effects on inflows (Nanda, Wang, and Zheng, 2004; Khorana and Servaes, 2007). Moreover, high average industry-adjusted returns by the fund family as well as industry-adjusted Morningstar ratings averaged across all funds in the family both positively affect net inflows into the funds from the same fund complex (Khorana and Servaes, 2007). A similar pattern emerges for fund rankings as discussed above.

The aim of creating a star manager is not generally speaking bad as it partly aligns the interests of investors and investment management companies. However, the incentive to create star managers results in a large variety in the investment strategies across funds from the same fund complex and lower family performance on average (Nanda, Wang, and Zheng, 2004). Moreover, investment management companies might try to improve the performance of some funds at the expense of other funds in the family (cross-subsidization) or systematically misguide investors with respect to track records of new funds (mutual fund incubation). Cross-subsidization refers to the strategic transfer of performance across member funds from the same family from low-value to high-value funds, i. e. investment management companies would not reduce the performance of one fund without a source of countervailing profit (Gaspar, Massa, and Matos, 2006). High value funds are determined by fee levels, fund age and year-to-date performance. Indeed, the empirical results of Gaspar, Massa, and Matos (2006) suggest that the spread in performance between high- and low-value funds from the same family is significantly higher than the spread between funds with similar characteristics across families.

[126] For a more detailed discussion of the performance-flow relationship see section 4.2.

Furthermore, Reuter (2006) suggests that investment management companies "bought" favorable access to the allocation of promising IPOs by paying higher commissions to the affiliated trading desks of the underwriters in the period from 1996 to 1999. This behavior results in significant returns from flipping IPOs. Ritter and Zhang (2007) document that especially during the internet bubble period between 1999 and 2000 lead underwriters had a strong tendency to allocate underpriced IPOs to funds of an affiliated fund complex while IPOs with less favorable future prospects were not allocated to these funds. Thus, private information about IPOs is strategically forwarded to affiliated funds in order to boost their performance. A similar pattern of private information diffusion has been documented by Massa and Rehman (2008) for financial conglomerates. The performance of mutual funds' positions in companies which have a lending relationship with affiliated banks is superior to the performance of similar companies without any relationship to the financial conglomerate. Also, sell-side analysts who are affiliated with a financial conglomerate that owns a mutual fund family issue more favorable stock recommendations on stocks that are overweighed by the funds of the affiliated fund family (Stanzel, 2007; Mola and Guidolin, 2009). Moreover, the likelihood of a stock being rated as a "strong buy" is positively related to the weight of this stock in the affiliated fund family. However, the relationship between investment management companies and affiliated banks might also be used to the disadvantage of fund investors.[127] Ritter and Zhang (2007) suggest that "cold" IPOs, i. e. those with not so fortunate prospects, might be dumped into affiliated mutual funds. However, their empirical results cannot support this hypothesis.

Another practice of cross-subsidization are opposite trades across two funds from the same family. Certain securities are traded outside their current market price favoring the performance of one fund to the disadvantage of the other. Furthermore, large fund families might be able to boost the performance of new and small funds by strongly buying securities held in these funds into their larger funds and creating price pressure (Chen, Hong, Huang, and Kubik, 2004).

[127] For example, Deutsche Bank paid a penalty of 750,000 USD in 2003 for not disclosing to its investment management clients that its investment banking arm was representing Hewlett-Packard in a potential merger with Compaq. In the course of Deutsche Bank's client relationship with Hewlett-Packard, Deutsche Asset Management, Deutsche Bank's investment advisory arm for institutional clients, switched from voting against the merger in proxies to voting in favor of the merger.

Side-by-Side Management

In recent years, side-by-side management, which refers to the practice of allowing one manager to simultaneously manage a hedge fund and a mutual fund, has become popular and also offers the potential for cross-subsidization. Investment management companies claim that side-by-side management allows them to attract highly skilled managers and that mutual fund investors benefit from a transfer of knowledge, research and investment skills from the hedge fund to the mutual fund. Opponents of side-by-side management argue that managers have an incentive to transfer performance from the mutual fund to the hedge fund because of differences in compensation contracts.

The empirical results of Cici, Gibson, and Moussawi (2010) are rather consistent with a negative view of side-by-side management: alphas of mutual funds that are in a side-by-side arrangement are lower than alphas of pure mutual funds. Furthermore, an analysis of the return gap, which measures the performance contribution of positions that deviate from the previously disclosed holdings in the short term, show that the actions of side-by-side mutual fund managers systematically destroy value. Even the allocation of underpriced IPOs is significantly smaller in these funds implying a preference of managers to allocate these IPOs to their hedge funds. In contrast to these results, Nohel, Wang, and Zheng (2010) document a significant outperformance of mutual funds managed side-by-side with a hedge fund compared to pure mutual fund managers. Furthermore, the hedge funds of the side-by-side managers deliver at best average performance. These results strongly imply that no conflicts of interest exist in this context and that mutual fund investors even benefit from such a constellation. Consistent with these results, Agarwal, Boyson, and Naik (2009) confirm that the performance of hedge mutual funds benefits from their manager simultaneously managing a hedge fund. Even though Gaspar, Massa, and Matos (2006) present convincing evidence that performance reallocation across mutual funds from the same family exists, the results of a transfer between mutual funds and hedge funds are not as clear cut.

Strategically Starting, Merging and Closing Funds

Another way of creating star funds in the family is to initiate several funds with a great variation in investment strategies across funds (Nanda, Wang, and Zheng, 2004; Khorana and Servaes, 2007). Karoui and Meier (2009) document that recently launched funds indeed have a higher performance on average as compared to established funds. However, these funds also show higher levels of total and unsystematic risk as well as less diversified portfolios with a tilt toward small and illiquid stocks. Some of these new funds persistently outperform the market but, at the same time, a significant fraction of young funds drops from the top decile to the bottom decile in two subsequent periods. These results indicate that the initial outperformance might not solely be a result of superior investment skills. Moreover, empirical evidence suggests that starting many funds with different styles results in lower average performance across all funds in the family (Nanda, Wang, and Zheng, 2004).

Thus, in order to hide the performance of those fund starts that do not provide superior returns, some investment management companies opt to start funds as private funds with their own seed money. They then have the option of taking these funds public conditional on their performance during a so-called "incubation period" (Deaves, 2004b; Evans, 2010).[128] In his empirical analysis, Evans (2010) documents that 39.4 percent of all funds are incubated. The SEC allows investment management companies to report to fund data providers not only the time series of returns after the official launch date of the fund, i. e. after it was being made available to investors to purchase, but from its start as a private fund. Unsuccessful funds are never taken public and do not show up in mutual fund databases. The bias in measured average fund performance resulting from this practice amounts to 4.7 percent in raw returns and between 1.9 and 3.3 percent in risk-adjusted returns. Hence, if many investment management companies follow these or similar strategies when staring new funds there is a capacity constraint in strategies with superior backtesting-performance. This may contribute to the reversal in performance in these strategies as documented for hedge funds by Naik, Ramadorai, and Stromqvist (2007).

Furthermore, investment management companies might strategically close or merge mutual funds with poor performance track records in order to protect the other funds in the family from negative spill-over effects and to avoid a decrease in the reputation of the fund family. On average, the annual attrition rate of funds in the period between 1962 and 1995 is 3.6 percent according to Carhart, Car-

[128] Evans (2010) further notes that in addition some funds are "technically public because they are registered with the SEC, but effectively private because the advisor does not apply for a ticker or advertise the fund until a track record has been developed'."

penter, Lynch, and Musto (2002), 2.2 percent of which disappear due to mergers and 1.0 percent due to liquidation while the rest of the funds are removed from the database initiated by the fund manager or the database provider. Slightly lower numbers are reported by Elton, Gruber, and Blake (1996b): about 2.3 percent of funds merge each year which becomes 2.9 percent when policy changes are also considered. Already Ippolito (1992) points out that funds which disappear due to merger or death tend to have poor performance just prior to disappearance.[129] Fund closures are even more sensitive to past performance if the portfolio management is outsourced rather than internally run (Chen, Hong, and Kubik, 2007). These high-powered incentives arise from contractual externalities due to firm boundaries. Brown and Goetzmann (1995) report that past performance of up to three years seems to predict fund closures. However, the link between past money flows and the decision to close funds is rather weak even though one could have hypothesized that mutual fund companies base their decision to close funds on the behavior of mutual fund investors. Aggressive growth funds tend to have the highest attrition rates of on average 4.5 percent per year (Carhart, Carpenter, Lynch, and Musto, 2002). Furthermore, high expense ratios and small fund size increase the likelihood of closure (Brown and Goetzmann, 1995). Zhao (2005b) reports that only the smallest funds are liquidated while larger funds tend to be merged, either through within-family merger or across-family merger. Also, mutual funds that pursue strategies different from the other funds in the family face a higher risk of being liquidated or sold to another fund family. These results are consistent with fund families starting a variety of investment styles and exiting the unsuccessful ones.

However, it should also be noted that from the investment management companies' perspective attracting only a highly performance-sensitive investor clientele involves the risk of large outflows after a period of bad performance. Thus, it might also be in the interest of fund management companies to attract performance insensitive investors in order to smooth assets under management over time. Empirical evidence has documented that outflows, in general, are less sensitive to poor performance and that an unsophisticated investor clientele exists that fails to withdraw money from poorly performing funds (Berk and Tonks, 2007).

[129] This finding has been confirmed by several more recent studies (e. g. Brown and Goetzmann, 1995; Elton, Gruber, and Blake, 1996b; Carpenter and Lynch, 1999; Carhart, Carpenter, Lynch, and Musto, 2002; Zhao, 2005b).

Some fund management companies try to exploit this pattern by strategically raising fee levels of loser funds as they can expect investors of these funds to stay invested (Christoffersen and Musto, 2002).

2.1.2.3 Benchmark Gaming and Performance Manipulation

Benchmark Gaming

Instead of creating star managers within fund families portfolio managers might also pursue strategies to manipulate the performance of their own funds. If this leads funds to assume risks which are inconsistent with their declared investment objective fund investors' interests might be hurt. For example, most of the common approaches of measuring mutual fund performance are subject to potential gaming (Goetzmann, Ingersoll, Spiegel, and Welch, 2007). Often, the ultimate objective of gaming a performance measure is to obtain favorable ratings by the large fund rating agencies, such as Lipper and Morningstar, because fund ratings are an important fund flow determinant (Del Guercio and Tkac, 2008).

This gaming can be successful, according to Goetzmann, Ingersoll, Spiegel, and Welch (2007), when rating agencies do not use manipulation-proof performance measures. A definition of the properties of manipulation-proof measure can be formally derived. In particular, existing performance measures suffer from two aspects (Goetzmann, Ingersoll, Spiegel, and Welch, 2007):[130] First, in reality portfolio returns do not follow a normal or lognormal distribution. This is especially true when derivatives or dynamic trading strategies can be used. Second, even if portfolio returns are well behaved the returns over time might not be independently identically distributed as a consequence of dynamic trading. Thus, specific trading strategies can be employed to bias the estimation of performance measures in the desired direction.

Kostakis (2009) suggests that fund managers load higher-moment risk in an attempt to game performance measures based on the CAPM, such as the one-factor alpha by Jensen (1968). For example, the empirical results of Kostakis (2009) indicate that U. K. fund managers load negative coskewness, which has been a priced risk between 1991 and 2005. Following this strategy they could falsely improve their performance numbers based on conventional measures. Furthermore,

[130] Goetzmann, Ingersoll, Spiegel, and Welch (2007) note that currently the Risk Adjusted Rating introduced by Morningstar in July 2002 fulfills these requirements.

managers might try to "smooth" the returns of their portfolios as several performance measures such as the Sharpe ratio are negatively related to fund return volatility by construction.[131] Usually, the assets held by mutual funds are marked to market for the calculation of the net asset value. However, if some securities are rather illiquid, the use of fair-value pricing is admitted and this gives some discretion to fund managers. Bollen and Pool (2009) provide empirical evidence in favor of such behavior among hedge funds.

In a similar vein, Elton, Gruber, and Blake (2003) argue that fund managers might deviate from their investment universe (or investment restrictions) in order to beat the declared benchmark and to avoid competition within their segment.[132] Accordingly, Sensoy (2009) reports that 31.2 percent of diversified U. S. equity funds specify a benchmark in their prospectus that does not match their actual style. Specifically, the average R^2 of these funds is 70.6 percent with the stated benchmark but 82.6 percent with a corrected benchmark. At least part of the investors are not aware of this mismatch and base their decisions on performance relative to the false benchmark from the prospectus, even after controlling for the impact of flows on performance relative to the true benchmark. About 14.6 percent of the annual flows of funds can be explained by performance relative to the self-designed benchmark. Elton, Gruber, and Blake (2003) confirm these results by documenting that the funds in their sample have significant exposure to size and value or growth benchmarks that are not captured by their stated benchmark. According to Chevalier and Ellison (1999b), older managers ($>$ 45 years) receive a reward for deviating from the benchmark if that strategy performs well. In contrast, young managers face the risk of being dismissed after a period of bad performance when these young managers diverge significantly from other funds

[131] For a definition of the Sharpe ratio see section 3.2.

[132] A prominent example is the Reserve Primary Fund, a money market fund, which suffered tremendous losses after the Lehman collapse in September 2008 as a result of a deviation from its benchmark. Specifically, the fund had started investing in commercial papers (some of which was issued by Lehman Brothers) yielding higher returns but also being riskier than treasury bills after a period of underperformance compared to its peers. Part of these holdings defaulted or at least depreciated significantly in value in September 2008 (Steve Stecklow and Diya Gullapalli, A Money-Fund Manager's Fateful Shift, Wall Street Journal, 08 December 2008). However, it might not be easy for fund investors to detect a deviation from the declared investment objective. For example, fixed income funds that are restricted to AAA bonds could still invest in AAA mortgage-backed securities (MBS), yielding spreads of up to two percent in recent years. Presumably, the rating was not an adequate measure of risk and high spreads should have made fund managers and investors sceptical. Some authors even argue that rating agencies were too lax in issuing AAA ratings which extended the circle of potential buyers (e. g. Daníelsson, 2008).

with respect to sectoral composition or riskiness which curbs their incentives to pursue risky strategies. Furthermore, Bhattacharya, Dasgupta, Gümbel, and Prat (2008) argue that the tendency to "overdifferentiate" oneself is more pronounced among analysts than among fund managers due to the more direct and costly consequences for the recipients of the advice.

Portfolio Pumping

Investors, focusing primarily on short-term performance when allocating their money, induce fund managers to pursue trading strategies that promise short-term profits (Jin, 2005). This behavior is inconsistent with the long-term character of mutual fund investments. Corresponding strategies of mutual fund managers to make performance statements look better include portfolio pumping and window dressing. "Portfolio pumping"[133] refers to purchases of stocks already held in the portfolio, especially shortly before performance disclosure dates, in an attempt to cause price pressure and to bid up the prices of these stocks (Carhart, Kaniel, Musto, and Reed, 2002; Gallagher, Gardner, and Swan, 2009).[134] Empirical results show that daily mutual fund returns are abnormally high on the last trading day of the quarter compared to the S & P 500 and abnormally small the following day (Carhart, Kaniel, Musto, and Reed, 2002). The magnitude ranges from 0.5 percent for large-cap funds to over 2 percent for small-cap funds. Furthermore, this negative autocorrelation in fund returns cannot be observed on other days. The abnormal trading pattern behind portfolio pumping is especially pronounced during the last half hour of the quarter (Carhart, Kaniel, Musto, and Reed, 2002). However, despite the empirical evidence in favor of portfolio pumping, Collins (2004) notes that the returns of passive index funds, which have both limited ability and limited incentives to follow portfolio pumping strategies, are also higher at quarter ends than the returns of the S & P 500. He concludes that other stock return patterns related to the size of the companies might be responsible for quarter-end shifts in mutual fund returns rather than portfolio pumping. Also consistent with a more sceptical view on portfolio pumping, Hu, McLean, Pontiff, and Wang (2009) find that at year end both, abnormal buying and abnormal selling, decline, with the latter declining even at a higher rate.

[133] In the literature, this practice is also referred to as "painting the tape", "marking up", "ramping up", "marking the close" or "high closing" (Carhart, Kaniel, Musto, and Reed, 2002; Duong and Mesche, 2007; Gallagher, Gardner, and Swan, 2009).

[134] For a theoretical model of portfolio pumping from an asset pricing perspective see Bhattacharya and Nanda (2006).

Carhart, Kaniel, Musto, and Reed (2002) distinguish between potential motives for funds: (1) funds with already high performance try to improve their ranking in order to benefit from the convexity of the performance-flow relationship ("leaning for the tape"); (2) funds currently falling short of the benchmark index try to break even ("benchmark beating").[135] Their empirical results are in line with the first explanation. Duong and Mesche (2007) indicate that not only winner funds but also extreme loser funds tend to follow portfolio pumping strategies. Applying a data set of daily trades of Australian mutual fund managers, Gallagher, Gardner, and Swan (2009) confirm the previous findings. In particular, poorly performing managers tend to upscale the holdings of illiquid positions in their portfolio prior to the quarter's end. According to anecdotal evidence, this strategy has also spilled over to hedge funds.[136] One result of this is that similar patterns can now be observed at month ends as well because hedge fund clients usually observe the performance of their funds on a shorter basis. Overall, portfolio pumping was widely applied up to 2001, but decreased sharply afterwards (Duong and Mesche, 2007). This was probably a result of both academic and media attention that made investors aware of such practices and led the SEC to take action.[137] Furthermore, the return impact of such activities was reduced in recent years because of improvements in market microstructure (Gallagher, Gardner, and Swan, 2009).

Window Dressing

"Window dressing" refers to a strategy where mutual fund managers try to look better by hiding out-of-favor stocks in the portfolios which have recently underperformed the market and, obviously, were a mistake to buy in the first place. Shortly before reporting dates such as quarter or year ends, portfolio managers dump these stocks from their portfolios and tilt the allocation toward well known and popular stocks. Usually, this shift is partly reversed after the disclosure date. Meier and Schaumburg (2006) apply a methodology similar to the return-gap analysis of Kacperczyk, Sialm, and Zheng (2008) in order to detect window dressing among a broad sample of more than 3,000 equity funds over the period from 1997

135 A similar pattern can be observed among cooperations trying to match analyst expectations when disclosing their earnings, the so-called "earnings game" (Dechow, Sloan, and Sweeney, 1995; Payne and Robb, 2000).

136 Jesse Eisinger, Lifting the Curtains On Hedge-Fund Window Dressing, Wall Street Journal, 07 September 2005.

137 John Labate and Elizabeth Wine, SEC probes mutual funds, Financial Times, 30 November 2000.

to 2002. They focus on mutual funds whose returns deviate significantly from the hypothetical returns they would have earned based on the most recent portfolio disclosure. About 14.8 percent of all funds show a pattern consistent with portfolio pumping, of which 5.5 percent seem to repeatedly follow this strategy. Liquidity costs, end-of-year effects and momentum trading cannot explain this pattern. Musto (1999) concludes, based on weekly portfolio holdings for money market funds, that fund managers increase the allocation to low-risk government bonds and decrease the allocation to corporate bonds around the reporting date. The negative impact of this practice on investors is not limited to misleading them about the investment strategy and performance of funds but also includes a performance drag due to transaction costs for the unnecessary trades. Transaction costs are presumably above average for these trades due to the immediacy requirement (Meier and Schaumburg, 2006).

2.1.3 Costs and Potential Third-Party Benefits

Consumers usually value the utility they derive from a product or service and compare this utility with its costs or the utility of alternatives. In the case of mutual funds, investors could compare the gross-performance with the management fee or with the gross-performance of alternative mutual funds. Alternatively, they might focus on net-of-fee performance measures of alternative products. In fact, Tkac (2004) argues that the fee level itself should not qualify as hidden action of the investment management company and does not constitute a conflict of interest. This argument no longer holds when certain fee components are disguised and not properly disclosed. Thus, investment management companies might not only maximize profits by directly or indirectly (via performance) affecting inflows, as discussed in the previous section, but might also, first, try to disguise certain cost components, second, try to minimize their own effort and costs while keeping fee levels up and, third, might even try to extract money from the mutual fund's assets with the aid of unaffiliated or affiliated third parties. Fund investors have the right to receive detailed information on transactions, the composition of fees and other expenses paid by the fund as well as who receives payments from the fund because they are not only consumers but primarily owners of the fund's assets.

2.1.3.1 Costs

Some of the costs involved in mutual fund investments are directly paid by investors (e. g. load charges), others are deducted from the fund's assets on a regular basis (e. g. management fees) and others are paid by the investment management company directly (e. g. research and information systems). All of these costs represent income to the investment management company or a third-party service provider which is usually selected by the investment management company (Mahoney, 2004). Barber, Odean, and Zheng (2005) document that the average operating expenses charged by U. S. diversified equity funds steadily increased between 1962 and 1999 while at the same time the number of funds charging front-end loads and the average level of front-end loads steadily decreased. This pattern suggests that the mutual fund industry is aware of the fact that mutual fund investors avoid funds with high fees that are easily visible but are less sensitive to annual fees and less visible fees. This observations indicates that mutual fund companies might be trying to disguise the costs of their products rather than allowing fund investors to participate in cost reductions resulting from potential economies of scale and efficiency gains.

Moreover, disguising costs makes comparisons between different funds for investors more complicated, especially because investors cannot observe all actions of their portfolio managers (Kacperczyk, Sialm, and Zheng, 2008). For example, trading commissions paid by the fund might result in a "return gap" between the fund's performance and a hypothetical portfolio investing in all shares disclosed by the fund in its quarterly statements. However, interim trading profits might lead to a positive gap to the benefit of the investors. Kacperczyk, Sialm, and Zheng (2008), analyzing the return gap of 2,543 funds from 1984 to 2002, document that the return gap is relatively small in aggregate but varies significantly in the cross section. More importantly, it is quite persistent over time indicating that systematic actions of the portfolio managers improve performance for some funds but decrease performance for others. One potential explanation is that those funds with systematically negative return gaps extract money from the funds' assets eventually involving (un-) affiliated third parties.

Related to hiding costs for the services provided is a strategy of reducing efforts by closely tracking the benchmark index while still pretending to offer active management and keeping fees on the level of funds that are truly active. Cremers and

Petajisto (2009) analyze the "activity" of mutual funds along two dimensions: (1) they compute the tracking error volatility which is a measure for active changes in fund style; (2) they develop a new measure termed "active share" which indicates the active deviation of the portfolio weights from the benchmark weights.[138] This measure can be interpreted as the fraction of the fund portfolio that deviates from the benchmark and, thus, it takes on values between 0 and 100 percent. Over time, the fraction of funds that claim to be active in their prospectus but in reality deviate from the benchmark by only 20 to 60 percent of their holdings has increased from almost zero in 1980 to more than 30 percent in 2003. Cremers and Petajisto (2009) term this practice as "closet indexing". Closet indexers charge fees for active management but seem to spare the effort. As active share is positively related to performance, this behavior has a negative impact on investors' utility. Herding, as discussed above, might be another investment approach which requires fewer resources but still allows the investment management company to charge fees at the level of those of active funds.

2.1.3.2 Directed Brokerage and Soft Dollars

Usually, mutual funds use third-party brokers to execute their trades and to acquire research. At the same time, these brokers might be directly involved in the distribution of mutual fund shares or might be affiliated with a distributor of the fund's shares. In this case, the investment management company has the incentive not to choose the broker with the best trade execution, minimizing transaction costs such as commissions and market impact, but rather to choose brokers based on their efforts in marketing fund shares and increasing assets under management. This practice is known as "directed brokerage" (Mahoney, 2004). However, this practice does more than increasing average transaction costs. The advice of the broker given to potential fund investors might also be biased resulting in a suboptimal selection of mutual funds.

Additionally, the costs for research services are often bundled with trade execution services under so-called "soft-dollar" arrangements.[139] For the investment management company this has the advantage that costs for research and information terminals are not paid out of their pockets but are shifted to the mutual fund.

[138] For a definition of active share see equation (1.7).

[139] Note that soft-dollar arrangements can also be interpreted as another way of hiding true fee levels.

Hence, this practice is not in the interest of fund investors.[140] Proponents of soft-dollar arrangements might argue that it does not make a difference whether the costs are paid for directly by the fund management company charging higher fees or if they are deducted from the funds' assets while management fees are lower. Indeed, the results of Edelen, Evans, and Kadlec (2008) support this notion of expense shifting. In particular, marketing expenses (12b-1 fees) tend to be significantly lower among high commission funds.[141] However, it is questionable if the savings of the investment management company are actually passed on to the investors in the form of lower fee-levels because fees are not subject to audit and accountability (Edelen, Evans, and Kadlec, 2008). Expense shifting seems to be accompanied by agency costs: The deterioration of performance following a one Dollar increase in expenses is lower than the reduction resulting from an increase of commissions by the same amount. Services related to soft-dollar payments might, furthermore, deter the investment management company from choosing the broker with the best execution services (Siggelkow, 1999).

Several studies indicate the extensive use of soft-dollar arrangements. For example, the commissions in the fund sample of Livingston and O'Neal (1996) are 0.06 USD per share while at the same time discount brokers offered commissions of less than 0.02 USD. Furthermore, Chalmers, Edelen, and Kadlec (1999) report a positive correlation between commissions and spread costs of 0.53 which is counterintuitive to the expectation that more expensive brokers provide better trade execution. Soft-dollar arrangements might serve as one possible explanation for this observation. Edelen, Evans, and Kadlec (2008) report a high dispersion in the level of commission rates ranging from 0.07 percent for the lowest quintile to 0.32 percent for the highest quintile based on a sample of U. S. equity, bond and balanced funds between 1994 and 2005. The commission payment, defined as the product of the commission rate and turnover, varies between 0.08 and 0.57 percent of total net assets for the lowest and highest quintile, respectively. Consistent with the earlier study of Chalmers, Edelen, and Kadlec (1999), performance is negatively related to commissions after controlling for fund-specific factors indicating that soft-dollars are not used to improve trading efficiency. However, conditional

[140] Tkac (2004) argues that from the perspective of brokers, soft dollars are a means of differentiation. However, this only applies to the provision of proprietary research because the provision of information terminals can easily be duplicated by other brokers.

[141] It can even be shown that the sensitivity of fund flows to past performance is higher among funds with high commission levels (Edelen, Evans, and Kadlec, 2008). It seems that the more opaque the compensation of the sales force the more effective their efforts.

on turnover it appears that the performance of more active funds benefits from higher commission payments suggesting that soft dollars might be used for buying superior information pointing toward potential benefits from soft dollars for fund investors rather than agency costs. In a similar vein, Schmidt and Schleef (2001a) report for the German market, that if trades are executed by an affiliated broker transaction costs do not tend to be significantly higher than in the case of an independent broker.

2.1.3.3 Market Timing and Late Trading

Market Timing

An extreme and prominent example for a wealth transfer from fund investors to investment management companies and associated third parties is the market timing and late trading scandal in the U. S. fund industry. Market timing refers to a practice that allowed certain institutional investors to quickly trade shares of mutual funds investing in illiquid and mostly international securities. If stale prices are used to calculate the net asset value, investors can exploit an information advantage.[142] If this occurs in a systematic and frequent manner, long-term investor suffer from increased transaction costs.[143] However, if the average volume of total net assets increases due to these frequent traders, the investment management company receives a higher fee income and has an incentive to tolerate market timing.[144] Although market timing is legal, it is usually seen as offensive against the funds' code of good conduct.

Zitzewitz (2003) estimates that the costs of market timing for mutual fund investors have grown from 0.56 percent in the period between 1998 and 1999 to 1.14 percent at the height of the scandal in 2001. Profits exploited by market timers are in the range of 10 to 70 percent abnormal returns per year. Greene and Hodges (2002) document similar costs from market timing of 0.48 percent in international funds and 0.94 percent for a subset of funds that is particularly

[142] Mutual fund shares are traded once a day, usually around 4:00 p. m. All orders placed prior to that time are executed at the net asset value of that day according to Rule 22c-1 of the Investment Company Act of 1940.

[143] Consequently, these practices can also be interpreted as conflicts of interest between different investor clienteles in mutual funds, private long-term investors on the one hand and rapidly trading institutional investors on the other hand.

[144] Johnson (2004) argues that in this case fund investors might even benefit from economics of scale and the costs of market timing have to be traded-off against these potential cost reductions.

exposed to market timing. Goetzmann, Ivković, and Rouwenhorst (2001), also using data from TrimTabs as Zitzewitz (2003) and Greene and Hodges (2002), employ a more sophisticated econometric methodology to differentiate between index predictability and true stale pricing. However, they still document strong evidence in favor of the profitability of market timing strategies and estimate a wealth transfer of about 1.5 billion USD during their sample period staring in 1990 and ending in 1998, well before the height of the scandal. Taking tax considerations into account, the negative impact of market timing on after-tax performance might be even larger (Dickson, Shoven, and Sialm, 2000).

Potential measures to reduce market timing are, first, an adoption of redemption fees for investors with short holding periods and, second, the use of fair-value pricing instead of market prices for illiquid or international securities.[145] Redemption fees seem to be a very effective tool for controlling the volatility of mutual fund flows (Greene, Hodges, and Rakowski, 2007). Investors who demand liquidity compensate long-term investors for the costs they cause for the fund.[146] However, the disadvantage is that any costs involved with the redemption of mutual fund shares reduces their liquidity. The results of Bhargava and Dubofsky (2001) suggest that fair-value pricing can, to a large extent, mitigate these effects. These results are supported by Chua, Lai, and Wu (2008) who develop a more sophisticated model based on endogenously determined stepwise regressions to adjust prices at the individual security level. Chalmers, Edelen, and Kadlec (2001b) question the usefulness of fair-value pricing algorithms as long as intermediaries do not have stronger incentives to set fair prices. Investment management companies are usually only evaluated based on investment performance but not on the correctness of the net asset value calculation. However, the departure from market prices imposes the risk of return smoothing, as observed by Bollen and Pool (2009) for hedge funds.

Late Trading

Late trading refers to a practice where primarily hedge funds were allowed to trade fund shares on today's close after the official closing date for fund orders often

[145] For example, Fidelity announced on March 1, 2000, that it would begin imposing a redemption fee of one percent on their international funds if there are less than 30 days between the purchase date and the sell date (Boudoukh, Richardson, Subrahmanyam, and Whitelaw, 2002).

[146] Note that redemption fees, in contrast to back end loads, are usually paid to the fund and not to the fund management company.

with the help of a broker that submitted the orders to the investment management company.[147] Mahoney (2004) interprets late trading as giving the hedge fund an option on the mutual fund shares with the closing time price as strike and an expiration date significantly after the closing time of that day. The price for the option is borne by the fund investors through a dilution of their fund shares. Late trading is an illegal offend against the forward pricing rule. In a recent study, Zitzewitz (2006) documents an annualized loss for fund investors from late trading of 3.77 basis points for international equity funds and 0.88 basis points for domestic equity funds. This amounts to an annual loss for fund investors of about 400 million USD per year. Zitzewitz (2006) estimates that almost a quarter of all equity funds were involved in late trading. After the regulators under the direction of Eliot Spitzer announced investigation into the late trading practice on September 3, 2003, the loss for equity fund investors fell to insignificant levels (Zitzewitz, 2006).

2.1.4 Discussion

From an analysis of the existing literature it is concluded in this section that significant conflicts of interest exist in delegated management. Theoretical arguments as well as empirical evidence support the existence of these conflicts. For example, portfolio managers follow their own interests with respect to their career and engage in tournament behavior with portfolio managers of other investment management companies but also with colleagues within the same fund family. This also involves a certain tendency for herding. Most of these actions are usually not in line with the objective of return maximization for investors.

Additionally, investment management companies usually engage in a variety of distribution and marketing strategies in order to boost the sales of their products. Even though superior performance attracts a lot of inflows and, thus, aligns the interests of investors and investment management companies, this also involves, in some cases, impure actions by the investment management company. For example, some investment management companies have been involved in influencing the advice of brokers given to retail investors and changing names of funds in an attempt to cater to recent fades. These actions directly aim to increase inflows.

[147] Indeed, Boudoukh, Richardson, Subrahmanyam, and Whitelaw (2002) report that at least 16 hedge fund companies offered 30 funds explicitly stating “mutual fund timing” as their strategy. For a list of mutual fund families involved in the scandal see the “Mutual Fund Scandal Scorecard” of the Wall Street Journal.

Alternatively, investment management companies might aim to exploit the positive and convex shape of the performance-flow relationship by "skewing" or even manipulating fund performance. For example, within the fund family investment management companies might strategically start, merge and close funds in order to disguise poorly performing funds, or cross-subsidize the performance of certain funds in the fund family at the expense of other less important funds. Individual funds of the family might game the benchmark and commonly used performance measures by loading on risk factors that are not considered in these benchmarks or try to manipulate their own performance by strategies such as portfolio pumping or window dressing. Usually, brokers try to disguise total costs associated with the fund, such as fees and transaction costs, because these costs have a negative impact on net inflows, especially if they are easily visible to investors. Lastly, investment management companies might aim to extract money from the fund with the help of third parties, such as brokers and research houses, by directed brokerage, soft dollars and market timing or late trading.

This discussion provides strong evidence that it is important to implement measures that reduce the potential for exploiting the inherent agency conflicts in delegated asset management to the cost of investors. However, because these strategies, which are followed by portfolio managers and investment management companies, are usually difficult to detect this requires a certain level of investor sophistication. Several measures that might help to align the interests of investors and portfolio managers as well as the investment management company are discussed in the following section.

2.2 Potential Solutions for Reducing Agency Conflicts

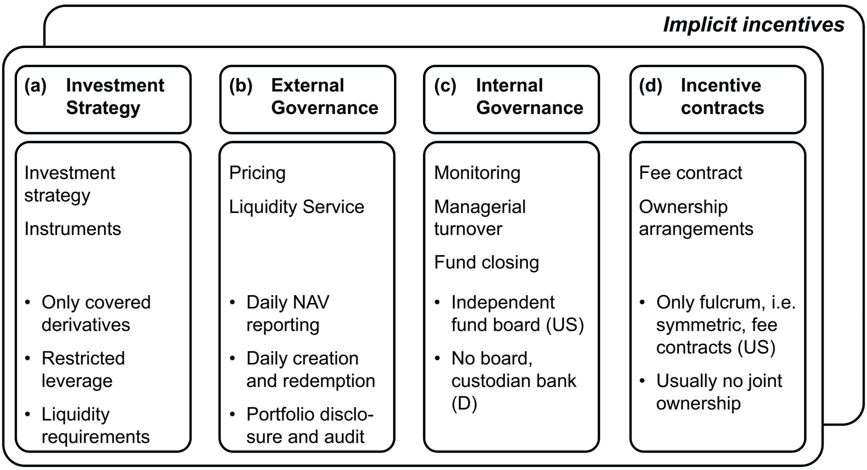
Several aspects of potential conflicts of interest in delegated portfolio management have been discussed in the previous section. These agency costs might help to explain why mutual funds on average do not outperform the market. Indeed, the governance of fund managers is an important issue in delegated asset management. A strict regulatory environment has been developed over the past 60 years with the ultimate objective of protecting private investors.[148] This includes restrictions on the investment strategy or bonding mechanisms, certain transparency require-

[148] Most of the following restrictions and regulations are governed by the Securities Act of 1933, the Securities Exchange Act of 1934, the Investment Company Act of 1940, and the Investment Advisors Act.

ments to enable efficient monitoring, the requirement of daily pricing and liquidity of fund shares (external governance), the facilitation of internal governance mechanisms, and the regulation of the use of incentive contracts (Figure 2.2). Incentive contracts also serve as a signalling and self-selection device. A second layer behind these four explicit control mechanisms are the implicit incentives resulting from the interaction of investors, investment management companies and portfolio managers. These are based on the reputation of fund managers and labor market monitoring as well as the reputation of investment management companies and peer review within the fund family. In addition, the existence of control mechanisms induces a risk shifting of the portfolio manager before facing the threat of outflows or a replacement.[149]

Figure 2.2: Regulation and incentives

This figure presents an overview of the different organizational and regulatory determinants of mutual fund performance and persistence. Most of these restrictions and regulations are governed by the Securities Act of 1933, the Securities Exchange Act of 1934, the Investment Company Act of 1940, and the Investment Advisors Act.



149 Almazan, Brown, Carlson, and Chapman (2004, p. 300) distinguish between "(i) direct monitoring and the role of fund directors, (ii) labor market monitoring and managerial career concerns, (iii) peer monitoring and the role of mutual fund complexes, and (iv) product market monitoring and the structure of fund sales charges." According to the definition used in the present work, (i) refers to internal and (iv) to external governance while (ii) and (iii) are implicit incentives.

2.2.1 Investment Strategy and Instruments

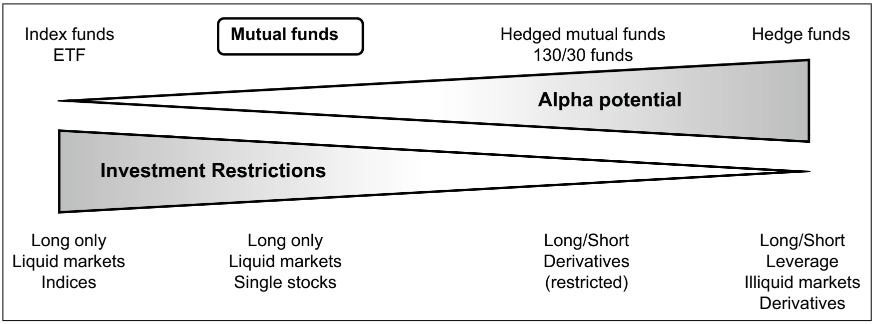
To ensure the ability of mutual funds to provide daily liquidity to investors, regulatory restrictions apply to the available instruments and markets. Mutual funds are required to report a daily net asset value. This is the combined market value of all assets held by the fund divided by the outstanding number of fund shares. Fund investors can buy additional fund shares at the net asset value (plus a sales load) and redeem fund shares on a daily basis, i. e. no lock-up periods, redemption notice periods or similar restrictions apply. Funds are only allowed to hold less than 15 percent of total assets in illiquid securities which should guarantee their ability to meet redemptions at any time. Moreover, certain diversification requirements apply and the portfolio composition must be consistent at least to 80 percent with the investment style implied by the fund's name according to SEC rules. The use of leverage and investments in derivatives such as options, futures, forwards and swaps are restricted to covered positions. Most funds voluntarily further constrain the use of derivatives to risk and liquidity management purposes in their prospectuses. The use of short sales is complicated and cost-intensive due to the requirement to daily reconcile all short sales between the mandatory independent custodian bank and the third-party broker executing the short sale. Additionally, up until 1997 the unfavorable tax treatment of profits from short-term trading and short sales prevented most funds from using these strategies.[150] All of this is especially relevant for mutual funds to facilitate external governance.

These rules not only help to maintain a certain level of liquidity in the funds' portfolio but are also aimed at sheltering investors from excessive risk taking of fund managers and to avoid misreporting of daily net asset values. This is especially relevant when the risk tolerance of investors deviates from the risk preferences of the investment management company. Furthermore, some investment management companies might impose additional restrictions in an attempt to avoid large deviations from the benchmark and to protect their own reputation. Consistent with the view that investment restrictions are substitutes for other governance mechanisms Almazan, Brown, Carlson, and Chapman (2004, p. 300) document that investment restrictions are more likely: "(i) when boards contain a higher proportion of inside directors, (ii) when fund managers are more experienced and funds are team-managed rather than run by an individual man-

[150] The 1997 Taxpayer Relief Act repealed Internal Revenue Code Section 851 (b)(3) which governed the taxation of short-term trading profits.

Figure 2.3: Investment restrictions

This figure presents the position of different investment products along the dimension investment restrictions.



ager (where the team members have less of their reputation at stake than would an individual manager), and (iii) when the fund does not belong to a large organizational complex (i. e. a fund family)." However, they cannot document a relationship between investment restrictions and the structure of load fees which determines product market monitoring.

However, these restrictions clearly limit the potential for the fund manager to generate abnormal returns which can be interpreted as indirect costs of the open-end fund structure (Figure 2.3). Hedge funds can serve as a comparable investment product that is exposed to less regulation than mutual funds.[151] Indeed, studies on hedge fund performance conclude that these products on average offer alphas of around five to seven percent annually (Kosowski, Naik, and Teo, 2007; Agarwal, Boyson, and Naik, 2009). In contrast, hedged mutual funds are governed by the regulation of traditional mutual funds and are obliged to offer daily pricing and liquidity. However, the restrictions with respect to the use of derivatives are relaxed. According to Agarwal, Boyson, and Naik (2009) hedge funds still outperform hedged mutual funds by 5.99 or 6.72 percent per year based on a Carhart (1997) four-factor model and a Fung and Hsieh (2004) seven-factor model,

[151] See footnote 104 for proposed changes in hedge fund regulation and Ackermann, McEnally, and Ravenscraft (1999) for a discussion of differences between the regulation of hedge funds and mutual funds.

respectively. However, hedged mutual funds outperform traditional mutual funds by 1.33 to 3.93 percent per year.[152] The difference in returns between hedged mutual funds and traditional mutual funds can be attributed to lower restrictions, which allows managers to successfully apply these skills.[153]

Consequently, investment restrictions, which should protect investors from agency costs, might at the same reduce the potential of generating abnormal returns. Exchange-traded funds and index funds usually have even stricter investment restrictions than active mutual funds, even though they are not imposed by law. In this case, the investment results should not differ significantly from the benchmark. This transparent and restricted investment policy reduces the discretion of the portfolio managers and, thus, reduces potential conflicts of interest. At the same time, there is no potential to generate alpha. The benefits of active and unregulated and passive and regulated products depend on the relative size of average alpha and average agency costs.

2.2.2 External Governance

2.2.2.1 Transparency and Competition

Internal governance mechanisms might be complemented by external governance mechanisms. Specifically, transparency and competition in the product market, in general, are usually beneficial for consumers and product market competition is often seen as the most powerful force toward economic efficiency (Ippolito, 1992; Shleifer and Vishny, 1997). Several measures are pursued in order to facilitate this mechanism in the mutual fund market. First of all, the SEC requires all mutual funds to report the benchmark that they try to beat in their prospectus.[154] Furthermore, the Global Investment Performance Standards (GIPS), which are effective in more than 30 countries, specify certain rules on the disclosure of performance metrics which allows a "fair" comparison between different funds even across country borders, which is especially relevant for an integrated European mutual fund market. In addition to a fair reporting of performance, mutual funds are required to disclose externally audited reports on a semiannual basis. These

[152] These results are robust to controlling for differences in fund size, age, expenses and flows.
[153] The results of Agarwal, Boyson, and Naik (2009) suggest that part of the performance differential is also due to differences in investment skills.
[154] However, Sensoy (2009) documents that almost one third of diversified U. S. equity funds deviate from their official benchmark.

reports contain information on the portfolio holdings at the end of the period and changes compared to the previous report. Furthermore, when investors value the disclosure of more information or a higher disclosure frequency and reward this by higher flows, investment management companies might voluntarily improve their disclosure policies. Indeed, a lot of funds voluntarily disclose their holdings on a quarterly frequency. Yet, some market participants ask for an official rule requiring more frequent disclosure.

However, Wermers (2001) warns that more frequent portfolio disclosure than semiannually would rather harm investors' performance. The main reason for this is higher trading costs as a result of front running by other investors. This is especially true for liquidity driven trades where portfolio managers work off recent inflows or sell stocks in order to meet redemptions as these trades are more easily predictable. Chen, Hanson, Hong, and Stein (2008) and Coval and Stafford (2007) document empirical results indicating that hedge funds benefit from mutual fund distress by exploiting the predictable relationship between asset sales and fund flows. Furthermore, more frequent disclosure could lead to free riding of other investors on the information of mutual fund managers and might complicate tax-management strategies (Wermers, 2001). In fact, Frank, Poterba, Shackelford, and Shoven (2004) document that "copycat" mutual funds, which immediately purchase the securities disclosed by actively managed mutual funds, earn the same or even higher net returns as their actively managed counterparts.

Ge and Zheng (2005) empirically compare funds voluntarily disclosing their portfolios on a quarterly basis with funds that only provide the mandatory semi-annual disclosure. Portfolio disclosure frequency seems to be negatively related to portfolio turnover, expense ratios and the likelihood of committing fraud. However, the general benefits of the portfolio disclosure frequency depend on the investment skill of the managers. Specifically, skilled managers optimally reduce their disclosure frequency leading to a higher performance of the previous year's winner funds that disclose their portfolios less frequently as compared to winner funds more often disclosing their holdings. These funds successfully protect and exploit their private information. In contrast, agency conflicts prevalent among loser funds can be substantially reduced by more frequent portfolio disclosure resulting in a higher performance for those funds compared to loser funds that disclose their portfolio only semiannually. Similarly, Meier and Schaumburg (2006) suggest enforcing the requirement of disclosing the largest trades of portfolio managers in order to prevent mutual fund managers from window dressing. This disclosure might be delayed in order to protect the managers' private information.

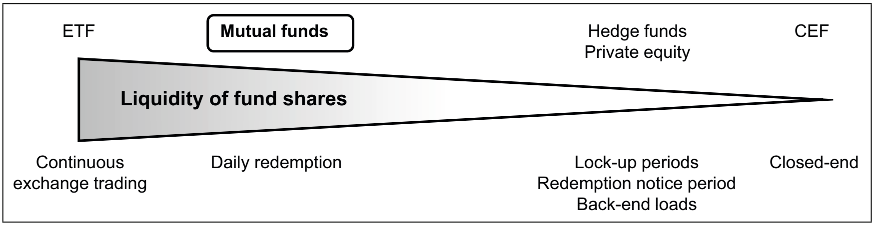
More transparency has intensified competition in the mutual fund industry and the average market share of a fund family decreased by two thirds between 1979 and 1998 (Khorana and Servaes, 2007). The assets of the industry increased by a factor of 20 in the same period and the number of fund families tripled. Fund families with more favorable fee arrangements gained market share. However, no study has directly addressed the question of whether mutual fund investors benefited from this increase in competition over time by a reduction of agency costs and an increase in net returns. Only the emergence and success of low-cost index funds and exchange-traded funds points toward a reduction of agency costs through innovation and competition. However, Keswani and Stolin (2006) provide empirical evidence that higher competition with certain fund sectors is not unambiguously related to better performance for investors. Even though poor performers are more quickly forced to exit when competition is high, performance persistence is also lower in highly competitive sectors.

2.2.2.2 Market-Based Control

Transparency not only intensifies competition but it is also an important prerequisite for a rational response from the product market (Ippolito, 1992). The daily liquidity of mutual fund shares at their net asset value enables an efficient external governance mechanism via the primary market for mutual fund shares. This mechanism is less efficient in regular corporations since it relies on secondary-market trading and the price investors can sell their stake in these corporations most likely already reflects the problems with the management (Chen, Goldstein, and Jiang, 2008). Fund investors do not have to rely on the investment management company or the fund board taking action after a period of unsatisfactory performance results but rather can quickly shift their assets to another, more promising, fund. Moreover, fund investors do not need to initiate or participate in proxy fights against the current management (Tkac, 2004). Specific investment products differ in the level of liquidity which is relevant for external governance (Figure 2.4). It becomes evident that only exchange-traded funds offer a higher level of liquidity than mutual funds, though this is based on secondary-market trading which is not relevant for external governance. Primary-market trading in exchange-traded funds is even less liquid compared to mutual funds because of the in-kind transaction which takes place only in large scales. The liquidity of hedge funds is usually highly restricted and closed-end funds do not offer any liquidity at all on the fund level.

Figure 2.4: External governance

This figure presents the position of different investment products along the dimension liquidity / external governance.



In general, there is not a strong empirical link between external governance and performance improvements for mutual funds. Only Anderson, Coleman, Gropper, and Sunquist (1996) suggest a negative relationship between agency costs and the liquidity of different fund types in a comparison between open-end and closed-end funds. Empirical evidence for the cross section of mutual funds, in contrast, suggests a rather weak relationship because investors are reluctant to withdraw money from poorly performing funds (Sirri and Tufano, 1998; Lynch and Musto, 2003). Johnson (2010) confirms these results based on a proprietary panel of all shareholder transactions in one no-load mutual fund family. This result is consistent with the empirical observation that performance is more persistent among losing funds compared to recent outperformers (Carhart, 1997). Berk and Tonks (2007) argue that this behavior of fund investors is comparable to the prepayment behavior of mortgage holders. Specifically, some mortgage holder refinance their debt when interest rates are low while others miss this chance. If now in the context of mutual funds the proportion of fund investors who remain invested in a fund after a year of poor performance for a second year is large enough, i. e. external governance is not exercised on a large scale, subsequently these funds remain poor performers.

Investors' sluggishness in withdrawing money from losing funds can be partly explained by the costs involved with this process and their reliance on the effectiveness of internal control mechanisms.[155] Investors might expect a strategy change at the fund level. Thus, past returns convey two facts to the investor: the skills of the current manager in the past, and the likelihood that the strategy will be changed (Lynch and Musto, 2003). This can either occur through a replacement of the underperforming manager by the investment advisor or by the same fund manager applying another investment algorithm. Indeed, strategy changes follow periods of poor performance. As a result, future performance of bad performers that change strategy is expected to be significantly less sensitive to past performance than performance of loser funds who do not change strategy. However, empirically this relationship can only be established if a strategy change is accompanied by a change in management. Furthermore, one could expect that the behavior of fund investors is similarly biased as observed among equity investors in the sense that they sell winner funds too early in order to cash in on marginal profits but stick to loser funds too long because they do not want to realize their losses. However, Ivković and Weisbenner (2009) conclude that this "disposition effect" is not prevalent among mutual fund investors and cannot explain their behavior. Johnson (2010) argues that outflows might be less sensitive to performance as they can only come from old investors whereas inflows may come from old investors increasing their existing investments or from new investors establishing an initial stake. He shows that both types of investors respond to past outperformance to a similar degree by buying new shares of the fund. However, outflows of loser funds are more sensitive to past outperformance of other funds of the family which attract the money after the withdrawal rather than to their own past performance. Fund investors are actively buying funds but they are not actively selling funds.

External governance mechanisms might be enforced by the services of rating agencies such as Morningstar or Lipper, media coverage and performance rankings as well as sophisticated investors such as funds of funds and wealth managers to the benefit of less sophisticated retail clients (Del Guercio and Tkac, 2008). The higher the sensitivity of funds flows with respect to bad previous performance, the more efficient the external governance mechanism is. If information intermediaries are able to condense information about past performance in a comprehensible way

[155] See also section 4.2.

for investors, more frequent and more detailed information disclosure might indeed be a value added. It reduces monitoring costs and provides a screening device. Yet, empirical evidence on the value from mutual fund ratings remains rather mixed (Blake and Morey, 2000; Morey, 2005). The results of Blake and Morey (2000) indicate that only Morningstar downgrades can be used to identify future poor performers. The new rating methodology introduced by Morningstar, however, has some predictive power with respect to future outperformance (Gottesman and Morey, 2007).

However, recent empirical evidence on the closed-end fund discount shows that if external control mechanism are nonexistent, which applies to closed-end funds, investors indeed closely monitor the internal control process. Specifically, the closed-end fund discount is related to invertors' belief about managerial abilities (Berk and Stanton, 2007; Wermers, Wu, and Zechner, 2007). For example, during the period around manager replacements, the closed-end fund discount initially widens due to poor performance but then decreases shortly before the replacement of the manager (Wermers, Wu, and Zechner, 2007). This indicates that investors anticipate the replacement of the manager and a subsequent improvement in performance and that internal and external governance mechanisms might indeed be related.

At the same time, the benefits of liquid fund shares for external governance are accompanied by liquidity costs through a higher trading volume of open-end funds.[156] These costs basically stem from transaction costs and a lower performance of liquidity-induced trades (Edelen, 1999; Alexander, Cici, and Gibson, 2007). Fama and Jensen (1983, p. 327) state that the "form of organization that survives in an activity is the one that delivers the product demanded by customers at the lowest price while covering costs." The most important cost components in this context are agency costs on one side and liquidity costs on the other. According to this argument, the dominating market share of open-end funds compared to closed-end funds might suggest that the benefits from external governance are larger than the costs from liquidity-induced trading.[157] But this conclusion might be misleading (Stein, 2005). In the presence of asymmetric information about managerial skill, there might be the tendency for too many funds to open up.

[156] Section 1.4.

[157] Total assets of open-end funds where 11,121 billion USD as compared to 228 billion for closed-end funds at the end of 2009 according to ICI (ICI Investment Company Factbook 2010).

Any manager with high skills prefers an open-end structure in order to signal quality and gain more assets under management. This signal can be copied easily by unskilled managers which results in all funds opening up their structure. Thus, the solution to only offer closed-end funds does not seem to be stable even if this solution was beneficial from the perspective of overall social costs.

2.2.3 Internal Governance

Internal governance mechanisms, which refers to a forced strategy change or a manager replacement, are rather weak in general which can be seen as a result of effective external control. Fund managers are employed by the investment management company which is legally independent of the mutual fund itself. Investors, therefore, do not have direct control over the decision to replace underperforming managers. In the U. S., fund boards exist that should control the investment management company in the interest of the fund investors. In 2004, as a result of the fund scandals in 2003, the SEC proposed a rule to increase the fraction of independent directors at fund boards to at least three quarters and required an independent chairman as well.[158] However, this rule was rejected twice in federal appeals court.[159] Fund boards in general do not have a direct impact on the replacement of the fund manager. Theoretically, the fund board could appoint another fund management company but in practice this usually does not happen.[160] Even worse, as the SEC delegates governance to boards of directors, which still lack the necessary power and full independence, investment advisors are insulated from direct SEC supervisory oversight (Haslem, 2010). In other countries such as Germany no fund board exists at all. The custodian bank is obliged to monitor the investment manager but has no means of action, though the German capital market supervision agency Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) also supervises investment management companies. It remains questionable if

[158] This was the last step in a sequence of reinforcements of this rule: The 1940 Investment Company Act requested that a maximum of 60 percent of the directors were affiliated with the investment company. The 1970 Amendment broadened that definition by allowing a maximum of 60 percent of *interested* persons. This was replaced by the 2001 Amendment that requested a majority of independent investors and, finally, in the 2004 Amendment three quarters were requested. In addition, the chairman of the board has to be independent as well.

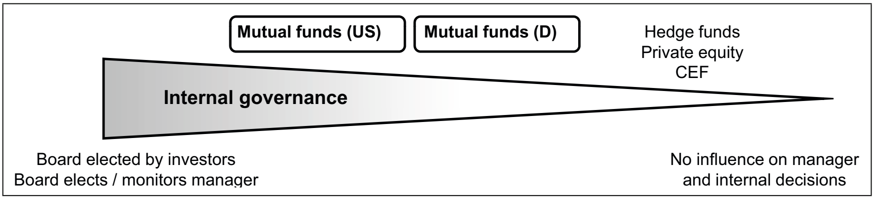
[159] Shefali Anand, SEC Remains Divided On Fund-Board Rule, Wall Street Journal, March 16, 2007.

[160] Tufano and Sevick (1997) report that only in three instances during the past 30 years fund boards replaced the investment management company against its wish.

these mechanisms are sufficient to urge the fund manager to generate abnormal returns and to replace him if he does not. An overview of the internal governance mechanisms is presented in Figure 2.5.

Figure 2.5: Internal governance

This figure presents the position of different investment products along the dimension internal governance.



2.2.3.1 Fund Board

It has been empirically documented by Ding and Wermers (2006) that both the size of the board and its independence have a positive impact on the likelihood of a manager replacement subsequent to a period of poor performance. In contrast, Adams, Mansi, and Nishikawa (2010) report an inverse relationship between board size and fund performance for a sample of passive funds. They link this relationship to the operational efficiency of the fund. However, the optimal board structure also depends on characteristics of the investment management company and the investment style. Kong and Tang (2008) argue that unitary boards of small size, i. e. one fund board oversees all funds of the family, are more beneficial to investors than large independent fund boards. Consistent with this, Tufano and Sevick (1997) document that fees are lower when fund boards are smaller and more concentrated in independent directors who sit on a large fraction of other funds from the same fund family. Furthermore, there is weak evidence suggesting that higher paid directors are more likely to approve higher management fees. With respect to the proportion of independent directors and the existence of an independent chairman Ferris and Yan (2007b) cannot find any empirical evidence that these measures have an influence on the likelihood of being involved in the fund scandals in 2003 (market timing and late trading).[161] Furthermore, the independence of the board does not seem to be related to the fee level, portfolio turnover or fund performance. Consistent with this argument, Adams, Mansi, and Nishikawa (2010) report that no single optimal board structure exists. Rather, an effective board structure improves performance only if the fund sponsor is publicly held but not for privately held sponsors implying different levels of agency conflicts depending on the ownership structure. In summary, the empirical evidence on the effectiveness of mutual fund boards remains mixed.

However, the implicit incentives of all funds from the same family might deviate from those of each fund individually (peer review). The investment management company might act as a monitor because its incentive structure differs with respect to the time horizon (Ferris and Yan, 2009). Short-term profit maximization might not, in some cases, be compatible with long-term targets regarding asset growth. Rather, reputation and the reduction of asymmetric information with respect to the skill of the portfolio manager play an important role. This is especially prevalent when fund investors are unable to distinguish between true investment skill and luck (good or bad). Gervais, Lynch, and Musto (2005) argue that in this case fund families may serve as delegated monitors and provide informative signals by firing some managers and by retaining others. This is the case as the managers can disclose more information, for example on their trades, to the fund family than they can provide to investors because they would face the risk of front running and free riding. However, as the fraction of (ex-ante) fired managers does not necessarily need to match the fraction of (ex-ante) unskilled managers the signal of the fund family does not completely solve the problem. But the signal becomes more precise the higher the number of funds that belong to the fund family. Indeed, as only well performing funds generate significant inflows investment advisors often fire underperforming managers.[162] Thus, in this case it is not the fund board but the investment management company taking action in the interest of fund investors because this is also in its own interest.

[161] Section 2.1.3.3.

[162] In fact, about 14 to 18 percent of fund managers are replaced every year (Ding and Wermers, 2006).

2.2.3.2 Manager Changes

Several studies document an inverse relationship between previous fund performance and manager turnover.[163] Replaced managers exhibit about two years of significant underperformance before being replaced (Khorana, 1996). However, more recent performance seems to play a greater role in the replacement decision than previous performance and investment advisors observe risk-adjusted performance measures when making decisions about the termination of a manager, i. e. higher underperformance is tolerated among more volatile funds. Managers in the lowest performance decile face a four times higher risk of being replaced than those in the highest decile.

Analyzing promotions (manager subsequently manages a larger fund) and demotions (manager subsequently manages a smaller fund) separately, Hu, Hall, and Harvey (2000) and Baks (2003) report that higher returns, both raw and risk-adjusted, lead to promotions and lower past returns lead to demotions. However, returns have a larger effect on explaining demotions than on the overall replacement probability or promotions. Promotion decisions by investment advisors seem to be driven by raw returns rather than by risk-adjusted returns (Hu, Hall, and Harvey, 2000). Additionally, the overall replacement probability for both, demotions and promotions, is higher in larger funds.

Manager replacements are also preceded by a period of fund outflows. Khorana (2001) and Gallagher and Nadarajah (2004) document that bad performing funds suffered redemptions before the manager was replaced.[164] This indicates that existing and prospective shareholders pay close attention to replacement decisions by investment advisors. Similarly, stronger results on the impact of outflows on the termination of a manager are obtained when looking at the flows of a fund's "block holders". The termination of a superannuation plan mandate significantly increases the likelihood of a fund company replacing the fund manager (Dishi, Gallagher, and Parwada, 2007). However, the empirical results of other studies on a causal link between flows and replacement are rather mixed. Even though

[163] Khorana (1996), Chevalier and Ellison (1999b), Gallagher and Nadarajah (2004), Dishi, Gallagher, and Parwada (2007), and Wermers, Wu, and Zechner (2007). An inverse relationship has also been documented in industrial companies between manager turnover and financial performance (Coughan and Schmidt, 1985; Gilson, 1989) or operating performance (Murphy and Zimmerman, 1993). Furthermore, financial performance improves after a manager replacement (Denis and Denis, 1995). Voting-by-feet of institutional investors even increases the likelihood for a forced CEO turnover (Parrino, Sias, and Starks, 2003).

[164] Khorana (2001) further states that the replacement actually reverses this trend.

negative asset growth rates increase the likelihood of being replaced, returns-based performance measures seem to dominate the asset growth measure in explaining the likelihood of a manager replacement (Khorana, 1996). Hu, Hall, and Harvey (2000) can only document a significant relationship between past flows and overall replacement probability whereas the coefficients on promotions or demotions separately turn out to be insignificant.

With respect to the effectiveness of internal control mechanisms to discipline fund managers it is interesting to understand how risk and return characteristics of the fund change after the replacement of the manager. Khorana (2001) and Gallagher and Nadarajah (2004) report significant improvements in returns after the replacement of an underperforming manager and significant deteriorations after the replacement of an outperforming manager.[165] Similarly, Wermers, Wu, and Zechner (2007) document that for closed-end funds, which do not offer an external control mechanism, performance improves after a manager replacement. However, the abnormal performance of new managers who replaced underperforming managers stays negative in the first year after replacement and is only slightly above zero after three years (Khorana, 2001). Similarly, Goyal and Wahal (2008) document that excess returns are insignificantly different from zero after plan sponsors have fired their investment managers. Furthermore, excess returns of fired investment managers are frequently positive.

However, Christopherson, Ferson, and Glassman (1998) document persistent underperformance of some managers in their sample of 273 pension fund managers. This finding is puzzling as one would expect that professional investors such as plan sponsors and their plan consultants tend to fire underperforming managers on a timely basis. Control mechanisms are expected to be more efficient in that field, as all parties involved are more sophisticated than in the case of retail mutual funds. Moreover, from a tax-sensitive investor's perspective, a manager change involves the disadvantage that most new managers realize a considerable fraction of unrealized capital gains when restructuring the portfolio according to their view (Bergstresser and Poterba, 2002). All investors suffer from such behavior in the form of tax liabilities and increased trading expenses.

Comparing the risk measures of replaced and new managers Khorana (1996) does not document a significant change in risk before and after the replacement.

[165] However, most of these results are based on performance measures that do not account for the general trend for mean reversion in fund returns over time.

In contrast, Khorana (2001) documents in another study a statistically significant but, according to the absolute level, small increase in total fund risk before the replacement and a decrease in the post-replacement period. He cannot find any significant change in the systematic risk level. Lynch and Musto (2003) compare the performance of replaced managers with the performance of non-replaced managers who altered their investment algorithm (as measured by a change in the funds' risk loadings). Only new managers change the strategy of a fund significantly enough to improve performance afterwards. This might be partly due to new managers selling momentum losers they inherited from their predecessors at a higher rate than continuing managers do (Jin and Scherbina, 2010).

Already anticipating their replacement poor performers have higher portfolio turnover rates, higher risk and higher expenses than non-replaced managers (Khorana, 1996, 2001; Baks, 2003).[166] Furthermore, they tend to follow momentum strategies (Gallagher and Nadarajah, 2004). The higher turnover rates might be a sign of window dressing and herding of the losing managers and decrease significantly after their replacement (Khorana, 2001). This behavior is more pronounced among younger managers and managers with a shorter tenure in fund management as these groups face a higher risk of being replaced (Chevalier and Ellison, 1999b; Ding and Wermers, 2006). Gallagher and Nadarajah (2004) document an increase of a tracking error in an attempt to reverse poor performance before the replacement. This risk-shifting behavior is consistent with the results for tournaments between fund managers (e. g. Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997).

In a nutshell, the empirical evidence on the value added to an investor from the replacement of a manager remains rather mixed. Facing the risk of replacement before it actually occurs managers might waste investors' money due to higher turnover rates. After the replacement, results are unclear whether the new manager can generate abnormal returns. A partial explanation for this might be that fund performance can only be explained to a certain degree (10 to 50 percent) by the manager and depends to a larger degree on the fund itself through e. g. information resources, in-house research and trading efficiency of the fund company (Baks, 2003; Kacperczyk and Seru, 2007).

[166] Note that if these strategies are successful on average that would make it harder in the empirical analysis to detect a significant difference between replaced and non-replaced managers that previously underperformed.

With respect to the benefits of a replacement to the investment advisor, no study directly reports any evidence of a link between manager replacements and subsequent fund flows. However, a viable strategy from the view of an investment management company for replacing a losing manager might be to close the fund or to merge it with another fund. Indeed, funds which disappear due to a merger or death tend to have poor performance just prior to disappearance.[167] This strategy seems attractive as it offers the possibility of opening a new fund that easily attains publicity and attracts new inflows. Indeed, small and young funds are shown to exhibit a higher flow sensitivity than large and old funds (Sawicki and Finn, 2002).[168]

2.2.3.3 Optimal Fund Size

Another important aspect of internal governance is to shelter the fund from excessive inflows in the interest of existing shareholders once it reaches a size that bloats organization and decreases the number of good investment ideas due to capacity constraints in the market. One possibility is to soft-close a fund which means that existing shareholders can still withdraw their money (and sometimes invest new money) but the fund is closed to new investors from the outside. For example, Fidelity decided to close the Magellan Fund to new investors in August 1997 as a consequence of high inflows and low relative returns in the three previous years.[169] However, investors have no direct influence on this decision. The fact that fees are usually based on assets under management might prevent the investment management company from closing a fund once it exceeds a certain size threshold. As a result, large funds remain in the market even though they might no longer be able to provide superior returns. In contrast, hedge funds do not have an incentive to grow over and above their capacity constraints due to different compensation contracts (Goetzmann, Ingersoll, and Ross, 2003).

Analyzing the changes in fund size and fees after funds are ranked into the top

[167] Brown and Goetzmann (1995), Elton, Gruber, and Blake (1996b), Carpenter and Lynch (1999), and Carhart, Carpenter, Lynch, and Musto (2002).

[168] Furthermore, almost all net inflows that have been attracted by DWS, one of Germany's largest investment advisors, came from funds newly established within the last year (DWS presentation at Morningstar's Investment Conference 11/2007).

[169] Several previously closed mutual funds including Fidelity's Magellan have recently started to reopen again stating that the recent market turmoil offered enough new investment ideas to accept fresh money from investors (Rate of fund reopenings speeds up, Financial Times, Weekly Review of the Fund Management Industry, 21 April 2008; Fidelity öffnet den Magellan Fonds wieder, Börsenzeitung, 16 January 2008).

decile Elton, Gruber, and Blake (1996a) conclude that skilled fund managers increase their salaries by increasing fund sizes rather than increasing the fees. However, fund closings appear more often at larger funds with better performance after a period of inflows (Zhao, 2004; Bris, Gulen, Kadiyala, and Rau, 2007). During closure, fees are usually increased in order to compensate for capped fund size (Bris, Gulen, Kadiyala, and Rau, 2007). However, this does not protect the performance of this fund (Zhao, 2004). According to Zhao (2004) closing rather brings positive attention to other funds in the family and triggers subsequent inflows. Bris, Gulen, Kadiyala, and Rau (2007), however, do not support the finding of Zhao (2004) on a positive spillover effect on fund flows. They document that after size declined funds reopen but do not earn superior returns. Thus, even sheltering funds from additional inflows does sot seem to guarantee the continuation of significantly positive abnormal returns. Investment performance tends to revert to average levels. However, these studies do not analyze whether there are differences in the extent of mean reversion between recent winner funds that are sheltered from excessive inflows and those that are not.[170]

2.2.4 Incentive Contracts and Ownership Structures

An alternative to monitoring and controlling mutual fund managers is to align the interests of managers with those of investors. The personal wealth of the manager needs to be linked to the performance of the fund by either performance-based compensation or requiring the fund manager to hold a stake in the fund. However, the incentive contract is negotiated between the portfolio manager and the investment management company and neither investors nor their representatives are involved. Thus, investors can only choose from the contracts that are being offered by different investment products (Figure 2.6).

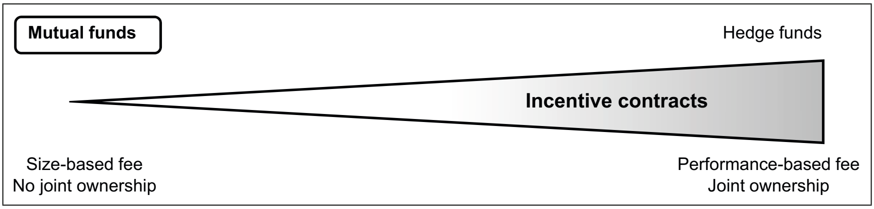
2.2.4.1 Performance-Based Compensation

Incentive fees can reduce moral hazard and adverse selection problems. In the first place, managers with the highest talent will choose to work for funds offering performance-based compensation contracts (Elton, Gruber, and Blake, 2003). Thus, incentive contracts determine the signalling of information about managerial skill by different investment advisors and, as a result, the competition be-

[170] This question is analyzed in the empirical part in section 7.3.

Figure 2.6: Incentive contracts

This figure presents the position of different investment products along the dimension incentive contracts.



tween them (Das and Sundaram, 2002). This is especially important for young managers because the level of asymmetric information about their true managerial skill is still high and can only be reduced over time by building up a track record. Learning over time about managerial skill is more efficient if the managers face incentives to deviate from the benchmark. In this case, the signal is more costly for young managers who face higher termination risks when they deviate from the benchmark and fail to deliver superior investment results (Chevalier and Ellison, 1999b). Moreover, for individual funds, as well as for the mutual fund industry as a whole, performance-based compensation is an important instrument for attracting and keeping talented managers. Otherwise these managers might leave and go to hedge funds or in-house trading desks of investment banks where their compensation is more strongly aligned with their performance.

Secondly, managers paid depending on their performance are believed to elicit the highest effort (Elton, Gruber, and Blake, 2003). Thus, the fee structure also has an impact on the selection and composition of the risky assets in the portfolio as well as the risk sharing between the advisor and the investor, i. e. how returns are distributed between the two (Das and Sundaram, 2002). Even though performance-based compensation contracts are heavily used in the hedge fund industry they can still be very rarely found among mutual funds.[171] One reason for this might be that only fulcrum fees are allowed according to the 1970 Amendment

[171] Only 108 out of 6,716 mutual funds used performance fees in 1999 according to Elton, Gruber, and Blake (2003). However, these funds constitute 10.5 percent of total fund assets and grew faster in subsequent years than non-incentive fee funds. Ippolito (1992) reports that less than 5 percent of the funds in his sample apply performance fees.

to the Investment Advisors Act of 1940 for mutual funds. A fulcrum fee increases or decreases symmetrically with the relative performance of the fund compared to a benchmark. It is supposed to avoid an option-like payoff structure and excessive risk taking by the fund manager associated with asymmetric performance contracts.

Indeed, incentive fees, i. e. option-like payoff structures, lead to riskier portfolio allocations than fulcrum fees according to a theoretical model by Das and Sundaram (2002). Fulcrum fees have the advantage for risk-averse investors of encouraging the fund manager to decrease the risk of the portfolio and to transfer mass from the tails of the return distribution to its center, i. e. making the return distribution less skewed which is preferred by investors. However, with respect to the separation of informed and uninformed managers, fulcrum fees increase the downside risk of mimicking strategies for uninformed managers making mimicking more expensive. Thus, in the presence of fulcrum fees informed managers can extract higher fees from investors lowering their welfare. If market entry costs are high or the competition in asset management industry is low, the separation in general is easier and the model of Das and Sundaram (2002) implies that the benefits of fulcrum fees with respect to risk-sharing and portfolio selection dominate. However, with low market entry costs incentive fees seem to dominate as they lower the ability of informed managers to extract much of the surplus. In contrast, Carpenter (2000) argues that in some cases the optimal volatility of the manager under the option-like pay-off structure is less than if the manager would be trading his own account. This is especially true for large funds and when the evaluation date is still far away. Under robust conditions, incentive fees dominate fulcrum fees with respect to investor welfare.

In addition, a measurement problem arises. In order to link the compensation of the manager to his performance, the skill and effort of the manager need to be measured which is complicated as the portfolio composition or trades usually cannot be observed. Relative performance compared to a passive benchmark index or other active funds can be applied as a substitute for information on trades. However, Admati and Pfleiderer (1997) question the usefulness of passive relative-performance benchmarks for an alignment of interests between portfolio managers and investors. Specifically, they suggest that benchmark-adjusted compensation schemes using passive indices have the following characteristics: (1) they are generally inconsistent with optimal risk sharing; (2) they are inconsistent with obtaining an optimal portfolio composition, especially as other assets of the investor are not taken into account; (3) they tend to reduce the managers effort; (4) they cannot be used to identify skilled managers. One of the reasons for these weaknesses is that managers can undo the payoff effects of the benchmark by changing the portfolio weights. Thus, even though passive relative benchmarks are useful in assessing the skill of a manager ex-post their relevance in aligning the interests of managers and investors are questionable. Yet, an alignment of manager compensation with absolute portfolio performance might still be beneficial. An alternative might be to benchmark the portfolio manager against other active managers because in this case the benchmark depends on other managers' portfolio choice and is unknown to uninformed managers.

Surprisingly, empirical evidence suggests that incentive fee mutual funds have lower market exposures than their peers without such a fee contract resulting in returns below the benchmark and on average add no value by security selection (Elton, Gruber, and Blake, 2003). Even though Elton, Gruber, and Blake (2003) document significantly higher after-expense alphas between incentive fee funds and non-incentive fee funds, this can be attributed completely to differences in fees and is no longer significant in before-fee alphas. This result suggests that incentive fee fund managers neither possess higher skills (self-selection) nor do they exercise higher efforts. In contrast, they have a higher tendency to increase their risk taking after a period of bad returns. In contrast, empirical results for hedge funds, where performance-based compensation is more common show that performance has a stronger tendency to persist (Kosowski, Naik, and Teo, 2007). A potential explanation for this is that interests are better aligned in the hedge fund industry as compared to the mutual fund industry.

While Elton, Gruber, and Blake (2003) focus on direct incentive fee funds, i. e. funds that have convex fee structures with respect to performance, Massa and Patgiri (2009) analyze indirect incentives from the performance-flow relationship by comparing funds with linear or concave fee structures with respect to assets under management.[172] A concave fee structure results if the percentage

[172] Specifically, the measure for concavity is Cole's incentive rate defined as the difference between the last and the first marginal compensation rates divided by the effective marginal compensation rate. Alternative measures which have been used in the study include: (1) the weighted incentive rate (WIR) defined as the ratio of the weighted average of the marginal compensation rates to the first applicable marginal compensation rate; (2) the Dollar Incentive Rate (DIR) defined as the difference between the last and the first fee rates multiplied by the total net assets of the fund times the performance-flow sensitivity

management fee decreases with an increase in assets under management. In this case, fees are less sensitive to inflows once the fund grows in size reducing the incentive to perform. About one third of the managers in the sample of Massa and Patgiri (2009) face a concave contract. Their empirical results indicate that funds with higher incentives, i. e. those with linear fee contracts, take on more risk which reduces their survival probability. However, on a risk-adjusted basis, higher incentives translate into higher performance. The top incentive quintile of funds outperforms the bottom quintile by 0.22 percent per month based on a four-factor alpha (by 0.23 percent based on raw returns). Moreover, high-incentive winner funds of the previous year have a significantly positive alpha of 0.41 percent per month in the following year. Most of this performance improvement results from beneficial short term trading as measured by the return gap of Kacperczyk, Sialm, and Zheng (2008).[173] These results indicate that indirect incentives via the performance-flow relationship are an important mechanism to align the interest of investors and fund managers.

2.2.4.2 Ownership Structures

In addition to performance-based compensation, similar incentives could be obtained by requiring the fund manager to invest in his own fund. First, this limits excessive risk taking by the manager (Kouwenberg and Ziemba, 2007). Second, it improves performance as compared to funds with managers who do not hold a stake in their own fund (Khorana, Servaes, and Wedge, 2007). French (2008) argues that fund managers usually do not hold significant portions of the funds they manage. In contrast, Evans (2008) reports that for a sample of 237 funds in the period between 2001 and 2004 over half of all managers own more than 100,000 USD in their own funds; 28 percent even hold stakes larger than 500,000 USD. Similarly, Khorana, Servaes, and Wedge (2007) document that 43 percent of the managers in their sample hold stakes of their own funds even though these stakes are usually relatively small with the 75th percentile falling into the category of a stake between 50,001 and 100,000 USD.

of the investment category of the fund; (3) the incentive ratio (IR) defined as the ratio of the fee rate that would apply after a 10 percent increase in total net assets compared to the fee rate that would apply after a 10 percent decrease in total net assets; (4) a dummy variable indicating whether the fee contract is linear or not. The results are not affected by the choice of the measure.

[173] For a definition of the return gap measure see page 39.

Accordingly, performance improves between 2.4 and 5 basis points (depending on the performance model and the included control variables) for each basis point of managerial ownership, even after controlling for several aspects of board effectiveness (Khorana, Servaes, and Wedge, 2007). Furthermore, manager ownership predicts future performance. Evans (2008) confirms these results: if fund managers own more than 100,000 USD of their own funds, the style-adjusted performance is about 2.6 percent higher per year compared to funds where managers own less than 100,000 USD or even nothing. Funds with significant managerial ownership also have approximately 61 percent lower asset turnover levels. This suggests that managers who do not own a significant portion of the funds they manage are engaged in churning activities, i. e. they trade without superior information and destroy value rather than creating it. However, Evans (2008) cannot document evidence that highly invested fund managers care more about tax implications of their trades than managers with a low stake in the fund or no stake at all.

Not only the investor-manager conflicts can be reduced by joint ownership. Also the incentives between the board of directors and investors can be aligned. The effort of directors in monitoring the fund manager is enforced by an investment of their own money into the funds they control. Indeed, Chen, Goldstein, and Jiang (2008) document that a significant fraction of mutual fund directors hold shares in the funds they oversee. About two-thirds of directors hold on average 14,000 USD in each fund they oversee, totaling at 267,000 USD in all funds of which they are board members. Indeed, if the funds' investor clientele is less sophisticated, or if the investment strategy is more complex, a larger fraction of directors hold a stake in the fund. There is no difference in fee levels between funds with and those without ownership of the board of directors. However, a high and concentrated level of ownership is associated with lower fees. Total board member ownership seems to be significantly related to current performance and also weakly predicts future performance, which might result from the fact that ownership levels are fairly persistent over time. Again, concentrated ownership is more beneficial for investors. Cremers, Driessen, Maenhout, and Weinbaum (2009) provide even stronger evidence in favor of a positive relationship between director ownership and fund performance. Based on governance-sorted portfolios of funds they document that funds with low ownership of nonindependent (independent) directors underperform their peers by statistically significant 2.48 (2.01) percentage points per year, a result which is mainly explained by the extreme underperformance of low or zero ownership funds. They conclude that ownership of board members aligns the interests of directors and investors while the results do not seem to be driven by private information of board members regarding future fund performance.

Additionally, Ferris and Yan (2009) argue that the ownership structure of the investment management company affects the level of agency costs within mutual funds through different time horizons. Fund families which are publicly owned tend to have a stronger focus on short-term profits as they are subject to semi-annual or quarterly disclosure requirements. Moreover, their stocks are usually exchange-listed and closely followed by analysts and the market. In contrast, privately held investment management companies such as Fidelity tend to have a more concentrated and dedicated ownership structure.[174] This allows them to focus on long-term value creation without suffering from the potential distractions of short term targets enforced by analysts and frequent disclosure of results. Consequently, Ferris and Yan (2009) conjecture that agency conflicts are less pronounced in privately held mutual fund companies.[175] Vanguard Group might serve as an extreme example. In fact, the mutual funds offered by Vanguards themselves are the shareholders of the investment management company. This might, on the one hand, help to reduce conflicts of interest between the investment management company and the fund investors. On the other hand, however, there is no external control for Vanguard Group itself as the portfolio managers exercise the voting rights. This might result in lower efficiency and lower abilities to attract skilled fund managers comparable to the problems among mutual banks (Tkac, 2004).

These hypotheses are empirically confirmed by Ferris and Yan (2009) based on a data set of 750 fund families over the period of 1992 to 2004: public fund families tend to charge higher fees even after controlling for factors influencing the fee level such as fund size and past performance. Even more importantly,

[174] Note that in continental Europe most of the large investment management companies, even though not being publicly listed, are subsidiaries of large public banks and, therefore, most likely follow short-term interests. In fact, the share of investment management companies owned by banking groups is 68 percent in Austria, 65 percent in Portugal, 59 percent in Greece and 58 percent in Germany even though the same figure is only 28 percent in the U. K. according to the European Fund and Asset Management Association (EFAMA, 2009, Asset Management in Europe: Facts and Figures).

[175] For example, allowing favored clients to pursue market timing strategies increases short-term profits through an increased asset size but potentially harms long-term fee revenue due to lower fund performance and reduced investor inflows (Ferris and Yan, 2009).

funds of public fund complexes significantly underperform the funds of private fund families both gross and net of management fees. The difference in objective-adjusted returns is between 0.29 and 0.34 percentage points per year while the spread in risk-adjusted returns is between 0.26 (insignificant) and 0.82 percentage points per year depending on the factor model used. Ferris and Yan (2009) explain this spread through different levels of agency costs.

In a related study, Ferris and Yan (2007a) argue that not only the ownership structure of the investment management company but the characteristics of the fund in a broader context affect agency costs. They define "namesake" mutual funds as funds where the fund manager typically sits on the board, usually as chairman, is the majority owner of the investment management company, and owns a significant portion of the fund's shares.[176] The sample of Ferris and Yan (2007a) extends from 1984 to 2004. During this period, between 3 (in 2004) and 7 (in 1992) percent of all funds were classified as namesake mutual funds. More than 98 percent of the portfolio managers of these funds also served on the board of directors and 73 percent were chairman of the board. However, being a namesake mutual fund is not unambiguously in favor of the fund investors. Specifically, namesake funds charge about 12 to 15 basis points higher fees which is in the interest of the fund manager as owner of the investment management company but not in the interest of investors. The boards seems to be less effective. In contrast, investors benefit from the finding that namesake funds are more tax-efficient, which, at the same time, is in the interest of the fund manager as owner of a significant part of the fund. Moreover, as the manager of a namesake fund is more independent and faces fewer career concerns he has a lower tendency to herd and assumes higher levels of idiosyncratic risk, i. e. he more aggressively picks individual stocks. However, this only translates into weak evidence that namesake mutual funds outperform their benchmark or their peers. Specifically, namesake funds have four-factor alphas which are insignificantly different from zero while the matched sample significantly underperforms significantly by 12 basis points per month. The difference between both groups is 9 basis points, but is not significant.

[176] The Baron Asset fund can serve as an example, whose portfolio manager is Ronald Baron, chairman and CEO of Baron Capital Inc.

2.2.5 Discussion

The previous section has shown that a variety of measures exist to reduce potential agency costs, the most important of which seems to be external governance via the product market and internal governance via the employment market for portfolio managers. Internal and external governance jointly determine an equilibrium level of asset size based on updated information on managerial ability (Dangl, Wu, and Zechner, 2008). Investors, at least in theory, withdraw money from underperforming funds. Benefiting from decreasing returns to active management these funds should theoretically return to average performance levels (Berk and Green, 2004). Similarly, the aim of a manager replacement is to bring in new investment ideas and to improve future performance (Khorana, 2001).

The empirical results on the effectiveness of these mechanisms remain rather mixed. First of all, investors do not seem to punish poor performance by withdrawing significant amounts of money from these funds. The reason for this weak relationship might be the investors' expectation about a strategy change at fund level or monitoring costs and a free rider problem. Based on these results, an increased information disclosure, as requested by some, would probably not help: "the power of any disclosure, regulated or voluntary, relies on the ability of individual investors to use the disclosed information to penalize firms" (Tkac, 2004, p. 20). A potential solution might be service providers such as Morningstar, that condense the disclosed information in a format that is comprehensible for investors and directs their flows in the desired direction. Currently, rather than voting by feet, investors rely on internal control mechanisms. Indeed, the empirical results are more in favor of a causal link between performance and manager replacement. This is especially true for demotions following a period of bad performance. However, one might argue that the threat of more severe outflows triggers the investment management company to fire the manager in an attempt to stop money flowing out of the fund because there seem to be outflows before a manager is replaced, at least by some investors. In this case, internal and external governance are interlinked.

This does not, however, apply to all cases. Indeed, even if fund managers possess real investment skill and generate outperformance they might still not act in the best interest of their shareholders and extract some of the returns for their own benefit. Then, external governance is not an option for investors to reprimand the manager because they might be reluctant to redeem shares in an outperforming fund. In such cases, internal governance mechanisms that do not rely on redemption are more appropriate (Chen, Goldstein, and Jiang, 2008). Moreover, Cremers and Nair (2005) argue for regular corporations that internal governance (blockholders and board of directors) and external governance (takeovers and the market for corporate control) reinforce each other. Large blockholders facilitate takeovers and make this governance mechanism more effective.

Furthermore, the above analysis has revealed distinct differences in the regulation of mutual funds as compared to the regulation of conventional cooperations. A mutual fund can be interpreted as a firm with highly liquid investment projects allowing a daily mark-to-market of its assets. However, an important difference exists with respect to the contractual relationship with the management. Managers of conventional cooperations are employed by these firms and are under direct control of the board of directors. Mutual fund managers, instead, are employed by an investment management company that sponsors the mutual fund while the board of directors of the fund does not have direct control of the portfolio manager. From the perspective of the fund its management is "outsourced". Another crucial difference refers to the equilibrium mechanism: While changes in the stock price of a conventional cooperation balances supply and demand, the price of a mutual fund is derived from its holdings and is determined by the prices of the underlying stocks (NAV). Instead, the number of outstanding fund shares varies with changes in supply and demand.[177] Thus, while bad performance of corporate managers leads to a decrease in the share price of their company, increasing the threat of a takeover (market for corporate control) and making capital raising more expensive, bad performance of fund managers results in cash outflows, decreasing the asset base of the fund and directly affecting the fund manager's compensation. Analyst downgrades for cooperations and rating downgrades of fund rating agencies enforce this relationship. Consequently, the investment performance of mutual funds is directly related to changes in the fund size through this unique equilibrium mechanism. This is explored in more detail theoretically in chapter 4 and empirically in chapter 7.

[177] Changes in the number of outstanding shares of a conventional cooperation are a result of corporate actions such as equity issues or share repurchases.

Part II Investment Performance

3 Performance Measurement

This chapter presents the methodologies used to determine the investment performance of fund managers. It is one of the most important but at the same time most complicated topics in delegated asset management to judge whether the portfolio manager added any value. The concepts presented here are used throughout this study to measure investment skills but also to evaluate the costs of other determinants such as agency conflicts, liquidity risk and capacity constraints.

Portfolio managers are usually judged by their ability to generate abnormal performance reflected by risk-adjusted investment returns. However, risk itself is not observable. A variety of concepts for measuring risk exist but different measures are applicable in different situations. Section 3.1 discusses the determinants of the choice of an appropriate performance measure. Existing performance measures can be divided into three broad groups: (1) Measures based on ratios of excess returns and some risk measure (section 3.2);[178] (2) "alpha"-measures based on systematic risk measured by factor models (section 3.3);[179] (3) measures based on endogenous benchmarks derived from portfolio information (section 3.5).[180] The major differences between these groups, but also between specific measures within these groups, refer to the definition of risk.

Ratio-based performance measures specify the return per unit of risk. They are usually simple to compute and have low requirements with respect to data availability.[181] Rankings based on performance ratios are meaningful because they correct for differences in risk levels.

Risk-based performance measures adjust for risk by computing the spread between actual returns and a hypothetical benchmark return which is determined

[178] Treynor (1965) and Sharpe (1966).
[179] Jensen (1968), Fama and French (1993) and Carhart (1997).
[180] Cornell (1979), Grinblatt and Titman (1993), and Daniel, Grinblatt, Titman, and Wermers (1997).
[181] Most of the ratio-based models determine inferences solely based on the return series of the fund in question and the risk-free asset. Exceptions are ratio-based measures that use the systematic risk instead of total risk such as the Treynor ratio (Treynor, 1965) which additionally require the return series of an adequate market index for computation.

P. Lückoff, *Mutual Fund Performance and Performance Persistence,*
DOI 10.1007/ 978-3-8349-6527-1_4,

by the fund's systematic risk exposures. Thus, riskier funds face a stricter benchmark. Even though these measures indicate whether the manager was able to beat the benchmark, strictly speaking, they do not allow a comparison of different investment products because risk-based performance measures are subject to manipulation by leverage. Risk-based performance measures draw heavily from the asset pricing literature for the identification of relevant and meaningful risk factors and the computation of "fair" or expected returns. Therefore, section 3.4 discusses recent developments in multifactor asset pricing. The data requirements of risk-based performance measures are similar to those of ratio-based measures, though the former use extended benchmarks. However, their computational requirements are higher, especially when more sophisticated statistical concepts are applied.

The last group of measures based on portfolio information usually relates the return of each security in the portfolio to the return of a "comparable" security in order to determine abnormal performance. These comparable securities are selected based on characteristics or are derived from portfolio holdings in another time period. Consequently, data requirements are higher for these models while the statistical concepts are relatively simple.

A common problem in all of these approaches is the ability to distinguish between skill and luck of the portfolio manager as fund returns are subject to random fluctuations in the underlying stocks. Therefore, several recent studies try to improve the statistical inferences by applying advanced methodologies such as Bayesian estimation or bootstrapping or by using daily rather than monthly fund returns. These approaches are reviewed in section 3.6. Section 3.7 discusses empirical results with respect to the performance of actively managed mutual funds and discusses the implications for active management. Lastly, section 3.8 presents evidence on cross-sectional determinants of managerial success.

3.1 Choice of the Correct Performance Measure

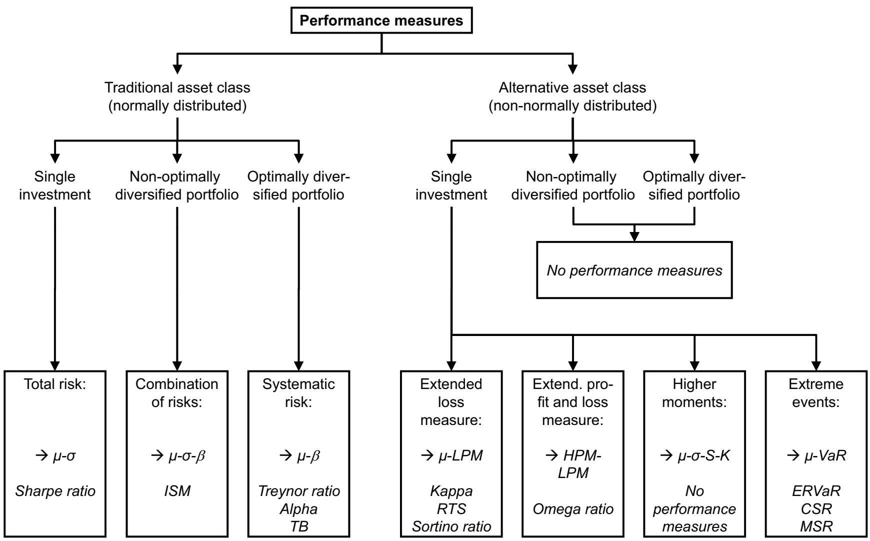
The discussion of how to correctly measure performance is not yet settled in the literature.[182] Academic studies as well as practical applications have used a variety of methods to measure the performance of mutual funds and other investment

[182] Lehmann and Modest (1987), Bessler and Lückoff (2007b), Eling and Schuhmacher (2006), and Bessler, Drobetz, and Zimmermann (2009).

products.[183] Different performance measures do not seem to be equally applicable to all situations. In particular, an appropriate consideration of the risk involved with a specific investment strategy is not trivial. One reason for this is that risk itself is not observable. Different concepts can be used to operationalize risk. Thus, the major difference between the existing approaches for performance evaluation is how they measure risk. The choice of a correct measure of risk strongly depends on the characteristics of the investment product to be evaluated and the characteristics of the investor who already holds it or intends to buy it (Figure 3.1). In addition, it is important to consider the chronological focus, i. e. whether the evaluation is ex-post or ex-ante, and the characteristics of the institutional and regulatory setting.

Figure 3.1: Choice of the correct performance measure

This figure presents a classification scheme for the choice of an appropriate performance measure. The choice depends on: (1) the distributional characteristics of the investment product which is to be evaluated; (2) the characteristics of the actual portfolio of the investor.



[183] This section partly draws on the ideas of Bessler and Lückoff (2007b).

3.1.1 Asset Class and Investment Strategy

In order to select an appropriate performance measure, the statistical properties of the return series must first be analyzed. The relevant question is whether the investment product belongs to a "traditional" asset class or to a "new" or alternative asset class. Traditional asset classes have returns that are close to a normal distribution, i. e. symmetric and not fat tailed. Investment products employing long-only strategies in equities or bonds that do not use derivatives, leverage or dynamic trading strategies belong to traditional investments. Diversified equity mutual funds usually exhibit returns that are very close to the normal distribution. In contrast, dynamic trading strategies and strategies making use of leverage, derivatives or short positions belong to new asset classes such as hedge funds and structured products. The returns of these asset classes are usually skewed and fat-tailed. Additionally, new asset classes are exposed to certain event risks that might not yet show up in historic return series. Usually these riskier strategies are offered only to sophisticated, so-called qualified, investors. However, through the advent of structured retail products, such as "Zertifikate" in Germany, these strategies also became available to retail investors.

Sharpe (1970, p. 187 ff.) argues that the μ-σ-principle is only valid if investors have a quadratic utility function or returns are normally distributed. Consequently, two different strands of performance measures have been developed for traditional and new asset classes, respectively. In the case of traditional asset classes, risk is measured either by total risk, i. e. the standard deviation of the return series, by systematic risk or even by a combination of both depending on the investor's existing portfolio. The risk of new asset classes can be measured by higher moments of the return distribution such as skewness and kurtosis, by partial moments of the return distribution such as higher and lower partial moments, and by value-at-risk measures (Eling and Schuhmacher, 2006; Bessler and Lückoff, 2007b).

Specific performance measures based on σ_i can only be found in the first group of ratio-based performance measures. With the exception of the Treynor ratio all performance measures based on systematic risk belong to the second group of risk-based models. Measures based on alternative specifications of risk for new asset classes usually belong to the group of ratio-based models. However, some extensions of risk-based models exist that take the special return characteristics of new asset classes into account (Fung and Hsieh, 2004; Kosowski, Naik, and Teo, 2007; Bollen and Whaley, 2009). It is important to choose a benchmark for performance evaluation that is appropriate to the asset class and investment style of the relevant investment product. If the investment product has high loadings on risk factors not considered in the benchmark, this beta exposure might actually show up as alpha in a return regression. Thus, fund managers could game their benchmark by loading on risk factors not considered in the performance evaluation.

3.1.2 Existing Portfolio

The second factor for determining the choice of the appropriate risk measure is the existing portfolio of the investor. It is relevant to measure the change in overall risk of the investor's portfolio when the investment product is added to his portfolio. The overall change in the risk of the portfolio not only depends on the investment product which is added to the portfolio but also on the composition and characteristics of the existing portfolio. Important factors are the degree of diversification of the portfolio as well as its correlation structure with the investment product that will be added. Based on normally distributed returns, these risk changes can be analyzed and determined according to the concepts of modern portfolio theory. However, in the case of non-normally distributed returns the assumptions of modern portfolio theory no longer apply. The question of how new asset classes change the risk and return characteristics of an existing portfolio is still open for debate.

For illustrative purposes, three base cases can be distinguished:[184] (1) the investor holds no portfolio at all before investing in the relevant investment product; (2) the investor already holds a perfectly diversified portfolio and invests only a small part of his wealth into the relevant investment product; (3) the investor holds a perfectly diversified portfolio as in (2) but invests a significant portion of his wealth into the relevant investment product.

In the first case, the change in overall risk of the investor's portfolio is equal to the total risk of the investment product. Thus, in this case an appropriate assessment of the performance of the investment product takes its total risk σ_i

[184] It is assumed that the existing portfolio of the investor is perfectly diversified, i. e. it is only a combination of the market portfolio and the risk-free asset, and that the investment product which is added is not perfectly diversified.

into account. In the second case, all unsystematic risk is diversified if the investment product is included with only a minimal weight into a perfectly diversified portfolio. Thus, measuring the change in overall portfolio risk requires measuring systematic risk β_i. In the third case the weight of the non-optimally diversified investment product is high enough to alter the degree of diversification of the portfolio. The change in overall portfolio risk can now be expressed as a function of both total risk σ_i and systematic risk β_i of the investment product. Performance measures can be constructed for this case which are a weighted average of measures based on total risk, such as the Sharpe ratio (Sharpe, 1966), and systematic risk, such as the Treynor ratio (Treynor, 1965).[185]

3.1.3 Chronological Focus

The chronological focus of performance evaluation can be oriented toward the past or the future. For example, if the objective of the performance evaluation is to determine the value of an investment product ex post the conclusions of the above sections apply. However, the objective might also be to extrapolate the performance measured over some period in the past into the future, for example in order to choose from different alternative investment products. Then, only the systematic risk component β_i should be taken into account, irrespective of the actual portfolio composition of the investor. Unsystematic risk does not follow any recurrent systematic pattern and therefore has no explanatory power for future risk of an investment product (Sharpe, 1966).[186]

3.1.4 Institutional Setting

The institutional setting refers to the level of delegation and the fund structure, both of which have an important impact on the choice of the correct performance measure. First of all, the benchmark used in performance evaluation should reflect the investment universe of the manager as closely as possible and should also mirror the skills of the investors without the advice from the investment manager. For example, the investor might be sophisticated enough to perform a sector rotation strategy based on public information, such as the dividend yield of a broad

[185] For a more detailed analysis and concrete performance measures see Bessler and Lückoff (2007b).

[186] If a systematic link exists between the unsystematic risks taken by the portfolio manager in successive periods it may still be reasonable to use measures based on total risk for performance prediction. This might be the case in certain hedge fund strategies.

market index or interest rate information. He may then delegate only the individual stock picking to an investment manager. The performance of the manager in this case might be evaluated by a conditional, i. e. time varying, Carhart (1997) four-factor model. Returns resulting from dynamic exposures to the market, size, value and momentum factor would not be credited as skill to the manager. In contrast, a private investor being unable to observe the relevant information and to implement a sector rotation strategy might only use a static Jensen (1968) one-factor model to evaluate the same investment manager giving him credit for rotating between different exposures.

A second important determinant of fund performance is the fund's structure with respect to the ease of investors to create or redeem fund shares. Kothari and Warner (2001, p. 2009) argue with respect to different performance measures that "all procedures' power will be a decreasing function of the amount of a fund's liquidity (i. e., non-information-based) trading and its trading costs". Thus, conventional performance measures are biased by fund flows. Conditioning performance on fund flows could mitigate this bias (Edelen, 1999; Alexander, Cici, and Gibson, 2007). However, so far no liquidity-adjusted performance measures exist in the literature. Thus, a rule of thumb has to be applied in order to adjust the performance of different investment products for the liquidity impact to allow for a fair comparison of the results. The better a manager is sheltered from investor flows the cleaner the conclusion drawn from usual performance measures about investment skills is.

3.2 Ratio-Based Performance Evaluation

Ratio-based performance measures are usually easy to compute and have only low data requirements. Consequently, these measures are of high relevance in practical applications and are frequently published in fund prospects or the media. All ratio-based measures follow a similar construction: a measure of the return of asset i in excess of the return on the benchmark is divided by a measure of the investment risk of asset i:[187]

$$\text{performance}_i = \frac{\text{return}_i - \text{return}_m}{\text{risk}_i} \ . \tag{3.1}$$

[187] In some cases a profit measure is divided by a loss measure.

This group of measures is based on the net returns received by investors. Fees and transaction costs, including the explicit costs of the liquidity service, are already deducted from the performance and the ratios are usually independent of the funds' level of cash holdings. However, as the return on a risk-free asset is usually used as the benchmark, only relative comparisons of the performance of different investment products are meaningful. Consequently, these measures play only a minor role in more advanced academic work on the performance of mutual funds.[188]

3.2.1 Information Ratio and Sharpe Ratio

The most general measure using this approach is the information ratio (IR_i) which is equivalent to the general form of the Sharpe ratio (SR_i^*) (Sharpe, 1966, 1994). It is the ratio between average return, μ_z, and standard deviation, σ_z, of a zero-cost portfolio z investing long in fund i and short in the benchmark m, i. e. $r_z = r_i - r_m$:

$$IR_i = SR_i^* = \frac{\mu_z}{\sigma_z} \ . \tag{3.2}$$

Outperforming funds can be combined with the benchmark in such a way that the Sharpe ratio is higher than the Sharpe ratio of the benchmark (Pástor and Stambaugh, 2002b). Because the denominator is essentially the tracking error between fund i and the benchmark m the information ratio is often used in institutional asset management. It rewards higher returns than the benchmark but penalizes high deviations from the benchmark. However, active sector bets are penalized more heavily than active stock picking as the latter does not necessarily lead to an increase in tracking error (Cremers and Petajisto, 2009).

If the return on a risk-free asset, r_f, is used as a benchmark, the Information ratio collapses to the well known version of the Sharpe ratio (SR_i) or reward-to-variability ratio:[189]

$$SR_i = \frac{\mu_i - r_f}{\sigma_i} \ . \tag{3.3}$$

[188] For a more detailed review see Bessler and Lückoff (2007b).
[189] Assuming that the return on the risk-free asset is constant over time.

The Sharpe ratio corresponds to the slope of a line between the risk-free asset and fund i in the μ-σ-diagram. It cannot be interpreted as a return measure. However, due to its general form and easy transformation into ranking it is probably one of the most widely used performance measures. This is even the case for new asset classes such as hedge funds where the assumption of normally distributed returns is usually not satisfied. In spite of this, rankings based on the Sharpe ratio are approximately correct even in the case of hedge funds (Fung and Hsieh, 1999; Eling and Schuhmacher, 2006).

3.2.2 Treynor Ratio

There are at least two cases in which it seems appropriate to use systematic risk instead of total risk in the numerator of equation (3.3). The first is when fund i is part of a well diversified portfolio because in this case all unsystematic risk is diversified. The other case is when the result of the performance evaluation should be used to predict future performance as unsystematic return movement does not tend to repeat in the future (Sharpe, 1966). The resulting measure is the Treynor ratio or reward-to-volatility ratio (Treynor, 1965):

$$TR_i = \frac{\mu_i - r_f}{\beta_i} \ . \tag{3.4}$$

A fund outperforms the market if its Teynor ratio is larger than the market risk premium. Analogous to the Sharpe ratio the Treynor ratio corresponds to the slope of a line between the risk-free asset and fund i in the μ-β-diagram.

3.2.3 Ratios for Non-Normally Distributed Returns

In addition to the Sharpe and Treynor ratios a variety of ratio-based measures exist that are primarily designed for ex post performance evaluation of instruments with non-normally distributed returns such as hedge funds. This section presents a brief discussion of the related concepts.[190]

Performance ratios for new asset classes basically substitute the risk measure in the denominator of the information ratio (equation (3.2)) by a more appropriate measure that accounts for the non-normality of returns especially below a certain

[190] A more detailed analysis is given in Eling and Schuhmacher (2006) and Bessler and Lückoff (2007b).

threshold return. Furthermore, the numerator of the information ratio can be replaced by a measure that also takes into account the non-normality above this threshold level. The specific performance measures may further be subdivided into measures based solely on the lower partial moments of fund i (LPM_i), based on lower and higher partial moments (HPM_i) and based on value-at-risk measures (VaR_i).

The Kappa ratio (κ_{in}) of n-th degree of fund i replaces the denominator of the information ratio by the n-th root of a lower partial moment with target return r_τ which is also used as a benchmark return in the numerator (Kaplan and Knowles, 2004):[191]

$$\kappa_{in} = \frac{\mu_i - r_\tau}{\sqrt[n]{\mathrm{LPM}(\tau)_{in}}} \tag{3.5}$$

with

$$\mathrm{LPM}(\tau)_{in} = \frac{1}{T}\sum_{t=1}^{T}[max(r_\tau - r_{it};0)]^n \qquad \text{for } n > 0\ . \tag{3.6}$$

The use of lower partial moments allows investors to use an investor-specific target return level. All returns below that level are perceived as losses by the investors. A higher degree of the lower partial moment penalizes returns below that target level more heavily. The Kappa ratio of second degree collapses to the well known Sortino ratio which is also frequently used in practical applications for hedge funds (Sortino and van der Meer, 1991; Bessler, Drobetz, and Henn, 2005):

$$SO_i = \frac{\mu_i - r_\tau}{\sqrt{\mathrm{LPM}(\tau)_{i2}}}\ . \tag{3.7}$$

Another prominent performance measure for new asset classes is the Omega ratio which, in its general form, is the ratio between a higher partial moment and a lower partial moment (Kaplan and Knowles, 2004):[192]

[191] Using r_f instead of r_τ as the target return in the denominator yields the return-to-shortfall (RTS_{in}): $\mathrm{RTS}_{in} = \mu_i - r_f / \sqrt[n]{\mathrm{LPM}(\tau)_{in}}$.

[192] Usually, the Omega ratio of first degree is used.

$$\Omega_{in} = \frac{\sqrt[n]{\text{HPM}(\tau)_{in}}}{\sqrt[n]{\text{LPM}(\tau)_{in}}} \tag{3.8}$$

with

$$\text{HPM}(\tau)_{in} = \frac{1}{T}\sum_{t=1}^{T}[max(r_{it} - r_\tau; 0)]^n \qquad \text{for } n > 0 \ . \tag{3.9}$$

The Omega ratio allows investors to take into account the shape of the return distribution at both the lower and the upper end while still offering the possibility to set an individual target return.

All of these measures are unable to take extreme events into account. Extreme risks are difficult to measure because they occur only very infrequently. Performance measures can only detect patterns that show up in historical data used as input. However, the value at risk (VaR_{ip}) of fund i to probability p is suggested as a potential approach to quantify these risks. Two modifications have been used to adapt the usual value-at-risk measure to non-normally distributed returns of new asset classes. First, the modified value at risk (MVaR_{ip}) explicitly takes the higher moments of the return distribution into account by using the Cornish-Fisher extension of the percentile u_{ip} of the standard normal distribution:

$$\text{MVaR}_{ip} = \mu_i + u_{ip}^{CF}\sigma_i \tag{3.10}$$

with

$$u_{ip}^{CF} = u_{ip} + \frac{1}{6}(u_{ip}^2 - 1)S_i + \frac{1}{24}(u_{ip}^3 - 3u_{ip})K_i - \frac{1}{36}(2u_{ip}^3 - 5u_{ip})S_i^2 \ . \tag{3.11}$$

S_i and K_i are the skewness and kurtosis of the returns of fund i, respectively. Alternatively, resampling methods can be used to determine the value at risk of a non-normal distribution. One criticism of the usual and the modified value at risk is that it provides only one number, namely the magnitude of the maximum expected loss that is not exceeded with probability $1 - p$. The shape of the return distribution below that point is not analyzed. The conditional value at risk ($CVaR_{ip}$) tries to circumvent this problem in that it specifically measures the expected loss below the value at risk:

$$\text{CVaR}_{ip} = E(r_i | r_i < VaR_{ip}) \; . \tag{3.12}$$

From the discussion above three modifications of the information ratio can be constructed for fund i to the probability p, the excess return on value at risk

$$\text{ERVaR}_{ip} = \frac{\mu_i - r_f}{VaR_{ip}} \; , \tag{3.13}$$

the modified Sharpe ratio

$$\text{MSR}_{ip} = \frac{\mu_i - r_f}{MVaR_{ip}} \; , \tag{3.14}$$

and the conditional Sharpe ratio

$$\text{CSR}_{ip} = \frac{\mu_i - r_f}{CVaR_{ip}} \; . \tag{3.15}$$

However, the rankings of hedge funds derived from these measures do not change significantly if one or the other performance measure is used (Eling and Schuhmacher, 2006).

3.3 Risk-Based Performance Evaluation

Risk-based performance evaluation is the most common approach for performance evaluation in academic research. The theoretical foundation of these models lies in the asset pricing literature. It requires the determination of the "fair" return of the fund's portfolio based on a particular specification of an asset pricing model and depending on the fund's risk level. In general, the performance of fund i is determined as its return minus the hypothetical return of the benchmark m at the same risk-level of the fund:

$$\text{performance}_i = \text{return}_i - \text{risk-adjusted return}_m \; . \tag{3.16}$$

In its simplest form, the market factor is used as the benchmark. First, the systematic risk of the fund's portfolio needs to be estimated. Then, the expected return of the market at this risk level is determined based on the CAPM and subtracted from the fund's realized return in order to compute the performance measure.[193] Commonly, risk-based performance measures are referred to as alpha because they can be obtained as the absolute term in a regression.

Risk-based performance measures are not standardized with respect to risk. Rather they can be interpreted as the return gap between the fund i and the hypothetical benchmark m at the risk level of fund i. However, the alpha of fund k might have been obtained at a significantly higher risk level and is therefore not directly comparable to the alpha of fund i.[194] In contrast, ratio-based performance measures according to equation (3.1) divide the funds' performance by their risk level and can be used for relative rankings. However, in practice performance measures are usually applied to a group of similar investment products. In this case, the differences in risk levels should be small enough to allow for meaningful comparisons.

Risk-based performance measures differ, first, with respect to the choice of the asset pricing model which determines the risk factors used as a benchmark, second, with respect to the functional form and, third, with respect to the estimation methodology. The choice of the factors has been influenced to a large degree by the developments in the asset pricing literature. However, some factors have also found their way in the opposite direction, from the performance evaluation literature to asset pricing. The functional form is usually linear.[195] This is due to the fact that liner regression models can be estimated with standard regression techniques. The most popular estimation technique for factor models in the field of performance evaluation is OLS. However, more recent approaches try to account for the low estimation efficiency which stems from short fund-return time series and time-varying risk exposures by using a Bayesian approach. Alternatively, some studies rely on bootstrapping methodologies or daily data instead of monthly returns.

[193] Usually, these two steps can be performed simultaneously in one regression.
[194] Thus, any alpha measure is sensitive to leverage and can be easily manipulated.
[195] However, several attempts have been made to introduce non-linearities into the linear factor structure by constructing factors with non-linear payoffs or time-varying factor sensitivities. For non-linear factors see, for example, the quadratic market factor in the model of Treynor and Mazuy (1966) or the option factors in Agarwal and Naik (2004). For time-varying exposures see Ferson and Schadt (1996) and Ferson and Qian (2005).

3.3.1 Jensen Model

The one-factor model of Jensen (1968) is the foundation for all risk-based performance measures. It rests upon the CAPM equation for the expected return of asset i:

$$E(r_i) = r_f + \beta_{mi}[E(r_m) - r_f] \; . \tag{3.17}$$

Restating equation (3.17) for realized returns and denoting returns in excess of the rate on the risk-free asset as er_i and er_m, respectively, implies:[196]

$$er_i = \beta_{mi} er_m + \epsilon_i \; . \tag{3.18}$$

If the portfolio manager has selection skills, i. e. overweights assets with positive idiosyncratic risks during the holding period and underweights assets with negative idiosyncratic risks relative to the benchmark, then ϵ_i is no longer well behaved but has a positive expected value, $E(\epsilon_i) > 0$. To measure these selection skills and to capture the positive expected value of the residual, ϵ_i in equation (3.18) is replaced by a constant α_{1i} and a new residual ϵ_i^*:[197]

$$er_i = \underbrace{\alpha_{1i}}_{\substack{\text{selection}\\ \text{skills}}} + \underbrace{\beta_{mi} er_m}_{\substack{\text{risk}\\ \text{premium}}} + \underbrace{\epsilon_i^*}_{\substack{\text{idiosyncra-}\\ \text{tic risk}}} \tag{3.19}$$

with

$$\epsilon_i = \alpha_{1i} + \epsilon_i^* \qquad \text{and} \tag{3.20}$$

$$E(\epsilon_i^*) = 0 \; . \tag{3.21}$$

The fund's return is broken down into security selection skills, a return component as compensation for holding systematic risk and an idiosyncratic risk term.

[196] Using excess returns also eliminates the problem of considering inflation (Grinblatt, 1987).
[197] Usually, the following time-series regression is estimated: $er_{it} = \alpha_{1i} + \beta_{mi} er_{mt} + \epsilon_{it}^*$.

A positive α_{1i} indicates selection skills of the manager of fund i.[198] The fund's return is higher than the hypothetical return of the benchmark at the same risk level. As these risk levels might well differ across funds, for example because of different degrees of leverage, their alphas are not directly comparable and rankings based on alpha are not meaningful. To mitigate this problem, the alpha measure can be divided by a risk measure similar to the approach of ratio-based performance measures in equation (3.1). Dividing alpha by idiosyncratic risk $\sigma(\epsilon_i)$ yields the appraisal ratio of Treynor and Black (1973). Alternatively, as beta increases linearly with leverage, alpha can be adjusted by the systematic risk β of the fund. Elton, Gruber, and Blake (1996a) and Kosowski, Timmermann, Wermers, and White (2006) propose to use the t-value of alpha instead which basically is alpha divided by its standard deviation. The advantage of this approach is that t-values of different funds remain normally distributed in the cross section even in the presence of divergent levels of idiosyncratic risk.[199] In addition, it adjusts for potentially imprecise estimates of extreme alphas of funds with short time series or relatively risky strategies.

However, several problems have been identified in the literature with the Jensen (1968) model. First of all, the market portfolio, which theoretically should be used in the estimation, is not observable and can only be substituted by market indices. Hence, these indices only contain traded securities and, therefore, cannot be a perfect proxy (section 3.3.1.1). Second, a fund manager might not only possess selection skills but also timing skill and alter the fund's beta over time. This leads to biased parameter estimates if not properly accounted for (section 3.3.1.2). Third, the return distribution might deviate from the normal (or lognormal) distribution, especially when derivatives or dynamic trading strategies are used, and the statistical methods might not be powerful enough to distinguish between skill and luck in light of the short time series of monthly fund returns (section 3.3.1.3). Therefore, numerous studies exist that modify the Jensen (1968) model in one or another way in order to mitigate some of these problems.[200] The following section discusses these approaches.

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[198] Note that a positive alpha implies a Treynor ratio of the fund that is larger than the benchmark's Treynor ratio.

[199] This assumes that individual fund alphas are normally distributed.

[200] An alternative to improved statistical methods are richer data sets as used, for example, in studies based on portfolio information (section 3.5) or based on daily fund returns (section 3.6).

3.3.1.1 Benchmark Problem

"I have never met a portfolio manager who has not been in the top quartile" (Fischer, 2001, p. VII). This quotation points out a problem which is especially relevant for the one-factor alpha. As brought forward by Roll (1977, 1980) the market portfolio is theoretically the correct benchmark, but it is not observable. The basic intuition is that the expected return of a security depends on its correlation with the consumption level. The current wealth available to investors for consumption is represented by their discounted future income. The market portfolio should, theoretically, include all assets of the investors including non-traded assets such as real estate and even human capital. Thus, the correlation of the asset with the market portfolio can be used as representation of its correlation with consumption. However, due to non-observability of the true market portfolio a proxy needs to be determined in practice which can only be an imperfect representation of the true correlation structure. Thus, CAPM tests are only valid conditional on the specific market proxy chosen. This critique directly translates into performance evaluation (Roll, 1978). Usually, a market-wide index of stocks is used as an imperfect representation of the market portfolio.[201] Because the correlation of the fund with the index is not identical to its correlation with the true market portfolio the performance results might be biased and strongly dependent on the specific index chosen as a benchmark (Lehmann and Modest, 1987; Grinblatt, 1987; Grinblatt and Titman, 1989b). Thus, all portfolio managers can be in the top quartile – but only based on different benchmarks. However, recent research suggests that conclusions based on empirical asset pricing tests are not very sensitive to the choice of the market proxy (Low and Nayak, 2009; Levy and Roll, 2010).

However, the market proxy has not only been theoretically criticized. Empirical studies also question the adequacy of the one-factor benchmark for performance evaluation. This stems from the observation that market risk does not seem to be the only relevant risk factor in the cross section of asset returns (e. g. Fama and French, 1992). Additional factors such as the size of a company or its book-

[201] Hence, this index ignores all asset classes other than equity and even relative weighting of different industries might be biased due to different propensities in becoming a listed company compared to the status of a privately owned company. In fact, the capital intensity of an industry is positively related to the likelihood of its companies becoming listed. Thus, market-capitalization based indices overweight these capital intensive industries compared to less capital intensive industries. This bias could be mitigated by using GDP-weighted indices.

to-market ratio as an indicator for a value or growth stock help to explain the cross-sectional return distribution. Additionally, other factors such as liquidity or higher-moment risk might be relevant as well. Consequently, multifactor models have been developed with the objective of identifying factors that more precisely explain the return distribution.[202] However, many of these factors lack a theoretical foundation and there is disagreement about their inclusion (model uncertainty). Empirically, the exact specification of the factor model significantly influences the performance results and should be given a careful judgement (Lehmann and Modest, 1987; Chan, Dimmock, and Lakonishok, 2009).[203]

The inclusion of the correct factors in the benchmark is also a practical problem. It is often claimed by practitioners that if all asset classes and investment styles were included into the benchmark no alpha could be left. However, this is only partially true as it ignores the difference between systematic and idiosyncratic risk. Recall that alpha only refers to selection skills which means collecting positive idiosyncratic risks. If a portfolio manager includes asset classes into the portfolio which have a positive loading on risk factors that are not considered in the benchmark this translates into positive alpha. Indeed, empirical results suggest that some portfolio managers follow this strategy in practice by loading on higher-moment risk (Kostakis, 2009), by gaining fixed-income exposure (Comer, Larrymore, and Rodriguez, 2009) or by purposely deviating from their self-declared benchmark (Sensoy, 2009). However, this is not a result of superior selection skills. Thus, the benchmark should include all risk factors relevant for the investment objective of the portfolio manager.[204]

However, a practical problem arises if the benchmark used for evaluation is not investable and therefore not a potential alternative for investors (Pástor and Stambaugh, 2002b). In this case, it is not guaranteed that the investor could have achieved a better performance by an alternative investment strategy. Grinblatt (1987) argues that even popular indices such as the S & P 500 cannot be tracked precisely because of the way how dividend payments are incorporated into the index calculation. Further problems include transaction costs and trading restric-

[202] These models are discussed in more detail in section 3.3.2.
[203] An empirical approach that neatly circumvents the step of factor specification by letting the data decide about the importance of potential factors is the Bayesian model averaging, which estimates all possible combinations from a set of potential factors at once and assigns probabilities to each combination. See section 3.6.4.
[204] Also compare the discussion about how the benchmark choice depends on the level of delegation in section 3.1 and the interpretation of risk factors in section 3.4.

tions, for example, with respect to short sales, which restrict the ability of fund managers to generate abnormal returns. Martínez Sedano (2003), therefore, argues for the incorporation of legal investment restrictions and transaction costs into the benchmarks. He documents that once these restrictions are accounted for, the investment results of Spanish mutual funds are significantly improved. Huij and Verbeek (2009) alternatively propose to use mutual funds instead of constructed stock portfolios as factor premiums. This methodology guarantees that the benchmark is an investable alternative for investors. In a similar vein, Cremers, Petajisto, and Zitzewitz (2008) argue that even passive investable indices exhibit significant alpha estimates when evaluated by the standard factors used in performance studies. Hence, this biases comparisons of active fund alphas with passive alternatives as it is usually assumed that passive funds do not contain alpha. Specifically, an active fund with an alpha of −0.5 percent might seem inferior at first glance but superior compared to a passive fund with an alpha of −1.0 percent. Pástor and Stambaugh (2002b) argue that the non-investability of many benchmarks might even help to explain why investors are willing to hold mutual funds even if average alphas are below zero: Active funds are an efficient way of generating exposure to certain risk factors which are not otherwise investable.

The problems discussed in this section are inherent in all risk-based performance models. Several attempts have been made to mitigate the potential biases by extending the benchmark, which is discussed below. However, these problems have also led to the development of alternative approaches of performance measurement without the need of determining an external benchmark such as measures based on endogenous benchmarks (section 3.5) or simulated benchmarks on the basis of random portfolios (Lerbinger, 1984).

3.3.1.2 Time Variability

Time variability imposes another problem on performance evaluation with risk-based models. If a manager possesses not only selection skills but also timing skills, then the factor exposures are not constant, i. e. beta in equation (3.19) varies over time. Furthermore, even if portfolio returns are well behaved, the returns over time might not be independently identically distributed as a consequence of dynamic trading (Goetzmann, Ingersoll, Spiegel, and Welch, 2007). Thus, specific trading strategies both accidentally or on purpose, in case the portfolio manager attempts to game the performance measure, bias the estimation of performance measures. Moreover, the use of options implies non-constant portfolio betas (Ferson and Schadt, 1996). Additionally, random variations in the betas of the portfolio constituents or in the relative portfolio weights affect the fund's beta.[205] Portfolio weights can change over time in response to inflows and outflows or due to random movements in stock prices (Ferson and Schadt, 1996; Benson and Faff, 2006).

This bias can be demonstrated by a simple example as taken from Grinblatt and Titman (1989b) in Figure 3.2. Assume a manager who possesses timing skills but has no selection skills. If only two periods exist, one with a high return on the market (r_H) and one with a low market return (r_L), and the manager chooses a high portfolio beta in the former state and a low portfolio beta in the latter state, then he realizes points A and B in Figure 3.2. Note that both points lie on a straight line through the origin (solid lines), i. e. the manager's true alpha is zero in both states. If performance is evaluated unconditionally on the market state the dashed line will be estimated as an optimal regression line. The estimated beta is even higher than the true beta in the high-market-return state and the alpha estimate is consequently biased downward (point C).

To correct for this bias, beta needs to be allowed to vary over time. In the example above, the two solid lines would have emerged as regression lines in this case yielding a true alpha of zero. Kon and Jen (1978) point out that timing skills might also bias the inferences of the coefficients. Specifically, if a large number of different states exist and the manager correctly adjusts the portfolio beta then the relationship between the excess return of the fund and the excess return of the market becomes convex rather than linear. If the researcher tries to fit a linear model the return realizations necessarily scatter over a wide range around the regression line. This results in large standard errors and potentially insignificant coefficients. Indeed, many performance studies using constant parameters report insignificant alphas.

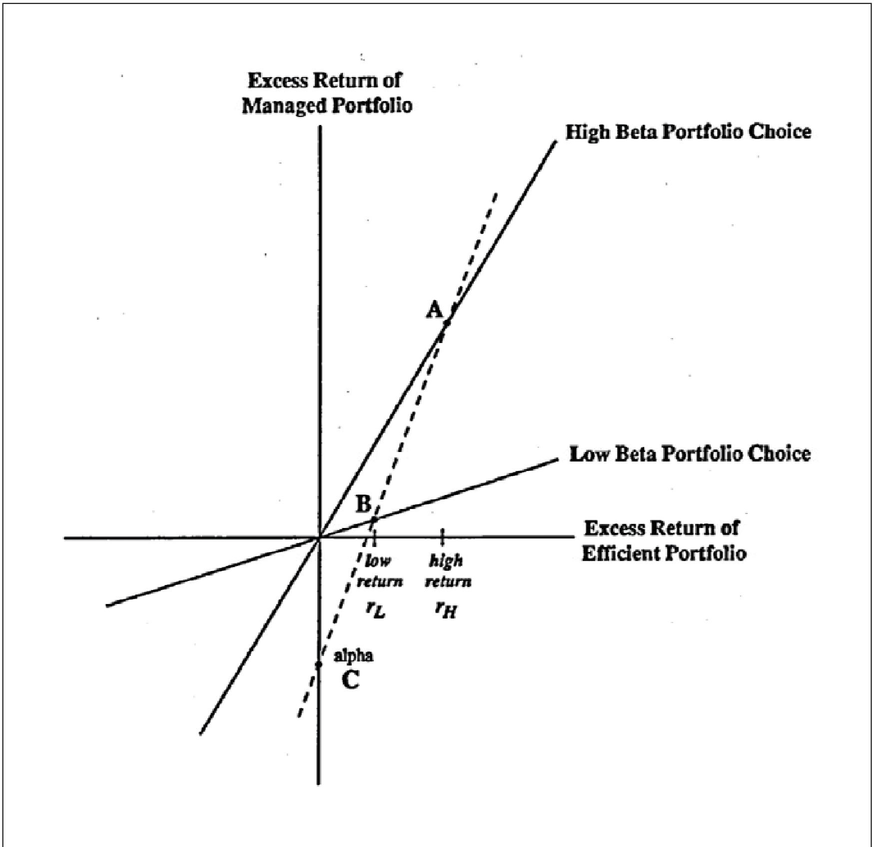
To account for this time-variability, conditional models can be used for performance evaluation (e. g. Ferson and Schadt, 1996; Ferson and Warther, 1996; Ferson and Qian, 2005).[206] In this specification, beta is allowed to vary in re-

[205] Francis and Fabozzi (1980) show that the betas of random portfolios fluctuate to a similar degree as those of active funds.

[206] See section 3.3.3 and equation (3.29).

Figure 3.2: Bias-in-beta

This figure presents a graphical illustration of the potential bias-in-beta in the presence of timing skills of a portfolio manager. Based on Grinblatt and Titman (1989b, p. 395).



sponse to variables related to the business cycle, such as the dividend yield or interest-rate variables. Instead of using macro variables, beta can also be modeled conditional on an unobservable information variable by applying a state space model (Mamaysky, Spiegel, and Zhang, 2008). This conditional performance evaluation approach can be taken one step further by allowing alpha to fluctuate over time as well (Christopherson, Ferson, and Glassman, 1998). Time-varying alphas are motivated by the observation that the skills of portfolio managers depend on the market state (Kosowski, 2006; Glode, 2010). Ang and Chen (2007) report that in the context of a conditional model the size and value factors turn out to be insignificant for most of their sample period. Thus, the use of benchmarks with multiple factors might be a proxy for time-varying exposures to the market factor.

As an alternative to conditional models, non-linear risk factors have been proposed in the literature to account for time-varying risk exposures or dynamic trading strategies. These approaches use a quadratic term to model the convexity of the relationship between fund returns and benchmark returns (Treynor and Mazuy, 1966).[207] Alternatively, a contingents claim approach based on a dummy-variable can be used to duplicate timing skills of the manager and to construct an option-like payoff structure (Merton, 1981; Henriksson and Merton, 1981).[208] Whatever statistical approach is used for modeling time-varying parameters it is likely to correct for the bias mentioned above and to improve the efficiency of estimated alphas.

3.3.1.3 Statistical Problems

Many studies on mutual fund performance suffer from short time series of fund data and a high degree of randomness in fund returns. This leads to inefficient parameter estimates which do not provide conclusions regarding managerial skill. Many performance studies report performance measures which are statistically indistinguishable from zero. Hence, it cannot be determined with a sufficient degree of statistical certainty whether the portfolio managers were able to beat the benchmark. Skill cannot be distinguished from luck.

Several biases have been identified in the literature that might affect the results in such a context. The first relevant issue is a potential small sample bias. The av-

[207] See equation (3.30).
[208] See equation (3.31).

erage length of fund return histories in Morningstar's Principia Pro database is 4.8 years, which results in less than 60 monthly observations (Busse and Irvine, 2006). According to Cornell (2009), assuming conventional levels of annual tracking errors of mutual funds, about 5 years of monthly data are required to estimate an alpha of 3 percent at a significance level of 95 percent.[209] Another issue might arise from non-stationarity in the variables, leading to a spurious regression (Ferson, Sarkissian, and Simin, 2003). A spurious regression and a small sample bias even reinforce each other. One potential approach to mitigate the small sample bias is a Bayesian approach as inferences are conditional on the data. Specifically, the application of the seemingly unrelated regression approach of Pástor and Stambaugh (2002b) seems appropriate for short samples. Alternatively, some studies suggest using daily instead of monthly observations in order to enhance the statistical significance (Busse and Irvine, 2006). Furthermore, an errors-in-variables problem stems from the fact that the market is not observable and commonly used risk factors are only proxies for the unknown true risk factors (Carmichael and Coën, 2008; Coën and Hübner, 2009).

In particular, funds in the extreme tails of the cross-sectional return distribution, i. e. funds with risky investment strategies and large deviations from the benchmark, are affected by these problems (Kosowski, Timmermann, Wermers, and White, 2006; Cuthbertson, Nitzsche, and O'Sullivan, 2008). This problem is especially severe for persistence studies because of two reasons. First, persistence studies require the estimation of performance metrics for individual funds instead of a portfolio of funds where high idiosyncratic risks of individual funds might cancel each other out. Second, to detect persistence these studies construct portfolios of funds based on their past performance in order to analyze if the "winner" portfolio still outperforms in the future and the "loser" portfolio continues to lose (e. g. Hendricks, Patel, and Zeckhauser, 1993; Brown and Goetzmann, 1995; Elton, Gruber, and Blake, 1996a). However, funds with the highest estimation error tend to end up having the most extreme alphas and thus, often end up in the winner or loser portfolio. Thus, funds are sorted into portfolios based on estimation error rather than true investment skill. To avoid these shortcomings, more recent studies apply statistical methods such as bootstrapping or a Bayesian approach to estimate individual fund alphas for portfolio formation (Huij and Verbeek, 2007;

[209] This calculation is based on the following equation: $t = (\frac{1.96\ \mathrm{TE}}{\alpha})^2$, where TE is the tracking error based on a multifactor model and t the required period length of data.

Bessler, Blake, Lückoff, and Tonks, 2010). For example, the Bayesian approach shrinks alphas toward zero (or even toward minus their fees) and shrinkage is higher the lower the precision of the alpha estimate.[210]

3.3.2 Multifactor Models

This section provides a comprehensive discussion of the literature on asset pricing factors. However, due to the vast number of asset pricing studies that have been published especially in recent years this review cannot be exhaustive in the sense of covering all studies. Rather, the focus is on factors that are relevant for performance evaluation of mutual funds.

3.3.2.1 Fama-French Model: Size and Value Effect

The CAPM has not proved to be sufficient in empirical tests to explain the cross section of stock returns.[211] This observation has led to the development of behavioral explanations, which are described later, but at the same time gave rise to the search for alternative factors with explanatory power and consistent with a rational pricing story. Multifactor models have been developed along both strands of the literature, asset pricing and performance measurement. The most prominent extension of the one-factor CAPM is the three-factor model of Fama and French (1992, 1993, 1996). Several studies report systematic cross-sectional differences in average stock returns depending on the companies' market capitalization (Banz, 1981; Fama and French, 1992) and their ratios of book equity to market equity (Fama and French, 1992; Lakonishok, Shleifer, and Vishny, 1994). If stocks are priced rationally, systematic differences in average returns can only stem from differences in risk. Thus, firm size and the book-to-market ratio seem to be proxies for risk.

Fama and French (1993) build upon this observation and use independent sorts to construct six portfolios with different size (as measured by the market capitalization) and value (as measure by the book-to-market ratio) characteristics. Based on these six portfolios they form two zero-cost portfolios, HML (high minus low

[210] Shrinking toward the negative value of the fee level follows from the market arithmetic of Sharpe (1991) as a result of which active funds on average yield the return of the market less their costs.

[211] A detailed discussion of empirical evidence contradicting the CAPM is given in Keim and Ziemba (2000).

book-to-market) and SMB (small minus big) as mimicking risk factors.[212] Based on this model, equation (3.19) can be extended to account for the size and value exposure of funds:

$$r_{it} = \alpha_{3i} + \beta_{mi} r_{mt} + \beta_{\text{smb},i}\text{SMB}_t + \beta_{\text{hml},i}\text{HML}_t + \epsilon_{it} \ , \tag{3.22}$$

However, the coefficients of this model should be interpreted with care. Using the three-factor Fama and French (1993), the investment performance of the fund manager, as measured by α_i, is only the abnormal return he generates by pure security selection corrected for returns stemming from a potential size or value tilt of the portfolio. The conclusion about the skill level of the manager depends on the personal belief whether SMB and HML are risk factors (or at least adequate proxies of unknown risk factors), a question which has not been settled in the literature so far, and the level of delegation. If SMB and HML are believed to be risk factors or if the mandate of the portfolio manager dictates a certain size and value tilt, then α_i is the appropriate performance measure. However, if SMB and HML are not believed to be risk factors, a size and value tilt might be interpreted as part of the performance attributable to managerial skill, especially if the investor would not have been able to realize the same risk exposure without delegation. In any case, the coefficients can be interpreted in the sense of a return attribution model and provide insights into a potential size and value tilt of the portfolio.[213]

Fama and French (1995, p. 131), however, do not claim that SMB and HML are systematic risk factors: "Size and BE/ME [book-to-market] remain arbitrary indicator variables that, for unexplained economic reasons, are related to risk factors in returns". Rather, they argue that some unknown state variables related to variation in consumption and wealth which is not captured by the market factor can explain the size and value effect. Small firms, for example, might be more affected than large firms by changes in the business cycle because they are financially more vulnerable when credit conditions worsen. The duration of

[212] For a detailed description on how to construct these factors see section 3.3.2.3.

[213] A positive (negative) $\beta_{\text{smb},i}$ implies that the fund holds a higher fraction of the portfolio in small (large) stocks compared to the weight of these stocks in the market portfolio. Similarly, a positive (negative) $\beta_{\text{hml},i}$ implies that the fund holds a higher fraction of the portfolio in high (low) book-to-market, or value (growth), stocks compared to the weight of these stocks in the market portfolio.

earnings of growth firms might be longer compared to that of value firms making them more vulnerable to shifts in the term structure. Consistent with this view the empirical results of Liew and Vassalou (2000) suggest that the returns on the SMB and HML factor can be used to predict future GDP growth. Thus, a risk-based explanation for the returns of HML and SMB cannot be rejected. However, the Fama-French factors are motivated purely on an empirical basis and lack, so far, a consistent theoretical foundation.

Several studies confirm the robustness of the initial empirical results of Fama and French (1992, 1993) that size and value explain the cross-section of stock return and are, therefore, relevant to include. Fama and French (1993) document that factors constructed based on one half of the data base can explain the returns of the other half. Fama and French (1998) provide international evidence for the value effect based on an analysis of 13 major stock markets. These results are out of sample compared to their initial results and, therefore, strongly support the value effect. Furthermore, Hawawini and Keim (1995) provide a summary of international evidence inconsistent with the CAPM and therefore give support to alternative factor models. Fama and French (1995) confirm that the behavior of returns with respect to size and the book-to-market ratio is also reflected in earnings.[214] Thus, it seems reasonable to extend the one-factor performance model of Jensen (1968) by the factors of Fama and French (1993) in order to account for these return patterns.

3.3.2.2 Carhart Model: Momentum Effect

Jegadeesh and Titman (1993) report that a strategy based on buying past winners (the stocks with the highest past returns) and selling past losers (the stocks with the lowest past returns) generates significantly positive abnormal returns. They term this the momentum effect. It was introduced as an additional factor to the three-factor model of Fama and French (1993) by Carhart (1997). The resulting four-factor model is the current empirical workhorse of performance evaluation and is also widely used in other fields of finance:

[214] Specifically, high book-to-market (value) stocks are relatively distressed with low earnings on book equity while low book-to-market (growth) stocks have high returns on capital. Furthermore, small stocks tend to have lower earnings on book equity than large stocks, though this is mainly driven by a sustained period of low earnings of small stocks following the 1981/82 recession.

$$r_{it} = \alpha_{4i} + \beta_{mi} r_{mt} + \beta_{\text{smb},i}\text{SMB}_t + \beta_{\text{hml},i}\text{HML}_t + \beta_{\text{mom},i}\text{MOM}_t + \epsilon_{it} \ , \quad (3.23)$$

The interpretation of equation (3.23) corresponds to the interpretation of equation (3.22), i. e. the relevant question is whether MOM is believed to be a risk factor (or an adequate proxy for some unknown risk factor) and whether it is a feasible risk exposure of the investor without delegation. Carhart (1997) documents that the performance persistence among mutual fund managers was to a significant part not "because fund managers successfully follow momentum strategies, but because some mutual funds just happen by chance to hold relatively larger positions in last year's winning stocks" (Carhart, 1997, p. 57 f.). Many funds in the winner decile hold the last year's winner stocks, some of them due to selection skills and some of them due to luck. Because returns earned by applying a "buying winners and selling losers" strategy should not be attributed to the manager's skill, adding a momentum factor to the performance model can help to distinguish between both groups of fund managers. The skilled managers are likely to hold this year's winners in their current portfolio while the lucky managers have a higher likelihood to hold on to the last year's winners and to benefit from stock return momentum. The four-factor model is able to attribute the actual performance of a manager to these two sources in addition to market risk and a size or value tilt. The momentum factor should not, however, be interpreted as risk factor because it is not motivated by theoretical asset pricing considerations. This becomes clear from the following quotation by Carhart (1997, p. 61):

> "The 4-factor model is consistent with a model of market equilibrium with four risk factors. Alternately, it may be interpreted as a performance attribution model, where the coefficients and premia on the factor-mimicking portfolios indicate the proportion of mean return attributable to four elementary strategies: high versus low beta stocks, large versus small market capitalization stocks, value versus growth stocks, and one-year return momentum versus contrarian stocks. I employ the model to 'explain' returns, and leave risk interpretations to the reader."

With respect to the empirical evidence, the momentum anomaly is one of the most robust anomalies which survived several rigorous tests by researchers (Fama and French, 2008). In contrast, many other anomalies, such as the size effect and the value effect, are found to be much weaker after the periods examined by the studies that initially identified those anomalies (Schwert, 2003). According to Fama and French (1996) momentum profits do not diminish once it is controlled for the size and value effects. Rouwenhorst (1998) provides international evidence for the momentum effect based on a sample of twelve European stock markets. Furthermore, the momentum effect in international markets seems to be correlated with the momentum effect in the U. S. which suggests that a common risk factor exposure might explain the profitability of momentum strategies.

3.3.2.3 Construction of Factor-Mimicking Portfolios

Many studies, not only in mutual fund research but also in corporate finance and other areas, have used the three- or four-factor model to adjust returns for risk. For U. S. studies, the factors are standardized because the return series can be downloaded from the website of Kenneth French.[215] For other countries, researchers have to construct their own Fama-French and momentum factors or have to rely on publicly available stock indices such as the S & P 500 Growth or Value and the Russell 2000 index for small caps.[216] According to Fama and French (1993) stocks are allocated to one of six portfolios based on independent sorts on size (L – large; S – small) and the book-to-market ratio (H – high; M – medium; L – low). The SMB and HML factors are then defined as follows:

$$\mathrm{SMB} = \frac{(\mathrm{SL} - \mathrm{BL}) + (\mathrm{SM} - \mathrm{BM}) + (\mathrm{SH} - \mathrm{BH})}{3} \,, \tag{3.24}$$

$$\mathrm{HML} = \frac{(\mathrm{SH} - \mathrm{SL}) + (\mathrm{BH} - \mathrm{BL})}{2} \,. \tag{3.25}$$

The momentum factor is usually defined as the spread between the last year's winner stocks (W) and loser stocks (L). Carhart (1997), for example, applies a sorting based on the cumulative returns over the previous 11 months lagged by one month:

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[215] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[216] For a detailed description on how to construct the Fama-French factors see Fama and French (1993) and for the momentum factor as used in most studies see Carhart (1997).

$$\text{MOM} = \text{W} - \text{L} \ . \tag{3.26}$$

However, the construction of the Fama-French and momentum factors involves considerable degrees of freedom for the researcher. Michou, Mouselli, and Stark (2007) identify at least nine different ways of how these factors have been constructed in the literature based on U. K. data. Decisions have to be made with respect to different aspects which are presented in Table 3.1.

First of all, the relevant investment universe has to be defined. In the second step, the data is usually cleaned for outliers and inconsistencies. An important decision has to be made with respect to the treatment of new listing such as IPOs and delistings because returns of these stocks are usually rather extreme and might therefore have a significant impact on the factor returns (Eisdorfer, 2008). Then, the sorting variables, i. e. company size and the book-to-market ratio have to be defined. Differences in accounting standards significantly affect the construction and the empirical results of the size and value factors (Gomez Biscarri and Lopez Espinosa, 2008). Moreover, a look-ahead bias potentially results if data is used prior to its disclosure date. For example, annual statements have to be submitted to the SEC according to form 10-K within 90 days after the due date but might not be available to investors before. After the sorting variables have been defined, the sorting procedure has to be devised. It can either be based on subsequent sorts or independent sorts. Additionally, the split points between small and large or high and low book-to-market companies have to be defined. This directly affects the number of stocks and the combined market capitalization represented in each of the six portfolios and has, therefore, a substantial impact on the empirical results.[217] In the last step, a decision has to be made with respect to the weighting of stocks within the portfolios and the weighting of the portfolios itself when constructing the zero-cost portfolios.

The conventional construction method as applied by Fama and French (1993) implies that relatively more market capitalization is centered in the big and growth portfolios as opposed to the small and value portfolios (Cremers, Petajisto, and Zitzewitz, 2008). Equal-weighting of the six portfolios then gives more weight per dollar market capitalization to stocks in the small and value portfolios which are

[217] For example, the small size groups contain 3,616 out of 4,797 stocks in 1991 but make up for only 8 percent of total market capitalization in the study of Fama and French (1993).

Table 3.1: Construction of the Fama-French Factors

Definition	Fama and French (1993)
(a) Investment universe Definition of the relevant investment universe.	All NYSE, AMEX and NASDAQ stocks.
(b) Data cleaning Winsorization in order to limit the impact of extreme outliers. Potential exclusion of stocks based on criteria such as the stock price (e. g. penny stocks), firm size (e. g. micro caps), book-to-market ratio (e. g. negative book-to-market stocks) or industry (e. g. financials and utilities).	Include only firms with ordinary common equity and CRSP stock prices for December of the previous year and June of the current year and Compustat book common equity for the previous year; exclude negative book-to-market companies.
(c) New listings and delistings Treatment of IPOs and delistings due to bankruptcy or merger.	Not mentioned in paper.
(d) Sorting variables Definition and time lag of sorting variables, i. e. which data items are used to measure market value and book value and at which point in time are these variables observed in order to avoid a look-ahead bias.	Portfolios are formed in June and returns are calculated from July in year t to June in year $t+1$; firm size is measured in June as price times the number of shares; the book-to-market ratio is measured in December of the previous year and book value is defined as the Compustat items book value of stockholders' equity, plus balance-sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock.
(e) Portfolio formation Independent sorts on size and book-to-market versus subsequent sorts in order to have the same number of stocks in each portfolio.	Independent sorts.
(f) Split points Definition of split points between large and small, high book-to-market and low book-to-market and past winners and losers.	Median of all NYSE stocks as the split point between large and small stocks and the 30th and 70th percentile of all NYSE stocks as the split points between low, medium and high book-to-market stocks.
(g) Weighting Weighting of stocks within the long portfolios and weighting of the long portfolios in order to compute the zero costs portfolios.	Value-weighting within the long portfolios; equal-weighting of long portfolios to form SMB and HML.

the ones that have historically outperformed. This might result in biased performance metrics. For example, Cremers, Petajisto, and Zitzewitz (2008) document that small-cap funds underperform large-cap funds by 2.13 percent per year based on the conventional four factors as available on the website of Kenneth French. However, a passive small-cap index, which theoretically should have an alpha of zero, yields a negative alpha of 5.07 percent per year. In order to overcome the unrealistic weighting, Cremers, Petajisto, and Zitzewitz (2008) propose to use stock indices instead of the academic factors. Based on these indices, the result on the superiority of large-cap funds reverses with small-cap funds outperforming large-cap funds by 2.94 percent per year.

Moreover, this construction methodology might result in significant short positions in some stocks (most likely in big growth stocks). However, instead of interpreting the Fama-French benchmark as a position in the market and two separate zero-cost portfolios it can also be interpreted as one portfolio with a tilt toward small and value stocks where SMB and HML measure this tilt. Fama and French (2006) argue that a tilt of the fund's portfolio toward small and value stocks would not in many cases involve a short position in large and growth stocks. To judge this statement the aggregate weight of each stock over all three portfolios (eventually including the momentum portfolio) and the average risk exposures have to be taken into account. So far, no such studies exist.

A further complication involves the appropriate consideration of transaction costs when calculating the factor returns. Huij and Verbeek (2009) propose to estimate the size, value and momentum factor based on realized returns of mutual funds, which are net of transaction costs, instead of hypothetical paper returns of stock portfolios. Specifically, they estimate the factor exposures of all funds in their sample with respect to three-factor model of Fama and French (1993) and then form portfolios based on lagged risk exposures. The HML factor, for example, is long in all funds with lagged HML betas which are greater than the median HML beta of all funds over the previous 36 months and short in those funds with HML betas lower than the median. Even though short positions in mutual funds are not attainable in reality, the authors claim that this procedure mitigates the biases in the risk premiums from the conventional methodology, especially with respect to transaction costs. However, performance metrics based on the factors of Huij and Verbeek (2009) can only be interpreted relative to the average skill of all other funds as, for example, a decrease in the average skill level or an increase in the fee level of all funds, which should result in a reduction of net-of-fee alphas, does not alter the alphas from their benchmark model.

In summary, this discussion reveals that there is nothing like *the* four-factor model and consequently not *the* four-factor alpha. Rather, specific details of the construction can have a significant impact on the conclusions. This is even more important for U. S. studies, as compared to international studies, as almost all of the U. S. literature relies on the factors constructed by Kenneth French that are available on his website and in the CRSP database of the University of Chicago. In international studies, researchers usually construct their own factors and, therefore, are more sensitive with respect to the robustness of their results. One way to avoid these potential biases all together is by using characteristic-based benchmarks as suggested by Daniel, Grinblatt, Titman, and Wermers (1997).[218] However, this comes at the cost of having access to portfolio holdings and high computational requirements.

3.3.3 Timing Models and Conditional Performance Evaluation

The three- and four-factor models presented so far are primarily concerned with measuring security selection skills of a fund manager. However, as argued in section 3.3.1.2, timing skills, reflected in non-constant betas, cannot be measured by these models and might even bias the alpha if not properly accounted for.[219] Timing skills, according to equation (1.4), are defined as a positive correlation between the factor exposure and the realized factor returns. The intuition is that fund managers will increase their betas if they believe in a rising market, a rising size or value premium or increased profits from momentum strategies and vice versa. To account for this time-variability, conditional models can be used for performance evaluation.[220] The betas of these models vary depending on different macroeconomic variables that are believed to predict the future state of the economy. In addition, alpha can also be time-varying depending on macroeconomic variables (Christopherson, Ferson, and Glassman, 1998):

218 Section 3.5.
219 Betas might also vary over time because of: (1) the use of options (Ferson and Schadt, 1996); (2) the use of option-like dynamic trading strategies; (3) random changes in the relative weights of portfolio positions due to differences in relative returns; (4) random changes in the betas of the underlying stocks over time (Ferson and Schadt, 1996).
220 Lockwood and Kadiyala (1988), Ferson and Schadt (1996), Ferson and Warther (1996), and Ferson and Qian (2005).

$$\beta_{it} = \overline{\beta}_i + \boldsymbol{\gamma}_i' \boldsymbol{z}_t + \nu_{it} \qquad \text{and} \tag{3.27}$$

$$\alpha_{it} = \overline{\alpha}_i + \boldsymbol{\delta}_i' \boldsymbol{z}_t + \omega_{it} \ , \tag{3.28}$$

where $\overline{\beta}_i$ and $\overline{\alpha}_i$ are the average beta and alpha of fund i, $\boldsymbol{z}_t$ denotes an $(L \times 1)$ vector of (unexpected) realizations of the macroeconomic variables (information variables) and $\boldsymbol{\gamma}_i$ and $\boldsymbol{\delta}_i$ are vectors of the sensitivities of beta and alpha with respect to the macroeconomic variables, respectively.[221] Plugging equations 3.27 and 3.28 into a K-factor model yields its conditional version:

$$r_{it} = \overline{\alpha}_i + \boldsymbol{\delta}_i' \boldsymbol{z}_t + \sum_{k=1}^{K} \overline{\beta}_{ik} f_{kt} + \sum_{k=1}^{K} \boldsymbol{\gamma}_i' \boldsymbol{z}_t f_{kt} + \psi_{it} \ , \tag{3.29}$$

where f_{kt} denotes the k-th factor's (excess) return.[222]

Based on conditional models, managers are no longer rewarded for using public information. Moreover, conditional models are likely to correct for the bias-in-beta due to timing and dynamic trading strategies that may lead to underestimated alphas (Grinblatt and Titman, 1993). If fund flows are affected by macroeconomic news, these models can also account for the impact of excessive inflows and outflows on the investment style of the fund (Ferson and Warther, 1996; Benson and Faff, 2006).

Empirical results on the effect of introducing conditioning variables are mixed. In a recent study, Bessler, Drobetz, and Zimmermann (2009) find lower performance with conditional models whereas Ferson and Schadt (1996) report improved performance compared to unconditional models. Christopherson, Ferson, and Glassman (1998) and Ferson and Qian (2005) for U. S. data and Otten and Bams (2002) for European data do not detect any difference in performance. Mixed results may be due to the fact that conditioning, on the one hand, mitigates the bias-in-beta (higher alpha) and, on the other hand, results in a stricter benchmark (lower alpha). The benchmark becomes stricter because managers are no longer

[221] In practice, expected realizations of the information variables are not observable and need to be estimated, for example by a time series model.

[222] Note that in a fully conditional model with L information variables and K factors the fund's excess return is regressed on a total of $(L + 1)(K + 1)$ variables. Adding more factors or information variables reduces the degrees of freedom very rapidly resulting in inefficient estimates.

rewarded for altering the loading on the different factors over time according to public information (macroeconomic variables). A fundamental problem with conditional models, however, is the identification of macroeconomic variables that sufficiently predict factor returns: "models such as the CAPM imply a conditional linear factor model with respect to investors' information sets. The best we can hope to do is test implications conditioned on variables that we observe. Thus, a conditional factor model is *not testable*" (Cochrane, 2001, p. 145).

To overcome this critique, Mamaysky, Spiegel, and Zhang (2008) apply a state-space model and Kalman filtering which allows them to improve alpha and beta estimation by assuming that the coefficients depend on an unobservable variable which itself follows an AR(1) process. They document that, based on this methodology, funds can be identified ex ante which subsequently produce abnormal returns as large as 4 percent per year which is a very strong result. As an alternative approach, some authors argue to estimate betas over rolling windows of shorter length using high frequency data instead of relying on conditioning information (Lewellen and Nagel, 2006). For example, Bollen and Busse (2001) apply this approach to mutual funds. In particular, they show, based on simulations, that the use of daily data can improve estimation efficiency for measuring timing abilities. Jiang, Yao, and Yu (2007) apply a similar approach. However, as daily mutual fund returns are available only for a subset of funds they estimate fund betas based on portfolio holdings information and daily stock price data. The individual stock betas are then aggregated to the funds' betas and used to compute alpha as the difference between the funds realized return and the expected return according to the estimated betas.

Instead of directly accounting for time variability in risk exposures some studies instead use dynamic factors. Thus, the estimated coefficients are constant but the construction of the factors aims to control for time variability of the underlyings investment strategy. The payoffs of these factors are usually non-linear. Treynor and Mazuy (1966) propose adding a squared market factor:

$$er_{it} = \alpha_{1i}^{TM} + \beta_{mi} er_{mt} + \gamma_i^{TM} (er_{mt})^2 + \epsilon_{it} \ . \tag{3.30}$$

The intuition is that managers with timing skill will increase the beta in times of high market returns, et vice versa. Timing skills are measured as a significantly positive γ_i^{TM}. However, this measure is biased in the case of negative market returns.

In contrast, Merton (1981) and Henriksson and Merton (1981) apply option-like payoff structures to model timing skills:

$$er_{it} = \alpha_{1i}^{HM} + \beta_{mi} er_{mt} + \gamma_i^{HM} d_t er_{mt} + \epsilon_{it} \ , \tag{3.31}$$

where d_t is a dummy variable which is one in the case of positive market returns and zero otherwise. Again, a significantly positive γ_i^{HM} is interpreted as timing skill. A shortcoming of this approach is that it only allows for two different beta states. Similar approaches have recently been applied to hedge funds (Fung and Hsieh, 1997; Capocci and Hübner, 2004). For example, Agarwal and Naik (2004) add out-of-the-money put and call option factors in order to capture dynamic trading strategies of hedge funds.

It seems important, in one way or the other, to account for time variability of factor exposures. This is especially true when investors delegate only security selection but dictate the tactical asset allocation or factor timing because, in this case, the manager should not be rewarded for changes in the systematic risk exposure. However, any change in the portfolio composition, which is what fund managers are ultimately paid for, induces variability in the exposures. In addition, even passive portfolios exhibit random fluctuations potentially inducing a bias (Francis and Fabozzi, 1980). Given the obstacles with the identification of adequate macroeconomic variables with a sufficiently high observation frequency, conditional models seem to be difficult to implement. Rolling window techniques, instead, in combination with high frequency data or improved statistical methods seem to be a more promising approach.

3.4 Interpretation of Multifactor Models

It might seem unsatisfactory to use the four-factor model of Carhart (1997) as an empirical workhorse in performance evaluation because the factors themselves are not theoretically motivated and still not understood very well in the literature. Alternative risk-based explanations for the cross-sectional patterns of stock returns have been identified in the literature and have led to the development of new pricing factors (Table 3.2).[223] In addition, behavioral explanations for the empirical success of the four-factor model have been proposed. In this case, however, the four factors might just be a way of operationalizing behavioral biases as benchmark factors in performance evaluation. Microstructure effects, which are also discussed in the literature, pose a bigger threat on the use of the four-factor model. Specifically, it can be argued that transaction costs prevent investors from exploiting size, value and momentum strategies. In this case, the four factors do not seem to be appropriate benchmarks for real-world portfolio managers. Furthermore, some studies argue that the empirical success of the four-factor model documented in the literature stems in a large part from potential biases in the research methods. Methodological issues are primarily related to the sorting procedure and also question whether the factors are investable in reality. Statistical issues question whether the effects documented in the literature are indeed significant once potential biases have been appropriately accounted for. All of this makes a thorough understanding of the four-factor model and the related issues highly important for its use as a benchmark in delegated asset management.

Moreover, if the four-factor model is an inadequate representation of relevant risk factors then portfolio managers can follow a simple strategy to improve the estimated alpha without true selection skills. The performance measure strongly depends on the factors of the pricing model used to compute the expected return for the funds' portfolio. The inclusion of assets which have an exposure to risk factors not considered in the benchmark shows up in the alpha term of the regression. Though, this alpha is not evidence of selection skills. In fact, Litterman (2008) refers to this source of "false" alpha as "exotic beta". Thus, a precise understanding of the interpretation of multifactor models is highly relevant.

3.4.1 Risk-Based Explanations

3.4.1.1 Time-Varying Asset Composition

Further empirical work can improve the understanding of the size, value and momentum effects. However, in order to distinguish between behavioral and risk-based explanations appropriate models that can generate these effects consistent with rational asset pricing are first required. Berk, Green, and Naik (1999) develop such a model and argue that the size, value and momentum effects can be

[223] Table A.1 in appendix A.1 presents a review of the relevant literature.

Table 3.2: Interpretation of factor-mimicking portfolios

This table presents risk-based and non-risk-based explanations for the empirical success of the three-factor model of Fama and French (1993) according to equation (3.22) and the four-factor model of Carhart (1997) according to equation (3.23). Columns (2) to (4) present which of the established factors can be viewed as a proxy for the explanation and column (5) presents potential advancements of the existing models by developing new factors or methodologies based on the explanation. Table A.1 in appendix A.1 presents a review of the relevant literature.

Economic risk / explanation	Established factors			New factor /
	SMB	HML	MOM	methodology
(a) Risk-based explanations				
Time-varying asset composition	•	•	•	
Business cycle / macroeconomic risk	•	•	•	•
Default risk	•	•	•	
Liquidity risk	•	•	(•)	•
Higher moments	•	•		•
Idiosyncratic volatility		•	•	•
Stochastic expected growth rates			•	
Investments			•	
Downside risk			•	•
Time-varying idiosyncratic volatility			•	•
Foreign exchange risk				•
(b) Behavioral explanations				
Extrapolation	•	•		
Underreaction			•	
Overreaction			•	
Fear of reversal			•	
Overconfidence (market state)			•	
(c) Microstructure / asymmetric information				
Trading volume		•	•	
Short sale constraints		•	•	
Transaction costs			•	
Analyst coverage			•	
Private information access			•	
(d) Methodological issues				
Micro caps	•	(•)		
Migration	•	(•)		
Delisting returns			•	
Industry effect			•	
(e) Statistical issues				
Time-varying factor exposure	•	•	•	•
Parameter estimation error	•	•	(•)	
Spurious regression	•	•	(•)	

explained by changes in firms' risks over time. In particular, firms own two different kinds of assets, current assets in place, which generate cash flows, and growth options on future investments, which will then, if successful, generate positive cash flows. These assets have a life cycle, with the cash flows from current assets dying off and new investment opportunities emerging. For example, new investments with low systematic risk will increase the firm value immediately but reduce the systematic risk and expected returns in the long run. Similarly, when low risk assets have to be replaced, the immediate response is a decrease in firm value and an increase in expected returns. The size, value and momentum effects might just serve as state variables picking up the time variability in the composition of a firm's assets. Book-to-market summarizes the firm's risk relative to its asset base. The market value summarizes the relative importance of growth options versus assets in place as firms with higher market capitalization tend to have larger current assets. Because the composition of a firm's assets and, consequently, systematic risk is relatively persistent the model also yields the time-series behavior of returns consistent with the momentum effect. Furthermore, expected returns are negatively related to lagged realized returns, consistent with mean reversion, because shocks to the composition of a firm's assets are negatively related to changes in its systematic risk.

Similarly, Johnson (2002) provides a parsimonious model which is able to explain the momentum effect without assuming investor irrationality, market frictions or asymmetric information. Rather, it relies on the simple idea of stochastic expected growth rates of the firms. Specifically, it is assumed that exposure to growth-rate risk carries a positive risk premium and that growth-rate risk is positively related to the level of the growth rate. This assumption seems intuitive as more extreme growth rates are not as sustainable as lower growth rates in the long run. Companies that have previously experienced positive (negative) shocks to their growth rate are more likely to end up in the winner (loser) decile based on a momentum sort. Thus, the higher (lower) average returns of momentum winners (losers) might just be a compensation for higher (lower) growth-rate risk. However, despite its intuitive appeal, the model has to be extended in order to match the empirical pattern of the momentum effect. Precisely, growth rate shocks have to be persistent in order to explain the difference in returns but at the same time they have to decay relatively quickly because momentum returns also decay over the longer run. Johnson (2002) solves this problem by introducing a regimeswitching model which determines the relevant length of the formation period in order to capture different levels of expected returns in the post-formation period. Avramov and Hore (2008) extend the work of Johnson (2002) and claim that high leverage, in combination with risky cash flows, reinforces momentum because the persistence in cash flow growth rates only slowly reduces risk.

3.4.1.2 Macroeconomic Risk, Business Cycle and Default Risk

Macroeconomic Risk and the Business Cycle

An empirically testable explanation for SMB and HML consistent with rational asset pricing is that they might proxy for business-cycle sensitivity or time-varying default risk of companies (Fama and French, 1993; Vassalou and Xing, 2004). Indeed, the inclusion of a factor that captures news related to future GDP growth significantly reduces the explanatory power of the Fama-French factors in the cross section (Vassalou, 2003). The performance of the three-factor model of Fama and French (1993) is comparable to the performance of asset pricing models based on a broad set of macroeconomic variables such as economic growth expectations, inflation, interest rate and term structure variables, and exchange rates in explaining the cross-section of stock returns (Aretz, Bartram, and Pope, 2010). Even both factors, SMB and HML, individually capture macroeconomic surprises otherwise left unexplained by the one-factor model (Simpson and Ramchander, 2008). The SMB factor offers high returns in good economic times when the marginal utility of consumption is low but the HML factor rather serves as a hedge against the business cycle, i. e. it offers relatively high returns when the marginal utility of consumption is high in bad economic times (Arshanapalli, Fabozzi, and Nelson, 2006). This would not be consistent with a positive risk premium.

Likewise, for momentum returns, Chordia and Shivakumar (2002) suggest macroeconomic risks in combination with time-varying expected returns as a potential explanation.[224] Specifically, stock returns are, to a certain extent, predictable based on lagged macroeconomic variables.[225] Once they control for this stock return predictability, momentum profits disappear. Momentum profits seem

[224] If the sensitivity of individual projects of firms depends differently on the state of the economy then the results of Chordia and Shivakumar (2002) are consistent with the model of Berk, Green, and Naik (1999).

[225] The macroeconomic variables are a short-term interest rate on the risk-free asset, the term spread, the default spread as well as the dividend yield.

to be positive only during periods of expansion while momentum returns are (insignificantly) negative during recessions. The same result applies to an industry-momentum strategy as analyzed by Moskowitz and Grinblatt (1999). However, the relationship between stock return momentum and macroeconomic risks is independent of industry momentum, indicating that stock momentum and industry momentum are separate effects. Moreover, the momentum factor still seems to contain information about the cross-section of stock returns in addition to a broad set of macroeconomic variables (Aretz, Bartram, and Pope, 2010).

Default Risk

Trying to associate macroeconomic risks with the explanatory power of firm-specific variables such as the Fama-French factors, Vassalou and Xing (2004) argue that default risk might be the missing link. In particular, small companies are believed to exhibit a stronger business cycle sensitivity due to their higher likelihood of distress. Indeed, the results of Vassalou and Xing (2004) suggest that the size effect exists only in the quintile of stocks with the highest default risk and small stocks within this quintile have even higher default risks than large stocks in the same quintile. Similarly, the book-to-market effect can only be observed within the two highest default risk quintiles. Once stocks with the highest default probabilities are excluded from the sample, both the size and book-to-market effects disappear. Furthermore, default risk is systematic and therefore priced in the cross section of stock returns. However, Vassalou and Xing (2004) also document that HML and SMB additionally contain information which is not related to default risk but is priced in stock returns leaving room for further risk-based explanations.

A similar risk-based explanation exists for momentum returns suggesting that they are merely a compensation for default risk not captured by the conventional market factor. This seems intuitive as firms behave “normal”, i. e. their returns can be explained by their market risk, as long as the distance to default is large. However, once they come closer to default, this additional risk becomes relevant for pricing. Indeed, firms with high bankruptcy risk as measured by their credit rating exhibit stronger momentum effects (Avramov, Chordia, Jostova, and Philipov, 2007).

3.4.1.3 Foreign Exchange Risk

Kolari, Moorman, and Sorescu (2008) analyze how foreign exchange risk is related to stock returns in the cross-section. Their results indicate a negative premium for foreign exchange risk. Companies with higher absolute exposure to foreign exchange risk have lower returns than others. A potential explanation is that firms which are more sensitive to foreign exchange rate risk tend to be in distress and tend to have a higher asset volatility. Based on option-pricing considerations these stocks would then trade at a premium explaining the lower returns. Thus, exchange rate risk might be interpreted in a similar vein as default risk. Kolari, Moorman, and Sorescu (2008) go on to construct a factor mimicking portfolio to account for foreign exchange risk in the fashion of Fama and French (1993). This zero-cost portfolio is long in stocks sensitive (in absolute value) to foreign exchange risk, as measured by a regression of stock returns against a currency basket of major industrial countries, and short in stocks that are not sensitive. This factor reduces the pricing errors if incorporated into the three- and four-factor models of Fama and French (1993) and Carhart (1997), respectively, suggesting that foreign exchange risk contains more than just default risk for which the size, value and momentum factors have been shown to be a good proxy.

3.4.1.4 Liquidity Risk

Liquidity seems to be a priced risk factor in asset returns (e. g. Chan and Faff, 2005; Acharya and Pedersen, 2005; Amihud and Mendelson, 2006).[226] Liquidity can be described best by the ease of converting an asset into cash (or cash into an asset), i. e. trading small and large quantities immediately and quickly with low direct (e. g. commissions) and indirect (e. g. price impact) costs. Due to market frictions this process is not without costs in reality. First of all, brokerage fees and commissions apply. Second, costs may arise in the process of finding a counterparty willing to take the offsetting position. Market makers act as intermediaries and offer immediacy but charge a bid-ask spread as compensation for inventory risks as well as the risk of facing a counterparty with private information. In addition, the transaction itself might drive the price away from its fundamental value in an unfavorable direction (market impact).

[226] See Amihud, Mendelson, and Pedersen (2005) for a comprehensive summary on liquidity and asset pricing.

Investors face these transaction costs due to the illiquidity of assets. As a result, they adjust their expected return according to the expected transaction costs and their expected holding period. Furthermore, as both future transaction costs and the holding period might be uncertain, illiquidity constitutes a risk factor that should be priced (Amihud, Mendelson, and Pedersen, 2005). Thus, liquidity enters into the usual expected return equation in addition to investment risk. For example, Amihud and Mendelson (1986) theoretically and empirically show that expected returns are a concave function of the bid-ask-spread as stocks with different spreads tend to attract investor clienteles with differing investment horizons. Moreover, Longstaff (2009) argues that theoretically the value of liquidity can represent a large portion of the equilibrium price of an asset and that it has important effects on optimal portfolio choice.

However, liquidity cannot be observed directly and depends on the asset, the market in which the asset is traded, and the characteristics of the trade itself such as size and immediacy (Keim and Madhavan, 1997). Four dimensions of liquidity have been identified in the literature in order to overcome the measurement problem: breadth, depth, immediacy, and resiliency. Breadth refers to the transaction costs of trading a certain number of assets, depth refers to the volume that can be traded, immediacy to the speed of trading and resiliency to the speed of the market returning back to its former price level after an imbalance due to a large trade. But still, the relationship between expected returns and liquidity could not be tested for a long time as adequate data was not available.[227] Only recently has adequate data on transactions or the order book become available.

There is still a controversy in research with respect to an appropriate and uniform measure of liquidity. Simple measures are the dollar volume of trading and the share turnover calculated as the volume of shares traded relative to the volume of shares outstanding. This follows the idea that the liquidity of an asset increases with trading activity (Chan and Faff, 2005; Keene and Peterson, 2007). One advantage of this approach is that the data is available in many commercial information systems. Related to these measures is the widely used illiquidity ratio of Amihud (2002). It is computed as the average (absolute) price change per dollar trading volume over all trading days of one month and can be interpreted as a measure of price impact. The illiquidity ratio can be averaged across

[227] The initial aim of the study of Banz (1981) was to analyze the impact of liquidity, though due to data restrictions he had to proxy liquidity by size.

all stocks to compute a market-wide liquidity measure. Pástor and Stambaugh (2003) construct a market-wide liquidity risk measure based on first-order return autocorrelation conditional on signed volume which is interpreted as the next day's price reversal depending on today's turnover. This measure aims to capture the systematic, i. e. non-diversifiable, part of liquidity risk rather than idiosyncratic liquidity risk because only the former constitutes a priced risk factor. Liu (2006) focuses on the continuity of trading related to the immediacy dimension of liquidity by using a normalized measure of days with zero trading volume during the last 12 months as illiquidity measure. To distinguish between stocks with the same number of non-trading days he also incorporates the total turnover of the previous 12 months into his liquidity measure.

Many studies document a significant relationship between systematic or market-wide liquidity and expected returns in that more assets with a higher sensitivity to market-wide illiquidity exhibit higher returns (Chordia, Roll, and Subrahmanyam, 2000; Pástor and Stambaugh, 2003). This relation holds in the cross-section of asset returns as well as in time-series data (Amihud, 2002). Miralles Marcelo and Miralles Quirós (2006) confirm a similar finding in an international context for the Spanish market, though they point out that the liquidity premium in their data set is largely driven by the month of January. Acharya and Pedersen (2005) separate the liquidity premium into three components. They document that the most significant part stems from the correlation between a stock's liquidity and the market return implying that investors are willing to pay a premium for stocks that are liquid when the market falls. The second part is the correlation between the stock's return and market liquidity. Consistent with Pástor and Stambaugh (2003) they find that investors require a higher return for stocks that perform badly when the market is in a downturn and in this situation prefer stocks with high returns. Third, the commonality between individual stock liquidity and market liquidity only explain a marginal part of the liquidity premium (Acharya and Pedersen, 2005).

Liquidity risk is able to explain most of the size, momentum or contrarian effects as well as the abnormal returns of strategies based on fundamental ratios such as cashflow, earnings, and dividends (Pástor and Stambaugh, 2003; Liu, 2006; Sadka, 2006). Specifically, Pástor and Stambaugh (2003) document that liquidity risk accounts for half of the profits of a momentum strategy. Moreover, the return spread of size-sorted portfolios can be fully explained by differences in liquidity betas. In other words, the size effect seems to be a liquidity effect. Sadka (2006) even provides empirical evidence that liquidity risk can explain up to 80 percent of the cross section of momentum returns. Further, he shows that the permanent component of the price impact rather than the transitory component is priced as liquidity risk which suggests that private information, or more specifically the aggregate ratio of informed traders to noise traders, are the underlying reason for the liquidity risk inherent in momentum investing. This observation relates liquidity risk in the context of momentum strategies to asymmetric information risk. According to the study of Liu (2006) a liquidity augmented two-factor model can explain the size and value effect.[228] Similar to the results of Pástor and Stambaugh (2003) and Sadka (2006), the three-factor Fama and French (1993) model cannot fully explain the momentum returns in his analysis. However, Liu (2006) documents that, when the economy performs badly, liquidity tends to be low and investors require a high liquidity premium linking liquidity risk to the business cycle or to the market state. Recently, Nguyen, Mishra, Prakash, and Ghosh (2007) point out that neither the three-factor model of Fama and French (1993) augmented by the liquidity factor of Pástor and Stambaugh (2003) nor models based on higher moments or stock characteristics can account for the alphas of portfolios sorted based on their turnover ratio.[229]

In order to account for liquidity risk a factor mimicking portfolio can be incorporated into an asset pricing model. Such an approach has been applied in an asset pricing context by several recent studies.[230] Usually, an advantage of liquidity factors is that, by construction, the short position is in liquid securities (Liu, 2006). This makes it easier to implement in the real world as compared to the HML or momentum factors which require a short position in growth stocks or loser stocks, respectively, that often tend to be smaller, less liquid and exhibit high idiosyncratic risk making them expensive to sell short. Including a liquidity factor into a performance evaluation model seems to be a reasonable choice for several reasons. First, in a static sense, the open-end structure of funds might force the fund manager to hold a relatively liquid portfolio. If instead the benchmark incorporates a liquidity risk premium the performance results are biased.

[228] In addition, it explains the cash-flow-to-price, earnings-to-price, dividend yield, and long-term contrarian anomalies.
[229] For a discussion of higher moments and characteristic-based asset pricing models see below.
[230] Pástor and Stambaugh (2003), Chan and Faff (2005), Miralles Marcelo and Miralles Quirós (2006), Liu (2006), and Keene and Peterson (2007).

Second, in a dynamic sense, the ability of a manager to predict fund inflows and outflows (creations and redemptions) and to manage the liquidity of the portfolio accordingly can be interpreted as managerial skill. Conditional models including a liquidity risk factor could be used to identify such "liquidity timing" skills. However, again as with most of the other factors it can be argued that the four-factor model provides a sufficient proxy for liquidity risk.

3.4.1.5 Higher Moments and Downside Risk

Higher Moments

Alternatively, it has been suggested in the literature that the Fama-French factors proxy for higher-moment risk born by investors (Chung, Johnson, and Schill, 2006). Specifically, the CAPM is derived based on the assumption that investors only care about mean and standard deviation of returns. However, it seems reasonable to believe that they also care about higher moments such as skewness and kurtosis, and higher comoments such as coskewness and cokurtosis.[231] As these higher moments are especially important in explaining differences in the tails of the return distribution they can be linked to extreme events. Hence, higher-moment risk might be related to distress and default risk. Interestingly, once these systematic comoments are added to the pricing equation the Fama-French factors turn out to be insignificant (Chung, Johnson, and Schill, 2006). Similarly, Harvey and Siddique (2000) report that conditional coskewness has explanatory power for the cross section of stock returns beyond the size and value factors.

Fund managers have an incentive to load on negative coskewness because it seems to pay a risk premium on average while most conventional performance measures do not account for coskewness. Kostakis (2009) develops a performance model that incorporates coskewness as an additional risk factor. Specifically, he estimates the standardized coskewness of each stock with the market based on the residuals of a market model regression over the previous 60 months. Then, he sorts the stocks into a high and low coskewness portfolio depending on whether the coskewness measure is higher than the 70th percentile or lower than the 30th percentile. Similar to the construction of the conventional Fama-French factors the coskewness factor is the return of a zero-cost strategy long in the portfolio

[231] Specifically, investors are believed to dislike moments of even degrees such as the standard deviation but to like moments of odd degrees such as the mean.

with the most negative coskewness and short in the portfolio with the most positive coskewness. Adding the coskewness factor to the three-factor model of Fama and French (1993) improves the explanatory power and has a nontrivial impact on performance (Kostakis, 2009). Ranaldo and Favre (2005) even apply a four-factor model with coskewness and cokurtosis to a hedge fund data set and confirm that these factors seem to be important to consider in performance evaluation for most of these funds. Hwang and Satchell (1999) document that higher-moment risk is especially prevalent in emerging markets. These results suggest that higher moments are relevant when evaluating mutual funds with special or exotic investment objectives.

Downside Risk

Ang, Chen, and Xing (2006) argue that, in addition to higher moments, investors dislike downside risk and expect a compensation for bearing that risk. Downside risk is defined as stocks being more sensitive to market movements when the market goes down as compared to market movements when the market goes up. According to their empirical results momentum winners indeed tend to have a higher downside risk exposure suggesting that the higher returns earned by winner stocks might only constitute a compensation for bearing higher downside risk once the market falls. This finding is consistent with the theoretical model of Johnson (2002) that growth-rate risk is positively related to the growth rate. Wang (2008) provides a similar explanation from the behavioral perspective and argues that the fear for a trend reversal increases once the price of a stock has moved to an unusually high or low level. By estimating betas conditional on the market movements the results of Ang, Chen, and Xing (2006) reveal that downside risk seems to pay a risk premium of between 5.6 and 6.9 percent per year depending on the exact model specification. A portfolio strategy long in the highest downside beta stocks and short in the lowest downside beta stocks offers an annual return of 11.8 percent which is highly statistically significant. Further regression analyses reveal that downside risk and coskewness risk seem to be two different risk factors. Moreover, the downside risk premium is not explained by liquidity risk, or size, value, and momentum characteristics and, thus, constitutes a new risk factor.

3.4.1.6 Idiosyncratic Risk

Consistent with a rational pricing story, the size and value effects might just be a proxy for priced idiosyncratic risk. Indeed, several authors have argued for a long time that idiosyncratic risk, in addition to systematic risk, enters the pricing equation. According to Merton (1987), idiosyncratic risk plays a role in asset pricing once some investors are restricted to holding a fully diversified portfolio due to some exogenous reasons. Then, the remaining investors are also unable to hold the market portfolio and require a compensation for holding idiosyncratic risk (Malkiel and Xu, 2004). For example, in the presence of incomplete information investors might only hold those securities with which they are familiar. Merton (1987) calls this the “investor recognition hypothesis”. Furthermore, transaction costs might prevent private investors from full diversification (Malkiel and Xu, 2004). Lastly, many investors hold active mutual funds which, by definition, should deviate from the market portfolio. Based on these arguments, the relationship between the idiosyncratic risk level and expected returns should be positive. In contrast, Miller (1977) argues that dispersion of opinion, which can be interpreted as a proxy for idiosyncratic risk, might result in a negative relationship between idiosyncratic volatility and future stock returns if short sales are restricted. Securities with high dispersion of opinion trade at a premium in this scenario, because the most optimistic investors set the security prices while pessimistic investors cannot bet against it, due to a lack of short selling facilities.

Based on a direct test in the form of portfolios ranked on idiosyncratic volatility Ang, Hodrick, Xing, and Zhang (2006) document a negative relationship between idiosyncratic volatility and stock returns. This is empirical evidence in favor of the story of Miller (1977). In a follow-up study, Ang, Hodrick, Xing, and Zhang (2009) provide international evidence for 23 developed markets that confirms their initial conclusions. Fu (2009), however, argues that the results of Ang, Hodrick, Xing, and Zhang (2006) are biased since they do not control for time variability in idiosyncratic volatility. Using an exponential GARCH model, Fu (2009) documents a positive relationship between conditional idiosyncratic volatility and expected returns. The more indirect test of Diether, Malloy, and Scherbina (2002) is based on analyst dispersion as proxy for idiosyncratic risk. They conclude, again, that there is a negative relationship between dispersion and future returns. Boehme, Danielson, Kumar, and Sorescu (2009) distinguish between stocks with high and low visibility as the model of Merton (1987) only applies to stocks with low investor recognition. As a proxy they use institutional ownership and analyst coverage and provide evidence in favor of the predictions of Merton (1987), namely that idiosyncratic volatility is positively related to stock returns for the subset of less visible stocks.

Ali, Hwang, and Trombley (2003) aim to link the value effect to idiosyncratic risk and indeed show that the value effect is concentrated among stocks with high idiosyncratic volatility. On the one hand, this might suggest that HML is a proxy for idiosyncratic risk. On the other hand, this evidence can be interpreted in favor of a behavioral explanation of the value effect (Arena, Haggard, and Yan, 2008).[232] In a rational market, investors would arbitrage away these systematic errors of others. However, arbitrage is restricted among high idiosyncratic volatility stocks because short selling is particularly expensive. This deters arbitrage activity and is an important reason for why the value effect persists.

Analogously, Arena, Haggard, and Yan (2008) argue that momentum profits are concentrated around high idiosyncratic volatility stocks, especially for momentum losers. Again, these findings would be consistent with momentum being a proxy for idiosyncratic risk or with behavioral explanations, specifically the underreaction to firm-specific news hypothesis. First, idiosyncratic volatility might be a proxy for firm-specific information and, second, high idiosyncratic volatility stocks are believed to be more expensive to sell short which limits arbitrage of the underreaction effect. Specifically, low idiosyncratic volatility stocks generate momentum returns of 0.55 percent per month while high idiosyncratic volatility stocks generate returns of 1.43 percent per month, a significant difference of 0.88 percentage points per month. Even after controlling for size and value this difference remains significant at 0.97 percentage points per month. Moreover, a long-term increase in the average levels of idiosyncratic volatility can even explain why the momentum anomaly remains persistent over a long time period without being arbitraged away after detection from rational investors (Arena, Haggard, and Yan, 2008).

Li, Miffre, Brooks, and O'Sullivan (2008) provide empirical evidence that time variability in idiosyncratic risk drives momentum returns. The underlying idea is

[232] According to this hypothesis, the value effect stems from investors underestimating future earnings for high book-to-market stocks and overestimating future earnings for low book-to-market stocks. For a more detailed analysis see below.

that investors' response to good and bad news is asymmetric between winner and loser stocks. Once they control for time-varying unsystematic risk by adding a GARCH term to the three-factor model of Fama and French (1993) the abnormal returns of the momentum strategy can be explained. Based on a comparison of different GARCH specifications they conclude that it is both the asymmetric response to news and the conditional risk premium itself that explain momentum returns.

In summary, the empirical studies of the relationship between idiosyncratic volatility and expected stock returns are not yet mature and results are inconsistent. However, idiosyncratic volatility still seems to be an important variable to consider even though it is not clear whether it is a risk factor itself or basically a proxy for short sale constraints and more consistent with behavioral explanations. Idiosyncratic risk can be incorporated into factor models directly as a factor mimicking portfolio in the fashion of Fama and French (1993). Drew, Naughton, and Veeraraghavan (2004) construct such a factor based on estimated idiosyncratic volatility as the fraction of total standard deviation of stock returns over the previous 24 months which is not attributable to market volatility. Then, they construct six portfolios based on independent sorts on idiosyncratic volatility (high / medium / low) and size (big / small) in order to control for a potential correlation between those two. Surprisingly, the resulting zero-cost portfolio, which is long in high idiosyncratic volatility stocks and short in low idiosyncratic volatility stocks, has a negative average return of −0.58 percent per month for their sample of Chinese stocks while the size factor shows the expected positive average return of 0.76 percent. Consistent with the empirical studies above one might argue that the value and momentum factors are sufficient proxies for idiosyncratic volatility and stick to the conventional four-factor model. In light of the empirical results of Drew, Naughton, and Veeraraghavan (2004) this seems to be the preferred specification.

3.4.2 Behavioral Explanations

Several empirical studies provide evidence for return patterns which are not in line with purely rational behavior. For example, investors tend to categorize stocks in certain styles and stocks that fall into the same category showing a strong comovement (Barberis and Shleifer, 2003). Moreover, stocks of the same industry (Chan, Lakonishok, and Swaminathan, 2007) or in similar price ranges (Green and Hwang, 2009) exhibit comovements not explained by other factors. Therefore, explanations based on investor irrationality have also been suggested in the literature to account for the size, value and momentum effects. Potential irrationalities include systematically wrong extrapolation of current information, under- and overreaction to news as well as overconfidence in their own skills.[233]

Extrapolation

Lakonishok, Shleifer, and Vishny (1994) argue that the market misinterprets past earnings growth and extrapolates historical figures too far into the future. Thus, the market overestimates the earnings growth of current growth stocks and underestimates the earnings growth of current value stocks ignoring the convergence of growth rates following the portfolio formation. Growth stocks then tend to have low average subsequent returns because realized earnings growth is lower than expected by the market and vice versa for value stocks. Lakonishok, Shleifer, and Vishny (1994) interpret this return pattern as a correction of the initial mispricing. In contrast, Fama and French (1995) argue that the market correctly anticipates the convergence in earnings growth rates following portfolio formation and therefore reject the initial mispricing hypothesis. Moreover, especially when people do not know whether a series is random or not they usually come to the conclusion that a series is too long to be random after a long sequence of positive returns, a behavior known as "hot-hand fallacy" (Baquero and Verbeek, 2008). Thus, there is a feedback loop of momentum returns with an increasing number of investors believing that past returns cannot be random.

Underreaction

The underreaction hypothesis suggests that new information is not reflected in prices immediately but rather gradually over time resulting in return continuation, i. e. a series of returns in the same direction or momentum. Hong and Stein (1999) call this the gradual-information-diffusion model and argue that heterogeneous investors receive different pieces of private information at different points in time.[234] In a similar vein, Albuquerque and Miao (2008) develop a theoretical model explaining the momentum effect by advance access of privileged investors

[233] Note that these effects are not mutually independent.
[234] Note that Hong and Stein (1999) do not exclusively pin down momentum to investor irrationality but also focus on the interaction of heterogeneous agents as a potential explanation.

to private information which is partially released into prices through their trades. Barberis, Shleifer, and Vishny (1998) instead assume that the representative investor suffers from a conservatism bias violating Bayes rule regarding rational updating of beliefs. Wang (2008) suggests, as an explanation for investors' underreaction, that the fear of reversal is positively related to lagged returns. In any case, as information is released into prices over time positive returns tend to follow positive returns, et vice versa, resulting in momentum.

Overreaction

Based on the overreaction hypothesis news are reflected immediately in prices (De Bondt and Thaler, 1985, 1987; Daniel, Hirshleifer, and Subrahmanyam, 1998). Even more, investors become overconfident about their private information because they interpret positive returns as affirmation of their investment strategy. As a result, they tend to overreact on past information driving prices away from fundamentals. Corrections on this deviation lead to long-run mean reversion in security returns. Over- and underreactions are usually related to firm-specific news rather than macroeconomic news. Because idiosyncratic volatility can be interpreted as a proxy for firm-specific news, the empirical results explaining the momentum effect by high idiosyncratic volatility stocks provide support for behavioral explanations (Arena, Haggard, and Yan, 2008). Overreaction and mean reversion is also consistent with the "gambler's fallacy" (Baquero and Verbeek, 2008). According to the gambler's fallacy investors who observe a sequence of positive or negative returns but believe that the true return-generating process is purely random mistakenly expect a reversal due to their belief in frequent alternations.

Overconfidence

Huang (2006) documents that momentum profits are largely restricted to up markets while a momentum strategy does not generate abnormal returns in down markets. This can be explained by a positive relationship between investors' overconfidence and the market state. Thus, the overreaction is more pronounced in up markets pushing up stock prices even more.[235]

[235] However, using an alternative definition of up market based on lagged growth of world industrial production instead of the return of a world stock market index shows that the results are less clear cut. Thus, the market state effect might be partly driven by the definition of the variable used to determine the market state.

Discussion

In summary, the major implication of the behavioral finance literature for asset pricing seems to be that the behavior of investors changes over time and that this time-variability translates into the relationships estimated in empirical asset pricing. Thus, models need to incorporate time variability. However, it is not yet clear whether the behavior of investors is completely unsystematic or if their irrational behavior follows some systematic response to observable factors. If the latter was true, including these factors could improve existing asset pricing models. At the current state of research it seems reasonable to believe SMB, HML and MOM pick up the irrational behavior of investors to a relatively large degree and can serve as a proxy. Thus, using the four-factor model might be an adequate representation of asset pricing in light of the irrational behavior of investors. However, based on these results it might also be reasonable to additionally include a mean-reversion factor into the performance evaluation model. This is especially relevant for persistence studies in order to control for stock return mean reversion when analyzing mean reversion in the investment skills of fund managers.

3.4.3 Microstructure Effects

Microstructure effects usually cannot explain why the size, value and momentum effects appeared in the first place but rather why they do not disappear. Either, they are only statistical effects which cannot be exploited in the real world due to trading frictions and, therefore, do not exist in an economic sense, or, they do exist but limits of arbitrage are responsible for their survival because opposing trades cannot be taken. In both cases, trading frictions explain the observed return patterns.

Transaction Costs

Jegadeesh and Titman (1993) provide early evidence that momentum profits are robust to transaction costs based on the trade-weighted average commission and market impact of NYSE stocks in 1985. However, Lesmond, Schill, and Zhou (2004) provide empirical evidence that after controlling for transaction costs momentum profits disappear. This is explained, first, by a high turnover of standard momentum strategies and, second, by a disproportionately high fraction of trades in stocks which are expensive to trade. Thus, the average transaction cost estimate used by Jegadeesh and Titman (1993) proves to be significantly downward biased once cross-sectional differences in transaction costs are taken into account resulting in an overstatement of net momentum profits. Moreover, around 53 to 70 percent of the abnormal returns of a momentum strategy are generated by the loser portfolio which is the most expensive to trade. Specifically, the average estimate for total transaction costs of the winner portfolio is 4.3 percent, for the loser portfolio 5.1 percent and 3.0 percent for the remainder of stocks being neither in the winner nor in the loser portfolio.

Korajczyk and Sadka (2004) also investigate whether the documented momentum effect can be exploited in the presence of transaction costs. Relying on intraday data to compute measures of direct and indirect transaction costs they document a significant impact of these frictions on momentum returns.[236] Conventional equal-weighted strategies suffer the most while value-weighted strategies suffer less from transaction costs because they are more heavily invested in large and liquid stocks. However, in contrast to Lesmond, Schill, and Zhou (2004), Korajczyk and Sadka (2004) cannot find evidence that transaction costs completely remove momentum profits once liquidity considerations are implemented into the construction of the momentum portfolios. Because transaction costs depend on the lot size of transactions Korajczyk and Sadka (2004) estimate break-even fund sizes up to which a single portfolio manager could invest in a momentum strategy before its profits vanish. Applying the liquidity-optimized momentum strategy, positive yet insignificant momentum alphas can be generated up to a break-even fund size of 4.5 to 5 billion USD, significantly positive alphas up to 1.1 to 2 billion USD.[237] This result is partly explained by lower transaction cost estimates of Korajczyk and Sadka (2004) as compared to Lesmond, Schill, and Zhou (2004).

Chelley-Steeley and Siganos (2008) provide empirical evidence based on U. K. data that momentum profits increase with improvements in the trading system that lead to lower transaction costs. This finding is contradictory to the hypothesis that more investors exploit the momentum anomaly due to lower transaction costs and drive away the profits. These results are consistent, however, with Arena, Haggard, and Yan (2008), who show that momentum profits are positively related to idiosyncratic volatility, because moving from floor trading to electronic

[236] Note that Korajczyk and Sadka (2004) only focus on the long position in the last year's winner stocks due to the potential asymmetry between the transaction costs for long and short positions and violations of the up-tick rule when implementing short positions.

[237] The profitability is in addition to the profits earned by investors already in the market. Fund size is measured relative to the market capitalization in December 1999.

trading has increased the volatility of U. K. stocks. Thus, the relationship between transaction costs and momentum profits does not seem to be unambiguous. However, they are still important to consider when constructing a momentum factor as a benchmark for performance evaluation to make benchmark returns reproducible for fund managers.

Short Sale Constraints

Several studies suggest that the value and momentum effects are more pronounced among stocks which are more expensive to sell short, for example as measured directly by stock characteristics (Ali and Trombley, 2006) or more indirectly by the level of idiosyncratic volatility (Arena, Haggard, and Yan, 2008) or the level of institutional ownership (Nagel, 2005). Specifically, Ali and Trombley (2006) construct a model to estimate short selling costs based on stock characteristics such as firm size, share turnover, cash flow, IPO status, and the book-to-market ratio to measure short sale constraints. They confirm the results that momentum profits are primarily driven by stocks that are expensive to sell short and, to a larger degree, by loser stocks rather than by winner stocks. Specifically, a pure momentum strategy yields monthly abnormal returns of significant 1.02 percent. For the quintile of stocks least expensive to short this abnormal return reduces to insignificant 0.13 percent while for the quintile which is most expensive to short the abnormal momentum return is significant 2.14 percent monthly, a significant difference of 2.01 percent. The empirical results of Arena, Haggard, and Yan (2008) support these findings. Nagel (2005) documents that both, the value and momentum effects, are more pronounced among stocks with short sale constraints. All of these results can be interpreted in favor of behavioral explanations for the value and momentum effects. Specifically, the ability of rational investors to arbitrage these profit opportunities are limited.[238]

Trading Volume

Lee and Swaminathan (2000) report that firms with higher trading volume, which can be interpreted as proxy for the speed of information diffusion, tend to have higher momentum profits compared to firms with lower trading volume. However, the momentum effect tends to persist among high-volume winners for a shorter period and high-volume winners begin earlier to revert to the mean than low-volume winners. The picture reverses for loser stocks: the momentum effect

[238] Note that high transaction costs might also limit the arbitrage opportunities.

persists for a longer period among high-volume losers and high-volume losers begin later to revert to the mean than low-volume losers. Moreover, low past trading volume is related to value characteristics and positive earnings surprises, the latter being partly explained by analysts providing lower earnings forecasts for firms with low trading volume over the previous years. Lee and Swaminathan (2000) propose a "momentum life cycle" (MLC) as a potential explanation linking most of the observed patterns of momentum stocks. Specifically, stocks experience periods of investor favoritism and neglect: Eventually, a stock with low trading volume, suggesting that most investors do not pay attention to this stock, becomes a momentum winner. As a result, trading volume and price increase, making it an "expensive" stock in terms of low book-to-market ratios. When realized earnings disappoint the market it becomes a loser stock and trading volume falls because investors start to neglect the stock. Consequently, trading volume links short-term and long-term momentum and mean reversion.

Analyst Coverage

Similarly, Hong, Lim, and Stein (2000) report that momentum profits are related to firm size and analyst coverage which also both proxy for firm-specific information diffusion. Holding size fixed, momentum profits are larger among stocks with low analyst coverage, especially for loser stocks. These results are consistent with investor underreaction to firm-specific news in the sense of Hong and Stein (1999) as a potential explanation for momentum returns. Hong, Lim, and Stein (2000) document that momentum profits are about 60 percent larger for the third of stocks with the lowest analyst coverage ratio as compared to the third with the highest level of coverage. The impact of analyst coverage on momentum returns is primarily driven by the loser side of the momentum portfolio suggesting that analysts play a special role in spreading bad news while good news are probably circulated by the company itself.

3.4.4 Methodological Issues

An alternative explanation for the pricing ability of the size, value and momentum factors would be that the sorting procedure itself generates the return patterns rather than underlying risks. Alternatively, the results might be driven only by a subset of stocks which are not representative for the market as a whole.

Micro Caps

The results of Fama and French (2008) present a sceptical view of the robustness of the size and momentum effects. In contrast to their earlier study, Fama and French (2008) use three size buckets. In addition to the median of the market capitalization of all NYSE stocks as the split point between large and small stocks they add a category for micro-cap stocks, defined as companies with a market capitalization below the 20th percentile of all NYSE stocks. These micro caps make up for only 3 percent of the total market capitalization but account for about 60 percent of the total number of stocks. Previous results on the size and value effect might indeed be biased by these very small companies, irrespective of whether ranked portfolio tests or regression analysis is applied, because tiny stocks have a large influence on the results.[239] However, these extremely small stocks are not investable on a large scale and the results based on samples including these stocks, therefore, do not represent real investment opportunities. The results reveal that a large fraction of the size effect which is evident in the whole sample is no longer apparent once micro-caps are removed. Thus, within the investable universe of stocks there is only weak evidence for a size effect. With respect to the value effect the results are more robust. A value premium can be detected in all size buckets, though slightly smaller but still significant once micro caps are excluded from the sample. With respect to the momentum effect, Hong and Stein (1999) document that the profitability of the momentum strategy strongly declines with firm size. According to this discussion, an evaluation of fund managers' investment performance using the conventional benchmark factors, including micro caps, might not be appropriate because fund managers, especially those of larger funds, can only invest in a subset of these benchmark factors.

Migration

Moreover, an alternative explanation for the existence of the size and value factors is that the sorting procedure itself generates the return patterns observed in the data (Fernholz, 1998; Fama and French, 2007b). Fama and French (2007a) argue that high expected profitability and growth in combination with low expected returns produce low book-to-market ratios for growth stocks while low profitability and slow growth combined with high expected returns generates high book-to-

[239] Note that using value-weighted portfolios instead of equal-weighted does not mitigate the bias either because then the results are mainly driven by large cap stocks which might not be representative for the market as a whole (Fama and French, 2008).

market ratios for value stocks. Over time, growth companies exploit their most profitable investment projects and profitability is further eroded by the competition from other companies entering the same market. The book-to-market ratios of these companies tend to rise primarily because prices fall. Conversely, value companies start efforts to restructure and improve profitability which are rewarded by the market with lower discount rates and higher stock prices. Consequently, the convergence of book-to-market ratios can be an important component of stocks migrating from value to growth portfolios or vice versa.

According to Fama and French (2007b) the value premium is driven by three distinct effects. First, some value stocks are acquired by other companies or migrate to a neutral or growth portfolio due to abnormal returns. Second, some growth stocks earn abnormally low returns and move to a neutral or value portfolio. Third, value stocks that do not migrate to another portfolio have slightly higher returns than growth stocks that do not migrate to another portfolio. Moreover, the size premium can be explained almost entirely by small-cap stocks that generate abnormally high returns and migrate to the large-cap portfolio (Fama and French, 2007b).[240] According to a similar argument by Fernholz (1998) the crossover effect, i. e. small stocks becoming large stocks due to price volatility et vice versa, is most important in explaining the size effect and contributes by more than 4 percentage points to the annual size spread. These results indicate that a large fraction of the returns of the size and value factors is merely created by the way these stocks are sorted into portfolios while the differences in characteristics only slightly contribute to this effect. However, slightly in contrast to these results and more in favor of a "true" size and value effect, Gharghori, Hamzah, and Veereghavan (2010) report that small-cap value stocks that do not migrate between different portfolios do account for large portions of both the size and value effect.

Delistings

Another methodological issue involves the handling of delistings. Not only bankruptcy risk has an important impact on expected returns, as documented above, but the subsequent delisting of bankrupt firms might also contribute to momentum profits (Eisdorfer, 2008). Delistings appear due to two reasons, bankrupt-

[240] Note that large-cap stocks migrating from the large-cap to the small-cap portfolio do only slightly contribute to the returns of the size factor because they account only for small fractions of the total market capitalization due to their low number and the value-weighting of factor portfolios.

cies or mergers and acquisitions. Bankrupt firms tend to experience negative abnormal returns before being delisted and are likely to be contained in the loser portfolio. As the delisting return in general is negative as well, these companies contribute to the abnormal return of the momentum portfolio. While on the contrary, acquired firms experience a run-up after the merger announcement and thus are likely to be contained in the winner portfolio. As their delisting returns are usually positive they contribute to the positive returns of the momentum portfolio. About 40 percent of the return of the momentum portfolio can be explained by these two effects, with the negative returns of bankrupt companies contributing most. As in practice all short positions must be closed before delisting, these results question whether a successful momentum strategy is implementable. Performance benchmarks should take these effects into account.

Industry Effects

Industry effects might also affect the results. In fact, most of the stock momentum effect can be explained by industry momentum (Moskowitz and Grinblatt, 1999). Buying stocks that belong to industries with past outperformance and selling stocks belonging to previously underperforming industries generates positive abnormal returns. This result holds even after controlling for size, book-to-market and individual stock momentum. Also, microstructure effects cannot explain the outperformance. Within an industry, however, strategies of buying past winners and selling past losers no longer lead to any significant profits in most cases. This result has two important implications. First, it rules out most of the behavioral explanations for stock return momentum because they are focused on firm-specific news. Second, it reveals that momentum strategies should be implementable at low cost using index futures or ETF and that delisting returns can be neglected because even if some underlyings of an index are delisted the index itself is computed and tradable continually. Thus, the momentum factor used as a benchmark might rather reflect whether fund managers buy into the last year's winner industries, i. e. follow certain investment fads, rather than the last year's winner stocks.

3.4.5 Statistical Issues

The arguments above assume that average stock returns are related to size, the book-to-market ratio and past returns. However, an alternative explanation is that this finding, in the first place, was due to data snooping or statistical biases.

Data Snooping and Estimation Error

Hawawini and Keim (1995) suggest that the size and value factors might just be proxies for estimation errors in betas. Parameter uncertainty is an inherent problem in empirical finance research as stock prices tend to contain a significant amount of noise which disguises inferences. Particularly for small stocks and illiquid stocks it seems reasonable to believe that betas cannot be precisely estimated. Thus, their positive abnormal return might just be explained by a downward bias in beta estimates and might be a "fair" compensation for market risk rather than an anomaly. This problem is enforced in the context of data snooping (Lo and MacKinlay, 1990). If researchers form portfolios in empirical tests based on characteristics that are known from previous studies to have an impact on performance inferences these tests might be severely biased. An omitted risk factor in the asset pricing model used in these tests translates into estimation error. In the case that the omitted factor is related to the characteristics used to form the portfolios, which makes it more likely in the first step that a certain characteristic appears to explain stock returns, it is impossible to determine whether the cross-sectional relationship between characteristics and alphas is due to a relationship between the characteristics and true alpha or between characteristics and the measurement error. Indeed, empirical results show that data snooping might be responsible for a substantial part of the documented momentum effect (Parmler and González, 2007).

Time Variability

Moreover, Ang and Chen (2007) argue that betas are not constant over time which is, however, an inherent assumption of the empirical approaches commonly used in the literature. They document that once beta is allowed to vary over time in the context of a conditional model the value factor turns out to be insignificant for most of their sample period. Lewellen and Nagel (2006), instead, document that the size, value and momentum returns cannot be rationalized by time-varying risk. First, they argue that under realistic assumptions for the monthly standard deviation of beta and the market risk premium (and even assuming they are perfectly correlated) the implied monthly alpha of a value strategy is only about one quarter of the observed premium, for a momentum strategy the implied is only one sixth of the observed premium. Thus, time variability cannot explain the observed risk premia. Second, they apply a novel test for the conditional CAPM that does not require the specification of conditioning information but uses high frequency data over shorter periods instead. Based on this methodology they provide empirical evidence that the conditional alphas of value and momentum strategies are large on average and still statistically significant. Thus, even though theoretically a conditional specification of the performance evaluation model could account for time variability, these empirical results cast doubt on any improvement in performance evaluation resulting from this approach.

Spurious Regression

Ferson, Sarkissian, and Simin (1999) raise the question of whether the explanatory power of SMB and HML is just spurious. Alternatively, SMB and HML might be the result of transporting an observed anomaly to asset pricing theory. To illustrate this, Ferson, Sarkissian, and Simin (1999) compare the development of the Fama-French factors with a hypothetical researcher who sorts stocks into portfolios based on the first letter of their name. If, by chance, low alphabet stocks outperform high alphabet stocks, the researcher goes on and constructs factor-mimicking portfolios to explain the observed "alphabet-anomaly". However, these new "risk" factors, in their view, are not at all related to pricing risk. Based on a simulation with artificial data, Ferson, Sarkissian, and Simin (1999) document that attribute-sorted portfolios, comparable to the Fama-French factors, can appear to be useful risk factors even though the attribute itself is not related to risk. They conclude that "as new data on equity attributes becomes widely accessible, we expect to see more studies that sort equities according to their attributes. We have seen that sorting procedures are subtle and easily abused. More work is needed to improve the understanding of the properties of such approaches" (Ferson, Sarkissian, and Simin, 1999, p. 63). In fact, the recent literature on an ever increasing number of risk factors proves their conclusions from 1999 to be an accurate prediction of future research as discussed below.

3.4.6 Discussion

Several risk-based interpretations of multifactor asset pricing models have been discussed in the previous section. However, the four factor model of Carhart (1997), which applies size, value and momentum in addition to the conventional market factor, proxies for a wide array of these additional risk factors identified in the literature (Table 3.2). It has not yet been convincingly demonstrated that another combination of factors is clearly superior in explaining the cross-section of stock returns (Chen, Novy-Marx, and Zhang, 2010). Consequently, it seems reasonable to stick to the conventional four-factor model in most applications bearing in mind the alternative explanations. Even behavioral explanations might be captured by these factors. Yet, in the context of performance evaluation it might be reasonable to include higher-moment risk as well as liquidity risk into the model based on the above discussion, because these two risks only seem to be partially reflected in the four-factor benchmark. First, liquidity risk and higher-moment risk are natural candidates to load on when a fund manager wants to beat the benchmark based on a four-factor alpha (benchmark gaming). Second, due to the open-end fund structure, mutual funds are especially exposed to liquidity risk. In the empirical part of this study, the four-factor model is, therefore, augmented by a liquidity factor. Moreover, because the focus of the empirical part is on mean reversion in security selection skills of portfolio managers, a stock-return mean-reversion factor is included in the model. However, this choice does not follow from asset pricing considerations but rather is motivated by the objective to attribute fund returns to different sources.

In general, however, a caveat seems appropriate with respect to the interpretation of funds' alphas based on multifactor models and potential conclusions about average skills and market efficiency. This caveat is related to the investability and the construction of the benchmark factors. Several issues such as transaction costs, the treatment of extremely small companies as well as new issues and delistings might severely affect the empirical results based on multifactor models. Thus, the absolute level of alpha might not be an appropriate measure of portfolio managers' skills. However, this should not be a serious problem for the empirical part of this study because it merely focuses on a performance comparison between different funds rather than relying on statements about the absolute level of skill.

3.5 Portfolio-Information-Based Performance Evaluation

Given the volatility of equity funds' portfolio returns, it is almost impossible to identify superior investment skills in a statistically efficient way and to distinguish skill from luck based on return time-series alone. The approaches presented in this section, therefore, apply more detailed data sets on fund holdings to improve the precision of performance estimates. Portfolio-information-based models do not use a factor model as a benchmark but rather derive the benchmark endogenously from portfolio information. The hypothetical benchmarks are based on the fund holdings (Grinblatt and Titman, 1993; Daniel, Grinblatt, Titman, and Wermers, 1997) or trades (Chen, Jegadeesh, and Wermers, 2000; Pinnuck, 2003) of the funds. Each security in the portfolio is matched to a specific benchmark security or portfolio.

All portfolio-information-based performance measures can be interpreted as the covariance between portfolio holdings (or trades) and excess returns of portfolio securities (Grinblatt and Titman, 1993):[241]

$$\sum_{j=1}^{m} \mathrm{Cov}(w_{ijt}, r_{jt}) = \sum_{j=1}^{m} E_t[(w_{ijt} - E_t(w_{ijt}))(r_{jt} - E_t(r_{jt}))] \;, \tag{3.32}$$

where w_{ijt} is the weight of asset j in fund i at time t and r_{jt} is the corresponding excess return of asset j.[242] The specific performance measures differ with respect to how expected returns and expected weights are determined. Characteristic-based models (section 3.5.1) derive expected returns from a matched benchmark portfolio based on a three-dimensional sort on firm characteristics. Holdings-based measures (section 3.5.2), instead, use the return of the same securities as in the funds' portfolio but at a different time period as a benchmark. Trade-based measures (section 3.5.3) perform in a similar way but focus on trades instead of holdings as a more active decision variable of fund managers. Expected weights should be determined based on the investors' information and the level of delegation which, in turn, determines the implicit benchmark. If the investor could, for example, follow a momentum strategy without delegation and does not want to attribute the return from momentum investing to the portfolio manager, the expected returns for each period should be determined based on a momentum strategy such that only deviations from this strategy can generate abnormal returns.

An advantage of the portfolio-information based models compared to risk-based models, which require the estimation of a regression, is that even funds with very short return histories can be evaluated because many more observations are

[241] Note that this corresponds to the active component in equation (1.2).

[242] Equation (3.32) can be interpreted as the sum over all portfolio constituents of the expected value of the products of the difference between actual and expected (relative) portfolio weights and the difference between actual and expected returns.

available on holdings than on monthly fund returns.[243] Furthermore, portfolio-information based models mitigate the critique and ambiguity raised with respect to the choice of an appropriate benchmark for risk-based models (Roll, 1977, 1978, 1980; Lehmann and Modest, 1987).

However, the use of portfolio-information-based models for performance evaluation is difficult because information on the composition of funds' portfolios is restricted. This information is usually not available for investors or researchers on a frequent basis. In the U. S., mutual funds are required to disclose portfolio holdings on a semi-annual basis but many funds voluntarily disclose quarterly holdings. The impact of disclosure frequency on the results has not yet been analyzed. It might be argued, however, that the disclosure frequency is set strategically by the investment management companies inducing a potential bias (Chevalier and Ellison, 1997). Elton, Gruber, and Blake (2007) and Elton, Gruber, Blake, Krasny, and Ozelge (2010) document that the use of monthly portfolio holdings data might lead to significantly different inferences compared to quarterly or semi-annual data.

3.5.1 Characteristic-Based Models

Daniel and Titman (1997) contradict the conclusion of Fama and French (1993) that loadings on the size (SMB) and value (HML) factor are associated with systematic risk and determine the cross section of stock returns. Rather, they argue that it is firm characteristics that are driving the differences in returns. In particular, comovements might result from similarities in characteristics such as the same business line or industry, or a similar region. Daniel and Titman (1997) propose a model where the covariance structure of returns is determined by a conventional factor model while the expected returns of securities depend on their characteristics rather than their factor loadings. Thus, changes in the form of characteristics affect returns without affecting risk loadings. Consequently, companies might load on a factor associated with a positive premium but have low returns because they do not exhibit the characteristic associated with the factor. This suggests, for example, that even if the returns of a specific large company behave similarly to the returns of small cap stocks resulting in a positive loading on the size factor, this large stock does not earn a size premium as, obviously, it is

[243] Note that the average length of fund return histories in Morningstar's Principia Pro database is 4.8 years which results in less than 60 observations (Busse and Irvine, 2006).

large. Knowing this, smart investors could earn a size premium without loading on the size factor by investing in the subset of companies that are small in size but do not load on the size factor. More importantly, based on this argument, multifactor models might not be an appropriate benchmark in performance evaluation.

Daniel and Titman (1997) criticize that the test procedure used in Fama and French (1993) cannot discriminate between a risk factor explanation and a characteristic-based explanation for differences in returns because the test portfolios are constructed based on the same characteristics, size and book-to-market, as the pricing factors. Consequently, the average firm in each portfolio also loads on the relevant factor. To overcome this problem, an appropriate test must separate out firms that have certain characteristics but do not behave like other stocks with the same characteristics in terms of covariances. In order to accomplish this Daniel and Titman (1997) form portfolios first on characteristics (size and book-to-market) and then on pre-ranking factor loadings. The results reveal no relationship between factor loadings and returns for the value factor.[244] A similar picture emerges for the size factor. Stocks with similar characteristics but different loadings on the size and value factors have similar returns and the explanatory power of SMB and HML disappears once it is controlled for these characteristics. Even stocks with different market betas but similar characteristics seem to have similar returns disputing the CAPM. These empirical results are supported by a follow-up study using Japanese data (Daniel, Titman, and Wei, 2001).

This result suggests that the size and value effects documented by Fama and French (1993) are merely a result of factor loadings picking up the correlation between loadings and characteristics itself. Conditional on characteristics, factor loadings have no additional explanatory power. Relating their results to distress as a potential interpretation for the value factor Daniel and Titman (1997) conclude that it is not distressed firms being exposed to a distress factor but rather firms with similar factor sensitivities becoming distressed at the same time that is driving the empirical observations. Already other authors have argued that stock characteristics might explain returns to a certain degree. For example, Lakonishok, Shleifer, and Vishny (1992) suggest an explanation for the value effect based on agency theory. Fund managers might prefer growth stocks which are easier to justify to investors. As a result, growth stocks trade at a premium which

[244] The weak positive relationship between factor loading and return for large stocks can be explained by variation of the average book-to-market ratio within the categories.

is associated with lower average returns. Thus, characteristic-based asset pricing seems to be justified.

In contrast, Davis, Fama, and French (2000) question the validity of the empirical results of Daniel and Titman (1997). Specifically, they argue that the evidence in favor of the characteristic-based model is restricted to the sample period of Daniel and Titman (1997). While Daniel and Titman (1997) used about 20 years of data (07/1973 to 12/1993) the empirical results of Davis, Fama, and French (2000) are based on a much longer period of 68 years (07/1929 to 06/1997) leading to different conclusions. Over the whole period, the empirical evidence strongly supports the three-factor model of Fama and French (1993) even though they can confirm the findings of Daniel and Titman (1997) for the subperiod from 07/1973 to 12/1993.

Despite the inconclusive empirical evidence with respect to the ability of characteristics-based models to explain stock returns, these models haven been extended to be applied in performance evaluation (Daniel, Grinblatt, Titman, and Wermers, 1997; Wermers, 2000). Basically, characteristics-based performance measures follow equation (3.32) and derive expected returns for each security of the fund from a portfolio that matches this security in its characteristics while expected weights are set to zero. Specifically, based on a three-dimensional sort on firm size, book-to-market ratio and previous return 125 ($5 \times 5 \times 5$) quintile portfolios are formed as benchmarks.

This measure can be broken down into a selectivity and a timing component as well as a component representing the performance due to a general tilt of the portfolio toward certain characteristics. The portfolio-weighted sum of the differences in returns between the stocks and the matched portfolios is interpreted as selection skill:

$$\mathrm{CS}_{it} = \sum_{j=1}^{m} w_{ijt}(r_{jt} - r_t^{b_{j,t-1}}) \ , \tag{3.33}$$

where $r_t^{b_{j,t-1}}$ is the return on a benchmark portfolio that is matched to asset j according to the three characteristics mentioned above and where characteristics are measured in $t-1$. The time-series average of CS_{it} over a certain evaluation period gives the CS_i measure for fund i. Timing skill is measured by the difference between the weighted returns of the benchmark portfolios the fund actually invests in and the weighted actual returns of the benchmark portfolios the fund invested in h periods ago:

$$\mathrm{CT}_{it} = \sum_{j=1}^{m} (w_{i,j,t-1} r_t^{b_{j,t-1}} - w_{i,j,t-h} r_t^{b_{j,t-h}}) \ . \tag{3.34}$$

Again, taking the time-series average of CT_{it} over the evaluation period gives the CT_i measure for fund i. If the fund has a long-term tilt toward characteristics that deviate from the market index, as, for example, a dedicated small-cap fund, the return coming from this tilt is assigned to the fund's average style return:

$$\mathrm{AS}_{it} = \sum_{j=1}^{m} w_{i,j,t-h} r_t^{b_{j,t-h}} \ . \tag{3.35}$$

Finally, the time-series average of AS_{it} over the evaluation period is fund i's AS_i measure. All three components sum up to the funds actual hypothetical return on paper. Consequently, transaction costs on the portfolio level of the fund are not considered and characteristic-based measures cannot be directly compared to risk-based measures.

Some problems arise with this methodology. First, returns are not risk adjusted in the sense of systematic risk factors. Thus, if managers choose from a group of stocks with the same characteristics, i. e. out of one of the benchmark portfolios, those stocks with high systematic risks, they might be assigned a high performance measure which does not account for that risk. Additionally, the timing measure might falsely assign positive timing skills even if either the return of a benchmark portfolio or its weight in the fund's portfolio stay constant. In fact, the timing measure should only be positive if a manager actively increases the holdings in a characteristics-matched benchmark portfolio that currently has positive abnormal returns compared to other periods. A third problem arises when managers trade in between two portfolio disclosure dates. Especially if these trades follow a systematic manner, e. g. when managers follow window dressing strategies, the performance results might be biased (Moskowitz, 2000). Furthermore, the results strongly depend on the concrete choice of characteristics used as benchmarks and the sorting procedure (Chan, Dimmock, and Lakonishok, 2009).

Moreover, data restrictions in many cases prevent the use of characteristics-based models. In this case, factor models based on SMB, HML and MOM might still be a valid tool for performance evaluation, despite the critique of Daniel and Titman (1997) that factor loadings do not represent sensitivities to systematic risk factors. Specifically, the four-factor model of Carhart (1997) might actually pick up much of the correlation between characteristics, which is what should be measured according to Daniel and Titman (1997), and factor loadings, which is what can be measured easily with the available data. Thus, the question "characteristics versus risk factor" is rather a philosophical one related to the underlying asset pricing theories but might not affect performance evaluation to a similar degree.

3.5.2 Holdings-Based Models

Holdings-based models also follow equation (3.32) and define managerial skill as a positive correlation between portfolio weights and returns of single stocks. Overweighting stocks with higher than expected returns and underweighting stocks with lower than expected returns leads to a positive performance measure. Thus, actual returns and holdings have to be compared to expected returns and holdings for each of the portfolio's constituents. The alternative approaches in the literature differ in how these expectations are calculated.

Cornell (1979) sets expected weights to zero and uses returns from a past period (benchmark period) as expected returns:

$$\sum_{j=1}^{m} \mathrm{Cov}^{C}(w_{ijt}, r_{jt}) = \sum_{j=1}^{m} E_t[w_{ijt}(r_{jt} - r_{j,t-h})] \ , \tag{3.36}$$

An informed fund manager should actually hold those securities in the evaluation period that offer abnormally high returns. The question is whether the portfolio pays more return in the evaluation period as compared to what an identical portfolio would have paid during the historical benchmark period. A crucial assumption with respect to unbiasedness of this approach, however, is that returns in the benchmark period are independent of weights in the evaluation period. Once portfolio managers choose securities based on past performance this measure is biased (Grinblatt and Titman, 1993). Therefore, Copeland and Mayers

(1982) propose to use a future period as a benchmark period instead as current weights should not be affected by future returns because these are unknown to the manager when he chooses the securities:

$$\sum_{j=1}^{m} \mathrm{Cov}^{CM}(w_{ijt}, r_{jt}) = \sum_{j=1}^{m} E_t[w_{ijt}(r_{jt} - r_{j,t+h})] \ , \tag{3.37}$$

However, in this case certain portfolio constituents might not be included in the performance evaluation due to delistings (Grinblatt and Titman, 1993). It is reasonable to believe that this procedure ignores the most extreme performers in the funds' portfolios because the main reasons for delistings are bankruptcy (negative abnormal returns) or acquisitions (positive abnormal returns). Consequently, Grinblatt and Titman (1993) propose a portfolio change measure (PCM) which uses past weights as expectation and sets expected returns to zero in order to avoid any potential biases:[245]

$$\mathrm{PCM}_i = \sum_{j=1}^{m} \mathrm{Cov}^{GT}(w_{ijt}, r_{jt}) = \sum_{j=1}^{m} E_t[(w_{ijt} - w_{i,j,t-h})r_{jt}] \ , \tag{3.38}$$

In this case, $w_{ijt} - w_{i,j,t-h}$ represents the difference in the portfolio weight of asset j of an informed manager from an uninformed manager. The measure of Grinblatt and Titman (1993) has superior statistical properties compared to the other measures.

If expected returns vary over time or the portfolio beta increases constantly over time, the measure of Grinblatt and Titman (1993) might still be biased. However, this bias can be mitigated by using a conditional weight measure (CWM) which uses the covariance between holdings and returns conditional on the information set Ω_t (Ferson and Kang, 2002):[246]

$$\mathrm{CWM}_i = \sum_{j=1}^{m} \mathrm{Cov}(w_{ijt}, r_{jt}|\Omega_t) \ . \tag{3.39}$$

[245] Note, however, that all three specifications of Cornell (1979), Copeland and Mayers (1982) and Grinblatt and Titman (1993) are asymptotically equivalent.

[246] Note that the conditional weight measure of Ferson and Kang (2002) is based on trades instead of holdings, i. e. w_{ijt} is replaced by Δw_{ijt} in equation (3.39). See also section 3.5.3.

Moreover, holdings-based measures suffer from a similar critique as characteristic-based measures because they may not correctly adjust for systematic risk and part of the return difference may result from applying certain passive investment strategies such as momentum investing. To correct for that bias, the time series of a holdings-based measure can be regressed on the usual factors from a risk-based model (Wermers, 2006).

3.5.3 Trade-Based Models

Portfolio holdings might not be the best choice for performance evaluation of fund managers as they mimic only the passive decision to hold the asset, especially in light of the incentive not to deviate much from the benchmark (Scharfstein and Stein, 1990; Cohen, Polk, and Silli, 2009). Trades, in contrast, represent active decisions by managers based on superior information. Therefore, several studies use the same methods as described above but substitute trades for holdings in their analysis:[247]

$$\sum_{j=1}^{m} \mathrm{Cov}(\Delta w_{ijt}, r_{jt}) = \sum_{j=1}^{m} E_t[(\Delta w_{ijt} - E_t(\Delta w_{ijt}))(r_{jt} - E_t(r_{jt}))] \ , \tag{3.40}$$

However, information is not the only motivation for trading. Transactions might also occur due to reasons such as cash inflows or outflows, tax reasons or window dressing. Conditioning the trades on information about the motivation to trade provides a more detailed analysis of fund manager's performance (Alexander, Cici, and Gibson, 2007). Moreover, Baker, Litov, Wachter, and Wurgler (2004) show that trades around earnings announcements are informative and represent a disproportionate fraction of fund's returns which can be interpreted as empirical evidence in favor of selection skills.

A shortcoming of these approaches is that information on portfolio holdings is only available on a quarterly or even semiannual frequency.[248] Thus, trades

[247] Chen, Jegadeesh, and Wermers (2000), Pinnuck (2003), Cohen, Coval, and Pástor (2005), and Gallagher and Pinnuck (2006). Hong, Kubik, and Stein (2005) also use trades in order to analyze herding among mutual fund managers and Brown, Wei, and Wermers (2007) use trades for an analysis of herding and analyst recommendations.

[248] Since May 2004 all U. S. mutual funds are forced to disclose their holdings quarterly with a 60-day filing delay. Before, the mandatory disclosure frequency was semiannually though many funds voluntarily disclosed their holdings on a quarterly bases. Only Pinnuck (2003) and Gallagher and Pinnuck (2006) use monthly data for Australian funds.

within these disclosure dates cannot be included into the analysis but might contribute significantly to portfolio performance. Moreover, portfolio managers have an incentive to hide some of their trades by neutralizing certain positions before disclosure dates. The recent availability of more frequent, i. e. monthly, portfolio disclosure might reduce this problem in future research (Elton, Gruber, and Blake, 2007; Elton, Gruber, Blake, Krasny, and Ozelge, 2010).

3.6 Improved Statistical Methods

In order to improve the ability of performance measures to detect real investment skill and to differentiate skill from luck more sophisticated statistical approaches have been developed. These studies focus on individual fund performance and apply methods such as bootstrapping (e. g. Cuthbertson, Nitzsche, and O'Sullivan, 2008; Kosowski, Timmermann, Wermers, and White, 2006) and Bayesian estimation methodologies (e. g. Pástor and Stambaugh, 2002b; Cohen, Coval, and Pástor, 2005; Jones and Shanken, 2005) or apply high-frequency return data (e. g. Bollen and Busse, 2005; Busse and Irvine, 2006). Moreover, some recent studies aim to address the commonality in fund returns, which biases inferences if not adequately controlled for (e. g. Fama and French, 2010).

3.6.1 Bootstrapping

Bootstrapping is a non-parametric approach for determining the significance of parameter estimates. It can be used to evaluate fund alphas and to improve the inferences (Kosowski, Timmermann, Wermers, and White, 2006; Cuthbertson, Nitzsche, and O'Sullivan, 2008). In particular, extreme funds in the cross-sectional performance distribution are subject to non-normal returns which violates the usual assumptions of OLS estimates. Therefore, bootstrapping approaches are especially relevant in performance persistence studies, where the focus is on the previous year's winner (top-decile) and loser (bottom-decile) funds. Moreover, bootstrapping proves important when analyzing the performance of dynamic trading strategies as applied, for example, by hedge funds (Kosowski, Naik, and Teo, 2007). Bootstrapping is not only applied to individual fund performance but can also enhance the inferences in a multiple hypothesis testing environment when, for example, the number of out- or underperforming funds within a sample should be determined. In this case, a false discovery rate specifies the rate of funds that have positive alphas only by luck (Barras, Scaillet, and Wermers, 2010). After correcting for this error, the identification of truly superior management skill can be further improved.

The basic procedure of bootstrapping is as follows. In the first step, a multi-factor model is estimated using OLS for each fund separately. The coefficients and residuals for each fund are saved. In the second step, a random sample is drawn (with replacement) for each fund from the residual vector of each fund corresponding in length to the initial residual vector, i. e. keeping the length of the time series of each fund. This residual vector is then used in combination with the factor returns and the estimated beta coefficients, while setting alpha equal to zero, to compute a simulated return time series under the null hypothesis of no managerial skill. This return time series is then used in the third step to estimate the performance model and to save the resulting alpha estimate. Ordering the alphas of all funds according to their level and repeating the process, for example, 1,000 times for each fund generates a "luck" distribution of alphas under the null hypothesis of no managerial skill for each performance rank. The estimated alphas from the first step for each performance rank can then be compared to their corresponding luck distribution representing sample variation in alpha under the null hypothesis of zero alpha. If the estimated alpha from the first step exceeds the 95th percentile of this distribution the performance manager is said to possess real skill. Similarly, alphas below the 5th percentile of low-ranked funds are interpreted as evidence for poor skill rather than bad luck.

However, a simulation study by Nuttal (2007) suggests that the performance of the bootstrapping methodology in detecting real skill depends strongly on the rank of fund and the level of skill in data, defined as the difference in performance between skilled and unskilled funds. If the general level of skill is high the methodology has a high detection rate but is overoptimistic about managerial skill. In the case of low average skills in the data set, the methodology is conservative but has only low detection rates. Thus, even using improved statistical models, the identification of true investment skills still suffers from severe obstacles.

3.6.2 Bayesian Approach

Almost all performance studies rely on the frequentist approach. A major common problem in these studies is that the high fraction of noise in fund return time series does not allow a reliable differentiation between luck and skill. Some recent studies propose using Bayesian statistics instead. The major difference between Bayesian and frequentist approaches is that the former assumes model parameters to be stochastic and allows researchers to incorporate a prior distribution on these parameters.[249] The estimated coefficients are not only based on the data, as with the frequentist approach, but rather combine the data with the prior in order to obtain a posterior distribution of the model parameters using Bayes' law. The weight of the data is positively related to the number of observations and the weight of the prior is positively related to its precision, i. e. how confident the researcher is about the prior information.[250] The estimates of a Bayesian approach are more precise and inferences are provided conditional on the data. Therefore, the parameters do not suffer from a potential small sample bias which often is a problem in performance studies due to short monthly times series of fund returns. In contrast, the bootstrapping methodology only improves the inferences but not the parameter estimates themselves.

The prior information does not necessarily have to be subjective, even though in some cases it is, which is why the Bayesian approach is sometimes criticized.[251] Note, however, that the researcher also has a high degree of freedom when setting up a frequentist model, for example with respect to the choice of the variables to be included. However, in the frequentist case the researcher faces a binomial choice: he can either include or exclude a certain variable. Bayesian modelling, instead, allows researchers to include many variables but to apply different priors on them indicating that the researcher feels more confident about the relevance of one variable compared to another. The Bayesian approach seems to be a reasonable choice in the context of asset pricing because the relevant pricing factors are not precisely known.

In performance evaluation, prior information can be derived from information on the subjective assessment on the validity of a certain asset pricing model (Baks, Metrick, and Wachter, 2001). Furthermore, information on the estimation error of "seemingly unrelated assets" with known alpha and longer return histories can be

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249 For a detailed discussion of Bayesian approaches in finance and other applications see Zellner (1971) and Rachev, Hsu, Bagasheva, and Fabozzi (2008).

250 In an extreme scenario, the researcher has no confidence in the prior at all and the estimated coefficients equal those of an OLS estimation.

251 Even subjective priors do not affect academic objectivity if interpreted appropriately. For example, a sensitivity analysis on the impact of different prior specifications on the results should be performed.

included into the prior (Pástor and Stambaugh, 2002b). Even information on the dependency structure between the alphas of funds in the same segment (Jones and Shanken, 2005; Huij and Verbeek, 2007) or on the similarity of portfolio holdings and trades of successful and unsuccessful managers (Cohen, Coval, and Pástor, 2005) can be used as prior. Most of these priors are statistically informative but economically uninformative avoiding a subjective influence.

Another advantage of the Bayesian approach in the context of performance evaluation is that the choice of the asset pricing model applied as the benchmark can be implemented smoothly rather than as an "all-or-nothing" decision, i. e. the researcher can specify a degree of certainty about the model's validity instead of assuming the model is completely true or rejected. This alleviates the problem associated with the choice of a fair and theoretically correct benchmark. Moreover, Bayesian models provide an elegant way to determine the beliefs of investors which are inherent in their behavior by fitting the prior in such a way that it optimally predicts the observed pattern in the data.

An innovative approach for improving the alpha estimation is provided by Pástor and Stambaugh (2002b). Two additional sources of information are incorporated into the estimation. First, the alpha of a non-benchmark asset ("seemingly unrelated asset"), which is usually a passive asset with known alpha of zero, provides information about the sample error. If a regression of the non-benchmark asset on the risk factors used as the benchmark results in a positive alpha estimate, despite the fact that the true alpha is zero, this implies that passive assets lie above the security market line. If the benchmark model is believed to price assets exactly, then all of the positive alpha estimate can be attributed to the sample error. Thus, if the fund also lies above the security market line and obtains a positive alpha this does not necessarily reflect investment skill but might just be a result of the same sample error. Second, a comparison of the alpha estimate of the non-benchmark asset for the same period over which the fund's performance should be evaluated and the alpha estimate of the non-benchmark asset for its entire history provides information about a potential bias due to the shorter time series of the fund. It is assumed that the maximum length of the non-benchmark asset's history provides a more precise alpha estimate. If the alpha over the entire history is zero but positive for the shorter period corresponding to the fund's time series this bias might also show up in the alpha estimate of the fund. Both bits of information, the alpha of the non-benchmark asset over the fund's lifetime and the difference in the non-benchmark asset's alpha between the fund's lifetime and the non-benchmark asset's lifetime, can be combined to improve the alpha estimate of the fund.

Incorporating the information about the ability of the benchmark assets to price the non-benchmark assets significantly improves the performance estimation (Pástor and Stambaugh, 2002b). Based on conventional estimation methodologies the average difference in one-factor and three-factor alphas is 2.1 percent per year. For growth funds it is even 8.1 percent. Estimating the one-factor model using the Bayesian approach and applying the size and value factor as non-benchmark asset reduces these differences to 1.2 and 2.0 percent, respectively. The same information is incorporated into the alpha estimated either directly or indirectly via the non-benchmark assets. Thus, in the Bayesian approach the choice of the benchmark only plays a minor role as long as a representative selection of assets is used as non-benchmark assets. Moreover, the rankings based on conventional OLS alphas and Bayesian alphas differ significantly.

The methodology of Pástor and Stambaugh (2002b) can be extended by relaxing the assumption that funds' alphas are independent of each other (Jones and Shanken, 2005; Huij and Verbeek, 2007). In this case, information from the cross-sectional alpha distribution of the other funds in the sample can be used to improve the alpha estimate of a specific fund. The intuition is that the potential to generate alpha or the degree of market efficiency varies across different segments and over time. If it is easier for managers in some segments, e. g. small caps, to produce significantly positive alphas compared to other segments, e. g. blue chips, then the alphas of different funds are no longer independent. The higher the average alpha of other funds in the same segment the more likely that there is a positive alpha for the fund in question. Technically, each funds' alpha estimate is a weighted average of its individual alpha and the average alpha of all other funds in the same segment with the weights depending on the precision of both terms. Thus, the learning across funds shrinks each individual fund's alpha toward a segment mean. This shrinkage might also be motivated on a purely statistical basis (Huij and Verbeek, 2007). Funds in the extreme tails of the cross-sectional performance distribution are more prone to estimation error. Shrinking them toward a grand mean should result in more reliable inferences.

Similarities in portfolio holdings might provide more detailed insights into managerial skills compared to similarities in fund alphas due to common investment objectives (Cohen, Coval, and Pástor, 2005). Good fund managers might possess similar information and, therefore, generate outperformance with similar trades. For example, Hong, Kubik, and Stein (2005) provide evidence that similarities in the portfolios of fund managers domiciled in the same city are not restricted to local companies, which would imply a home bias, but rather seem to be driven by similar information sources or informal information sharing. Therefore, Cohen, Coval, and Pástor (2005) assess a better performance to managers who generate their outperformance with similar strategies as other successful managers as compared to managers with rather exotic strategies. The abnormal returns of the latter are more likely a result of luck. To measure similarities they rely on portfolio holdings as well as trades. Similar to Jones and Shanken (2005) the resulting performance measure can be interpreted as weighted average of the manager's alpha and the alphas of all other managers where the weights depend on the degree of similarity.[252] The empirical results of Cohen, Coval, and Pástor (2005) indicate, however, that there are also managers who generate real outperformance with strategies that deviate from the masses.

Some of the studies mentioned above have applied the Bayesian approach to analyze performance persistence (e. g. Pástor and Stambaugh, 2002b; Cohen, Coval, and Pástor, 2005; Busse and Irvine, 2006). All of them document a significant improvement in the ex-ante identification of future outperformers based on these methods. It is possible to use the predictability of manager skills along with predictability in fund risk loadings and benchmark returns to design investment strategies based on funds that outperform the three- and four-factor models (Avramov and Wermers, 2006). Investing in funds rather than the underlyings themselves has the advantage of very low implementation costs even for large amounts of money because transaction costs associated with the purchase of portfolio stocks are socialized among all existing and new fund investors. A similar result is obtained in a hedge fund context where Bayesian methods also improve the prediction of abnormal returns (Kosowski, Naik, and Teo, 2007).[253]

[252] Strictly speaking, Cohen, Coval, and Pástor (2005) do not rely on a Bayesian approach even though their methodology of incorporating additional information into the estimation is closely related to Bayesian modeling.

[253] However, the results of Gibson and Wang (2009) suggest that these models might pick up liquidity risk which is rather persistent over time. Thus, hedge funds with persistently high loadings on liquidity risk continue to outperform hedge funds with lower liquidity loadings. Thus, even though the empirical results in favor of Bayesian performance evaluation techniques are quite strong for mutual funds still some open questions remain when the results for hedge funds are taken into account. Consistent with this argument, Sadka

3.6.3 Daily Data

To further enhance efficiency of performance prediction daily data can be used instead of monthly data (Busse and Irvine, 2006). This provides the possibility of estimating the model based on a real time span of less than a year and this way accounts for the dynamics of the model. However, as Bollen and Busse (2001) mention, standard stock selection test can theoretically not be improved by the use of daily data instead of monthly data because the estimates for the intercept depend more on the sample lengths than on the observation frequency. Thus, the major advantage of daily data is not necessarily a higher precision due to more observations but that it can account for time variability in the parameters if combined with a rolling window estimation.

3.6.4 Controlling for Cross-Correlation

A further statistical problem arises when mutual fund managers follow similar strategies inducing commonality in fund returns. For example, different managers might select similar stocks or industries, load on common factors and vary these loadings over time in a similar fashion. This creates correlation in the residuals of commonly used benchmark models, especially when some of the risk factors are omitted in the benchmark model (Hunter, Kandel, Wermers, and Kandel, 2009). Not controlling for the cross-correlation between alpha estimates due to omitted factors can significantly alter the results (Fama and French, 2010). Theoretically, the cross-correlation problem could be mitigated by adding more factors to the performance model. However, the large number and variety of potential factors make this approach complicated. A Bayesian model averaging could prove useful in this context. Specifically, model uncertainty is explicitly accounted for by estimating all 2^N possible linear regression models based on N potential variables and weighting these models according to their posterior weights in a hyper-model (Cremers, 2002; Avramov, 2002). A simpler approach to account for these commonalities, according to Hunter, Kandel, Wermers, and Kandel (2009), is to apply what they call "endogenous benchmarks". An endogenous benchmark is an additional factor which is formed based on all other funds with the same investment objective. This procedure significantly reduces the cross-correlation between indi-

(2010) provides empirical evidence that hedge funds that significantly load on liquidity risk subsequently outperform hedge funds with low loadings on the liquidity factor by 6 percentage points annually.

vidual funds and improves the identification of outperformers. Fama and French (2010) extend the bootstrapping methodology of Kosowski, Timmermann, Wermers, and White (2006) and Cuthbertson, Nitzsche, and O'Sullivan (2008) that accounts for commonality by jointly sampling the returns of funds and explanatory variables.

3.7 Empirical Results on Active Mutual Funds

3.7.1 Fund Performance

Various studies evaluating performance with risk-based models show that active U. S. mutual funds on average do not add value based on net returns.[254] Similar results have been documented for Europe (Otten and Bams, 2002), the U. K. (Blake and Timmermann, 1998) and Germany (Bessler, Drobetz, and Zimmermann, 2009; Stotz, 2007). Therefore, more recent studies focus on whether a subset of active funds is able to generate abnormal returns. Indeed, only a few funds among the best performers seem to have sufficient skill to generate significantly positive alphas after costs based on a bootstrapping analysis (Kosowski, Timmermann, Wermers, and White, 2006; Cuthbertson, Nitzsche, and O'Sullivan, 2008). Fama and French (2010), however, question these results and document based on a very similar methodology that even the best performing funds' alphas are not statistically significant. The important difference between both studies is that Fama and French (2010) account for cross-correlation in alphas potentially induced by omitted factors in the performance model.[255] Thus, even if there are a few skilled fund managers they are usually hidden in the mass of unskilled managers.

In contrast, most studies using portfolio-information-based measures document a better performance by fund managers compared to risk-based models and compared to a passive benchmark (Grinblatt and Titman, 1989a; Daniel, Grinblatt, Titman, and Wermers, 1997; Wermers, 2000). Based on a comprehensive study by Wermers (2000), stocks commonly held by funds outperform a passive index by 1.3 percent a year, 0.6 percent of which can be attributed to funds holding stocks

[254] Jensen (1968), Malkiel (1995), Gruber (1996), Carhart (1997), Wermers (2000), and Pástor and Stambaugh (2002b).

[255] Two further differences also contributing to the opposing conclusions are a potential survivorship bias in the study of Kosowski, Timmermann, Wermers, and White (2006) because they require funds to have at least five years of data and the earlier time period from 1975 to 2002 as compared to 1984 to 2006 in the study of Fama and French (2010).

with different characteristics than the market index and the remainder denotes true selection skills. These 1.3 percent, however, are hypothetical paper returns gross of any transaction costs or management expenses. Net abnormal returns are instead −1.0 percent. The difference between gross and net returns is 2.5 percentage points per year for U. S. funds and can be further broken down into fees (0.8 to 1.0 percent), transaction costs incurred by the fund (0.8 percent) as well as a cash drag (0.7 percent) due to non-risk holdings such as a cash position.[256] Low correlations between alpha measures based on gross and net returns of between 0.6 and 0.7 indicate that a significant cross-sectional variation exists with respect to these costs (Wermers, 2000; Chalmers, Edelen, and Kadlec, 2001a).[257] These results suggest that active management generates an additional value, though not large enough to cover the associated costs.

However, the gap between gross and net returns might also be attributed to trading activity between reporting dates. Portfolio-information-based performance measures might be biased if a manager is involved in a significant amount of short-term trading (Moskowitz, 2000). Moreover, it seems important to note that two distinct trading motives exist: (1) active decisions of the portfolio manager based on superior information; (2) trades that are induced by fund investors through cash inflows or outflows. Consequently, the fund manager can only be held directly responsible for the former while he cannot actively control the magnitude of fund flows.[258] Conditioning trades of fund managers on their motivation reveals that information-induced trades significantly outperform liquidity-induced trades (Alexander, Cici, and Gibson, 2007). This indicates that externalities such as fund flows distort trading decisions and that fund managers execute value-enhancing trades if their decision is not affected by fund flows.

With respect to timing abilities the empirical results of risk-based performance measures are rather weak indicating that no timing skills exist (Treynor and Mazuy, 1966; Henriksson and Merton, 1981). A similar result is confirmed for portfolio-information-based measures (Wermers, 2000). More recent studies applying daily data are more in favor of timing skills (Bollen and Busse, 2001; Jiang, Yao, and Yu, 2007). About three times as many funds exhibit significant timing

[256] Grinblatt and Titman (1989a) report a similar difference of 2.3 percentage points between gross and net returns.

[257] Taxes and the impact of flows on the investment strategy are not accounted for in this analysis.

[258] The fund manager can only aim to minimize the costs from liquidity-induced trades, for example by trading patiently.

ability based on daily data as compared to monthly data. These results underline the importance of accounting for time variability in funds' investment decisions when analyzing timing abilities. Glassman and Riddick (2006) provide evidence on the timing ability of international mutual fund managers. Even though these managers are unable to successfully switch between exposure to the world market and cash they do have significant skills in generating abnormal returns by reallocating money between different national markets.

Other asset classes provide mixed results. In an early study, Blake, Elton, and Gruber (1993) suggest that bond fund managers not only cannot generate outperformance but even systematically destroy value. However, their results are based on two samples as small as 79 and 361 funds. Accounting for a potential interim trading bias by the use of a continuous stochastic discount factor approach, Ferson, Henry, and Kisgen (2006) cannot reject the hypothesis of neutral average performance for a U. S. sample of bond funds. Focusing on average fund performance, Silva, Cortez, and Armada (2003) confirm these findings for the European market. They document no evidence of abnormal performance which is robust to several model specifications and the inclusion of conditioning information. Slightly more promising results, at least for a subset of funds selected based on past returns, are presented by Huij and Derwall (2008) who apply a much larger sample of 3,549 funds compared to Blake, Elton, and Gruber (1993). The performance of the top decile of U. S. bond funds seems to be significantly positive before fees though insignificant net of management expenses. Nevertheless, if the funds in the top decile are weighted according to modern portfolio theory the resulting alpha is highly significantly positive. This result is robust to bootstrapping inferences. Thus, at least some bond fund managers seem to possess enough skill that investors can earn abnormal returns.

Pension fund managers can serve as an interesting comparison for the results of mutual fund managers due to different regulatory settings. Blake, Lehmann, and Timmermann (1999) document negative though insignificant security selection skills and significantly negative market timing skills for a data set of U. K. pension funds for the period from 1986 to 1994. This result is somewhat surprising as U. K. pension funds, at that time period, were one of the least regulated institutional investors imposing only limited external restriction on the ability to generate abnormal returns. However, Tonks (2005) provides evidence that at least some pension fund managers are able to beat their benchmark and, even more, that these skills are persistent. For the U. S., studies have documented superior performance of pension fund managers based on risk-based methods (Christopherson, Ferson, and Glassman, 1998; Ferson and Kang, 2002). However, using conditional holdings-based measures indicates that the findings of previous studies might be a result of interim trading bias. After accounting for interim trading based on public information, the performance of U. S. pension funds seems to be neutral (Ferson and Kang, 2002).

However, the results presented in this section have to be interpreted carefully because performance results can crucially differ depending on the model applied (Chan, Dimmock, and Lakonishok, 2009).[259] For example, even if one agrees that size and value should be incorporated into the benchmark, the sign of the performance measure based on risk-based or characteristic-based methods differs for 11 to 50 percent of the funds depending on their segment (Chan, Dimmock, and Lakonishok, 2009).[260] Similarly, it has been shown that neither risk-based nor characteristic-based models are able to detect superior performance consistently in a sample of simulated fund returns (Kothari and Warner, 2001).

3.7.2 Investor Performance

Average fund returns as reported in most studies are not equivalent to the returns earned by the average fund investor. For example, investors might choose to switch between funds, withdraw their money completely in order to meet external liquidity needs or increase their allocation to funds over time. The two related concepts of performance measurement are conventional time-weighted and dollar-weighted returns.[261] Usually, time-weighted returns are reported in fund prospectuses and applied in academic studies to compute alphas assuming a buy-and-hold investment. However, if investors reallocate money within the measurement period then fund returns are a biased measure of investment performance and dollar-weighted returns should be used instead. The timing of reallocation decisions might even

[259] In contrast, Eling and Schuhmacher (2006, 2007) and Eling (2008) argue that the choice of the performance measure does not have any impact on the ranking of hedge funds or mutual funds, respectively. However, those studies only focus on ratio-based performance measures which follow a similar construction. Therefore, the result should not be generalized to all performance measures.

[260] Note that part of this result might be driven by a different treatment of transaction costs between risk-based and characteristic-based methods. However, Chan, Dimmock, and Lakonishok (2009) do not provide details on transaction costs.

[261] The dollar-weighted return is calculated as the internal rate of return (IRR) interpreting a fund investment as a sequence of net inflows.

have a stronger impact on the financial success of fund investors than picking the right fund within a certain segment. However, this important decision is usually not delegated to professional advisors. There seems to be an apparent misallocation of delegation.

Empirical results reveal that, on aggregate, investors seem to systematically lose money by ill-timed investment decisions because equity market returns are negatively related to aggregate inflows into equity funds (Braverman, Kandel, and Wohl, 2005).[262] Conventional time-weighted fund returns are on average 0.72 and 0.75 percent per month for the sub-samples from 1984 to 1990 and 1991 to 2003, respectively. Dollar-weighted monthly returns are only 0.45 and 0.37 percent implying that investors participate stronger in bear markets than in bull markets.[263] Similar results are provided for Germany by Stark (2006). Friesen and Sapp (2007) estimate the forgone returns of fund investors due to ill-timed investments based on fund-level data and report a loss of 1.56 percentage points annually for equity funds.[264] This number is larger for funds with higher alphas, more or less offsetting the abnormal returns generated by fund managers with higher skills.[265] Moreover, investors' bad timing skills are not restricted to active funds but are also present among index funds, though to a lesser extent. Interestingly, the difference between time-weighted and dollar-weighted returns is twice as high in load funds as compared to no-load funds implying that investors who purchase their funds through brokers make significantly worse investment decisions compared to their unadvised counterparts.

If fund investors make ill-timed investment decisions fund managers do not seem to have many opportunities for avoiding inferior timing performance. Once they receive large amounts of money at inopportune times their investment mandate forces them to invest the majority of this money. They have only minor flexibility to adjust the portfolio beta through the portfolio composition and the cash ratio.

[262] A similar relationship is also found for bond and money market funds (Braverman, Kandel, and Wohl, 2005).

[263] Braverman, Kandel, and Wohl (2005) do not provide test statistics on the significance of the differences.

[264] In contrast to Braverman, Kandel, and Wohl (2005), Friesen and Sapp (2007) cannot document a similar finding for bond or money-market funds.

[265] Note, however, that in light of Berk and Green (2004) an alternative explanation for this finding could be that the fund flows of investors who chase recent winner funds are the reason that these funds grow in size and subsequently cannot continue to outperform the market. Thus, if decreasing returns to scale exist in active management and investors respond to past performance, internal rates of return cannot be larger than time-weighted returns.

Also if withdrawals are ill-timed by investors the scope to avoid a negative impact on performance is limited because they have to redeem shares on a daily basis.

Moreover, the actions of corporate managers affect the relationship between time-weighted and dollar-weighted returns. In fact, the dollar-weighted stock returns of all U. S. investors is 1.3 percentage points below the time-weighted average return of all U. S. stocks (Dichev, 2007). For international markets, the same gap is 1.5 percentage points. Even more impressive, for more frequently traded NASDAQ stocks, the corresponding number is 5.3 percentage points. However, this is not a result of investors' bad timing of direct equity investments but rather depends on the timing of financing decisions by corporate managers. Thus, differences between time-weighted and dollar-weighted returns can only arise as a result of changes in the outstanding number of shares due to SEOs, IPOs, share repurchases or dividend payments (among more complicated items).[266] If these changes to the capital structure are timed by corporate managers, i. e. shares are issued in bull markets and bought back in bear markets, one could expect that dollar-weighted returns are below time-weighted returns. This is consistent with the findings of Frazzini and Lamont (2008). They show that stocks held by funds with large inflows, which is interpreted as high sentiment, underperform in the following months partly because they respond to the high investor sentiment by issuing additional shares. Keswani and Stolin (2008a), however, argue that the results of Dichev (2007) are not robust and depend, among other things, strongly on the data set and the time period analyzed. The performance gap between time-weighted buy-and-hold returns and dollar-weighted returns varies considerably over time and across markets. Specifically, the gap is high during economic recessions but investors end up slightly ahead of the market in expansionary periods. Irrespective of the empirical conclusions, this discussion shows that there is an endogenous relationship between fund performance, investors' response and the actions of corporate managers, all of which affect fund performance.

In addition to the timing decisions of fund investors taxes affect their net returns. The overall tax component is estimated to be around 1.2 percent per year for the U. S. (Dickson, Shoven, and Sialm, 2000). Bergstresser and Poterba

[266] Specifically, in the context of stocks, the number of stocks outstanding is determined by financing decisions of corporate managers and all issued stocks must be held by investors in aggregate. In the context of mutual funds, however, the number of shares outstanding is determined by the inflows and outflows of investors. Thus, in this case investors are responsible for the timing of the investment decisions.

(2002) even document an average spread of between 3.2 (equal-weighted) and 3.5 percentage points (value-weighted) between the before-tax returns and after-tax returns of a large sample of mutual funds assuming a hypothetical upper-income taxable investor.[267] Moreover, pre-tax returns are usually reported in mutual fund rankings, which induces a conflict between the objectives of investors and fund managers and implies that fund managers do not aim to maximize after-tax performance (Fong, Gallagher, Lau, and Swan, 2009).[268]

3.7.3 Implications for Active Mutual Fund Management

Based on the discussion above, active fund managers seem to generate on average abnormal gross returns though in most cases costs associated with research and trading turn this result into negative abnormal net returns.[269] At best, a small subset of managers delivers abnormal performance on a net return basis. However, according to equilibrium accounting this result is not surprising (Fama and French, 2010). Sharpe (1991) offers a simple but intuitive explanation. According to his "market arithmetic" all investors as a whole earn the market return before costs. "The average investors must hold the market" (Cochrane, 1999b, p. 60). If investors are grouped into active and passive, both groups earn exactly the market return before costs because passive investors track the market return by definition and both groups together make up the market. Assuming that the costs involved with active management are higher compared to passive management it becomes clear that active investors, on aggregate, can only earn the market return less the costs for active investing. The gain of one active investor must be offset by the loss of another. If the costs for passive investing are lower than those for active investing, active investors underperform their passive peers. Consistent with this argument, French (2008) documents that investors could save 0.67 percent of their total assets each year if they switched from an active approach to a passive approach because this equals exactly the weighted average of the additional costs

[267] Japan provides an example that taxes can have extraordinary effects on mutual fund performance (Brown, Goetzman, Hiraki, Otsuki, and Shiraishi, 2001). Tax dilution, which results from a unique feature of the Japanese tax system, has contributed to the extreme underperformance of Japanese mutual funds of more than 7 percent per year between 1981 and 1992. Net inflows into Japanese funds generate a wealth transfer from existing to new shareholders.

[268] Note that different tax treatments across investors would complicate an after-tax objective tremendously for mutual fund managers in most tax systems.

[269] Thus, it is interesting to question how these costs can be minimized in a way that investors receive at least part of the gross outperformance in their pockets.

involved with active management of different investor types such as hedge funds, mutual funds or pension funds.

However, active mutual funds do not represent all actively managed assets.[270] In fact, U. S. mutual funds held only 32.7 percent of all U. S. equities in 2007 (French, 2008). Thus, it remains theoretically possible that active mutual funds on average outperform a passive benchmark at the expense of other active investors such as direct holdings by private investors (21.5 percent), pension funds (12.3 percent), banks and insurance companies (11.8 percent), hedge funds (2.2 percent) or other types of institutional investors. However, it has not yet been analyzed in the literature whether one of these groups can exploit the investment strategies of another.[271] Moreover, Grossman and Stiglitz (1980) tackle the conclusions from equilibrium accounting and argue that active management should produce returns high enough to compensate investors for costs associated with research, paid for as fees in mutual fund investing. In fact, if no profit opportunities existed no one would engage in research making the market less efficient which, in turn, would provide profit opportunities. Thus, markets are, according to Grossman and Stiglitz (1980), in an equilibrium level of disequilibrium. Indeed, empirical results reveal that before fees, the performance of active mutual funds is around zero (Otten and Bams, 2002; Bessler, Drobetz, and Zimmermann, 2009).

If these results are simply interpreted as evidence that fund managers do not possess superior investment skills it appears paradox that still the dominant fraction of investors around the world is willing to pay high fees for placing their money in active funds. For example, according to State Street Global Investors only 19.1 percent of mutual fund assets were managed passively at the end of 2008.[272] However, this represents an increase of about 100 percent compared to passively managed assets at the end of 2001.[273] Also the volume of stock trad-

[270] Studies on the investment performance on other groups of investors, with the exceptions of hedge funds and pension funds, is usually rare due to data restrictions.

[271] Two exceptions are Coval and Stafford (2007) and Chen, Hanson, Hong, and Stein (2008) who document that hedge funds benefit from mutual funds which experience excessive fund flows.

[272] SPDR University, Passive and Active Management: A Balanced Perspective, September 2009.

[273] Moreover, actively managed mutual funds lost 208 billion USD in 2008 while index funds and exchange-traded funds gained 206 billion USD over the same period. However, in the U. K. only 2.6 percent of the 70 billion GBP of new funds bought by retail investors in 2009 were passive according to the Investment Management Association (‘Risk’ Fears Threaten Trackers, Financial Times, 17 May 2010). Part of this low number might be explained by the financial crisis during which investors seemed to perceive passive funds as riskier than active funds.

ing which can be explained by transactions in the value-weighted portfolio has increased from a low of 32 percent in the 1920s to a high of 68 percent in the 2000s (Bhattacharya and Galpin, 2007). Several potential explanations have been proposed in the literature. For example, investors might be willing to hold mutual funds because they offer additional valuable services. First of all, funds offer cheap and liquid access to a diversified portfolio for a broad spectrum of investors. Additionally, many funds provide banking services such as cheque writing. Koppenhaver and Sapp (2005) estimate that these additional services are worth 0.43 percentage points per year. Moreover, mutual funds are highly regulated making them a save product for long-term investing such as retirement saving. The daily redemption feature of open-end funds offers insurance against personal liquidity shocks by socializing liquidity costs among all investors (Guedj and Huang, 2008). Investors might, therefore, accept a lower return which can be interpreted as a liquidity insurance premium.

However, all of these services can also be provided by passive mutual funds for lower fees.[274] Thus, some authors argue that one potential reason to hold active funds is that passive funds cannot generate an exposure desired by investors. For example, it is impossible for private investors to generate an exposure to the Fama-French factors with a long-only strategy, i. e. the benchmarks used in most performance studies are not investable (Pástor and Stambaugh, 2002a; Huij and Verbeek, 2009). According to Pástor and Stambaugh (2002a) active mutual funds in contrast deliver a risk exposure that comes closer to a loading on the size and value factors of Fama and French (1993) though it is still not possible to replicate their performance completely. Moreover, actively managed mutual funds might be an effective tool for retail investors to exploit the momentum effect with relatively low transaction costs (Sapp and Tiwari, 2004). Indeed, a portfolio of active funds can generate a Sharpe ratio which corresponds to 66 percent of the Sharpe ratio of an investment according to the model of Fama and French (1993) and 54 percent of the Sharpe ratio of an investment according to the model of Carhart (1997).[275] This is a very strong result and puts the average underperformance of mutual funds in a different perspective.

[274] The insurance against liquidity shocks is only provided by conventional index funds while in exchange-traded funds these costs are born individually by the investors who demand liquidity.

[275] Though, Sapp and Tiwari (2004) cannot provide evidence that investors actively buy those funds which give them the highest loading on the momentum factor.

Furthermore, some recent studies argue that active mutual funds are able to deliver positive abnormal returns in down markets which is when it matters most for investors (Kosowski, 2006; Glode, 2010). These studies question whether the average performance of mutual funds as analyzed by previous studies is the correct approach for measuring the value of active funds.[276]

An alternative explanation for the paradox mentioned above might be that some active fund managers are able to beat the benchmark and that at least a subset of investors is able to identify these managers. The literature on the smart money effect argues that a few smart investors can predict mutual fund performance based on private information and that flows of these investors outperform the market (Gruber, 1996).[277] Early empirical results seem consistent with this conjecture (Gruber, 1996; Zheng, 1999). Zheng (1999) documents that conditioning all funds on net inflows yields a significant spread of 0.58 percentage points per month in three-factor alphas between funds with higher than median inflows during the previous three months and those with lower than median inflows, even though this effect is largely driven by small funds.[278] The positive spread holds for holding periods of up to 30 months after which the smart-money effect reverses. However, these abnormal returns cannot be earned by uninformed investors mimicking the trades of informed investors.[279]

In contrast to these earlier results, the smart money effect vanishes after controlling for positive autocorrelation in fund returns due to stock return momentum (Sapp and Tiwari, 2004). The intuition is that investors buy into recent winner funds and that these funds necessarily have disproportionate holdings of recent winner stocks. Thus, investors benefit unwittingly from stock return momentum but do not seem to be able to identify winner funds ex ante. Wermers (2003) proposes an alternative explanation for the smart money effect. He suggests that

[276] How to measure performance correctly is discussed in chapter 3.

[277] Gruber (1996) argues that, under the assumption of the existence of managerial skill, future performance is predictable because manager skills are not priced in the net asset value and skilled managers do not raise fees to the level that their net performance is equal to that of unskilled managers.

[278] Portfolios are rebalanced every three months.

[279] Specifically, if a gap of one or three months is introduced between the observation of flows and the evaluation period, to allow uninformed investors to trade on the information of others, the return spread between inflow funds and outflow funds is no longer significant (Zheng, 1999). Only by restricting the choice to small funds can investors earn superior returns when they choose funds conditional on past flows of informed investors. Thus, a smart money effect can be detected in the data even though it cannot be exploited by uninformed investors who are only able to observe fund flows with a lag.

mutual funds receiving high inflows use this money to scale up existing positions, which is consistent with the behavior documented by Pollet and Wilson (2008). Thus, they push up the prices of these stocks and fund returns through their own trades. In this case, the higher performance of funds receiving inflows can no longer be interpreted as a result of superior skills. In line with these results, Baquero and Verbeek (2005) also do not find evidence of smart money among hedge funds.

Keswani and Stolin (2008c) provide a recent analysis which is consistent with the initial results of Gruber (1996) and Zheng (1999). They document a smart money effect for the U. K. even after controlling for momentum in stock returns.[280] The different results of Keswani and Stolin (2008c) compared to Sapp and Tiwari (2004) are explained by the pre-1991 period in the study of Sapp and Tiwari (2004) and, to a lesser extent, by their use of quarterly instead of monthly data, which is revealed by an analysis of Keswani and Stolin (2008c) based on U. S. data. There is no evidence of a smart money effect before 1991 but there is evidence in favor of smart money after 1991 for both the U. S. and the U. K., which is consistent with the conclusions that investors became more sophisticated over recent years (Keswani and Stolin, 2008c).[281] Moreover, Gharghori, Mudumba, and Veeraraghavan (2007) confirm the findings in favor of a smart money effect for a sample of Australian mutual funds even after accounting for stock return momentum.

If some fund managers possess superior skills and are able to beat the benchmark over several consecutive periods, investing in the last year's winner funds should result in an outperformance. However, although recent studies point toward the predictability of short-term fund performance, there is overwhelming empirical evidence that mutual fund performance does not persist in the long run, once

[280] This finding seems to be quite robust. The effect is present among both small and large funds and is distinct from the impact of fund size on performance as documented by Chen, Hong, Huang, and Kubik (2004) and distinct from performance persistence. Differences in fees cannot explain the results either.

[281] More detailed results on disaggregated data show that the smart money effect can be explained to a larger degree by high gross inflows than by low gross outflows implying that investors spend more resources in the decision to buy a fund compared to sell decisions. A separate analysis for different investor clienteles reveals that both institutional and individual investors are able to identify successful funds. Two potential explanations exist: either institutional investors are no more sophisticated than private investors or private investors exert more effort because the actions of private investors are more closely linked to their personal wealth compared to institutional investors who only indirectly benefit from the performance of the chosen funds.

survivorship bias is taken into account.[282] Thus, performance persistence does not appear to be exploitable for the average retail investor.

If superior investment skill leading to performance persistence exists in the short-run, why can no evidence of investment skill be documented over the long run? According to Berk and Green (2004) fund flows as a rational response of investors to past performance might be an explanation that wipes out persistence due to decreasing returns to scale in active management. In addition, Bessler, Blake, Lückoff, and Tonks (2010) propose manager changes, which are the response of winner-fund managers to career incentives and an internal governance response of the fund management company among loser funds, as an additional mechanism for driving away performance persistence. Both explanations are consistent with the empirical observations of existing studies but at the same time with the existence of superior investment skills. Thus, even though an extensive literature has documented that active mutual funds only very rarely generate abnormal returns net of costs, it is not yet clear whether this is an indication of a lack of skill or if other systematic factors related to the construction of mutual funds explain the mediocre performance.[283] Moreover, certain investor groups, but not all investors, might be able to exploit value from active mutual funds. The dynamics of mutual fund performance in the context of these potential explanations is discussed in chapter 4.

3.8 Cross-Sectional Performance Determinants

If only a subset of active mutual funds adds value to investors' portfolios it is relevant to identify characteristics that explain fund performance in the cross-section. However, the investment performance of a fund is determined by both the manager through personal skills and the investment management company through the provision of in-house research. Baks (2003) and Kacperczyk and Seru (2007) argue that about 10 to 50 percent of fund performance can be attributed to the manager. Thus, it is relevant to analyze manager-specific characteristics, such as education, age, and behavioral aspects, as well as portfolio or fund charac-

[282] For short-term performance persistence see Bollen and Busse (2005), Busse and Irvine (2006), and Huij and Verbeek (2007). For long-term performance persistence see Hendricks, Patel, and Zeckhauser (1993), Elton, Gruber, and Blake (1996b), Carhart (1997), and Pástor and Stambaugh (2002b).

[283] Note that most of the results on active management are based on mutual funds even though other active investors exists. This is due to data restrictions.

teristics, such as security concentration, fund size or costs. Moreover, it can be distinguished between characteristics that positively affect managerial skill and information advantages and those that negatively affect costs, both of which would improve net returns. Table 3.3 provides an overview.

3.8.1 Managerial Skill and Information-Related Determinants

3.8.1.1 Investment Style

Portfolio Turnover

If fund managers possess real investment skill than those who engage more heavily in trading should be able to exploit their knowledge more intensively and provide higher returns. In this context, portfolio turnover might serve as a proxy for the informational advantage of the manager. However, each trade involves transaction costs which are not known in advance.[284] Therefore, turnover is also a proxy for costs. It remains an empirical question of whether high turnover leads to high net returns or low net returns. Empirical results are mixed. Elton, Gruber, Sanjiv, and Hvlaka (1993) and Carhart (1997) report a negative association between trading volume and performance. Shukla (2004) compares the performance of interim trading of fund managers with the performance of the funds assuming that no trade had occurred. His empirical results clearly reveal that the trading decisions do not add value beyond the incremental trading costs. Wermers (2000) does not document any relationship between performance and turnover once he controls for stock characteristics. The difference in four-factor alphas between the lowest and highest turnover quintiles are insignificant at 0.89 percent in the study of Chalmers, Edelen, and Kadlec (2001a). In contrast, Dahlquist, Engström, and Söderlind (2000) and Chen, Jegadeesh, and Wermers (2000) find that turnover is positively associated with fund returns. However, Chen, Jegadeesh, and Wermers (2000) focus on returns before costs not taking into account trading expenses.

However, it should be noted that trades in the fund portfolio occur due to two reasons: (1) discretionary trading based on superior information; (2) liquidity-induced trading due to cash inflows (creation of fund shares) or outflows (redemption of fund shares). The definition of turnover in the CRSP database, which has been used by most studies, is the smaller of buys and sells divided by average

[284] Hence, a skilled manager should only execute those trades that generate value net of expected trading expenses.

Table 3.3: Cross-Sectional Performance Determinants

Determinant	Performance impact
(a) Investment style	
Portfolio turnover	Mixed results.
Active share	More active funds outperform more passive funds.
Portfolio concentration	Mixed results.
Style consistency	Funds following a consistent investment style over time outperform those that alter their style or risk level.
(b) Information access	
Financial centers	Funds located in financial centers outperform those located elsewhere.
Regional proximity	Funds located closer to their target companies outperform those located further away form their target companies.
Political proximity	Funds outperform in trades of politically-connected stocks.
Information networks	Funds outperform in trades of stocks which they share an information network with.
(c) Manager characteristics	
Education	Positive relationship between SAT score and investment performance. No relationship between possession of an MBA and investment performance.
Experience	No relationship between manager age or tenure and performance but having investment experience at a hedge fund improves investment performance also at the mutual fund.
Gender	Female managers follow less risky investment strategies but do not outperform based on risk-adjusted returns.
Management structure	No performance difference between single-managed and team-managed funds.
(c) Cost-related determinants	
Fees	Negative relationship between fees and investment performance, even based on gross returns.
Transaction costs	Funds with higher operational efficiency, i. e. with lower transaction costs per traded volume, outperform less efficient funds based on net returns.
Taxes	More tax-efficient funds, i. e. realizing lower capital gains, outperform less tax-efficient funds based on net returns.
(d) Fund-related determinants	
Fund size	Small funds outperform large funds.
Fund family size	Funds of large families outperform funds of small families.
Fund age	Young funds outperform old funds.
Regulatory environment	Funds with less regulated investment strategies outperform more heavily regulated funds.

fund assets. The aim of this turnover metric is to capture only the volume of discretionary trades (Chen, Jegadeesh, and Wermers, 2000). However, this is only true if flows occur solely in the same direction during one measurement period. Otherwise, some trades captured by the CRSP turnover definition may well be liquidity driven. This assertion is supported by the finding of almost twice as high turnover rates, according to the CRSP definition, for open-end funds than for closed-end funds (Anderson, Coleman, Gropper, and Sunquist, 1996). Thus, the CRSP definition of turnover might capture on the one hand higher turnover due to better information of a manager and, on the other hand, higher costs due to liquidity-induced trades. This might explain the mixed results in the literature on the relationship between turnover and fund performance.

Indeed, Edelen (1999) decomposes turnover into a non-discretionary component related to fund flows and a discretionary component related to superior information. Liquidity-induced trading is negatively related to fund returns whereas the discretionary trading is not related to fund returns. Controlling for liquidity-induced turnover, the previously negative alphas revert to neutral levels. Based on a more detailed data set, Alexander, Cici, and Gibson (2007) support these findings. Conditioning individual transactions on the trading motive provides evidence that discretionary trades significantly outperform liquidity-induced trades by 3.2 percent over the following year.

Moreover, turnover itself might be an odd measure of cross-sectional differences in transaction costs because it neglects differences in the level of transaction costs (Chalmers, Edelen, and Kadlec, 2001a). Turnover is a reliable measure of transaction costs only when the average bid-ask spread of portfolio holdings is constant over time and across funds and the trading volume of a fund in each holding must be proportional to the weight of each holding and unrelated to the transaction costs of the portfolio holding (Chalmers, Edelen, and Kadlec, 2001a). These results suggest that not only turnover as a measure for the amount traded is relevant but also the cross-sectional differences between funds in the costs associated with transactions. Therefore, a more complete measure of the operational efficiency of a fund is required.[285]

[285] See below for a discussion of operational efficiency.

Active Share

Instead of taking the trading activity of a manager as proxy for his private information and superior skill one might argue that the degree of benchmark deviation, or active share, resulting from the trades is a more appropriate measure (Cremers and Petajisto, 2009). However, measuring benchmark deviation requires the availability of portfolio holdings data. Active share is defined as the average absolute deviation of a funds portfolio positions from the corresponding benchmark weight.[286] Indeed, funds with a higher value of the active share measure tend to outperform the benchmark. This implies that some managers possess enough skill to generate abnormal returns when they are courageous enough to deviate from their benchmark. Not only deviations from their benchmark but also deviations from their peers are a signal of superior investment skills. For a data set of hedge funds, Sun, Wang, and Zheng (2009) develop a Strategy Distinctiveness Index (SDI) which measures the distinctiveness of a hedge fund's investment strategy. Their results reveal that the distinctiveness measure varies considerably in the cross-section, is persistent over time and most importantly predicts future abnormal returns. Funds with the most distinctive investment strategy outperform those with the most common strategies by about 6 percentage points in the subsequent year.

Portfolio Concentration

Portfolio concentration might also be a natural candidate to predict managerial skill. Focusing only on a subset of stocks managers can generate larger information advantages. Indeed, based on some studies, focused funds investing in a small number of stocks seem to outperform more diversified funds by a significant margin (e. g. Baks, Busse, and Green, 2006). Moreover, those funds concentrated on only a few industries also provide superior performance compared to funds with a broad industry spectrum (Kacperczyk, Sialm, and Zheng, 2005, 2007). This result holds even after controlling for differences in expenses, turnover, fund age and fund size. This implies that fund managers possess company-specific and sector-specific private information. Also specialized pension fund managers provide superior returns compared to their less specialized peers, supporting these results (Blake, Timmermann, Tonks, and Wermers, 2009). Even for private investors, portfolios concentrated in fewer stocks outperform more diversified portfolios, especially

[286] See definition of active share in equation (1.7).

when the total portfolio value is high indicating financial sophistication of the individuals (Ivković, Sialm, and Weisbenner, 2008).

These results are consistent with the argument that managers can only generate a limited number of successful investment ideas, termed “best ideas” (Cohen, Polk, and Silli, 2009; Pomorski, 2009). To identify which portfolio components are best ideas, Cohen, Polk, and Silli (2009) employ four different measures for overweighting portfolio holdings relative to the weight implied by their market capitalization or the weight in a benchmark index. The outperformance of the stocks identified as best ideas is an impressive 1 to 4 percent per quarter. Also Pomorski (2009), who identifies best ideas as common trades of managers from the same investment management company who are believed to have access to the same superior information, provides empirical support in favor of an outperformance of best ideas. However, fund managers have an incentive to add more stocks, which are not among their best ideas, to the portfolio in order to reduce portfolio volatility in an attempt to maximize the Sharpe ratio (Cohen, Polk, and Silli, 2009), to allow for larger fund sizes because fees are usually linearly related to total assets under management, and as a response to incentives to herd (Scharfstein and Stein, 1990). The results of Cohen, Polk, and Silli (2009), however, suggest that investors could benefit from smaller and more concentrated portfolios.

In contrast, there are also reasons and empirical evidence to believe that focused funds underperform. For example, tilting the portfolio toward more concentration might also be associated with risk-shifting behavior of underperforming managers as a response to their relative ranking (Sapp and Yan, 2008). In an attempt to increase the chance of extremely positive returns these managers might decide to put all their eggs in one basket. Then, focused portfolios might be associated with unskilled managers and high risks but low returns. Moreover, large funds tend to underperform small funds due to capacity constraints related to the liquidity of large funds’ portfolio positions (Yan, 2008). Small funds with highly concentrated portfolios might face similar liquidity constraints for individual portfolio positions (Sapp and Yan, 2008). Gross of management fees, these two effects seem to cancel out the positive impact of portfolio concentration resulting in no relationship between portfolio concentration and performance. As more concentrated funds tend to have higher fees, concentrated portfolios even tend to underperform on a net return basis. Focused funds also have higher return volatility and tracking error, consistent with the risk-shifting explanation for underperformance, and lower portfolio liquidity, consistent with the capacity constraints explanation (Sapp and Yan, 2008). Higher turnover of focused funds might even point toward overconfidence of these managers (Kacperczyk, Sialm, and Zheng, 2005, 2007). Moreover, highly concentrated funds tend to have higher attrition rates. Neglecting a potential survivorship bias might explain why earlier studies document a positive effect of concentration on performance in contrast to Sapp and Yan (2008).

Style Consistency

If fund managers can build up information advantages through experience and a network, it is reasonable to believe that managers who stick to their investment principles outperform those who seesaw between different styles. Indeed, according to Brown, Harlow, and Zhang (2009) fund managers who consistently follow "their" style tend to outperform those who do not. The results are robust using two different methodologies, one using holdings-based measures to compute the style consistency and another one that only uses the time series of fund returns as input.[287] Similarly, fund managers who significantly alter their risk levels over time underperform those with more consistent risk levels (Huang, Sialm, and Zhang, 2009). Brown, Harlow, and Zhang (2009) suggest that managers can use the consistency of their style as a means of signaling investment skill which has additional explanatory power as compared to past performance. The positive effect of style consistency on performance documented by Brown, Harlow, and Zhang (2009) is robust with respect to the impact of turnover and expenses on performance. However, one admittedly extreme interpretation of these results is that low-cost passive investment strategies, being very consistent over time by definition, are superior as compared to active management.

3.8.1.2 Information Access

Financial Centers and Regional Proximity

If informal information networks exist, then fund managers located in financial centers should have informational advantages (Christoffersen and Sarkissian,

[287] Specifically, the holdings-based measure is the standard deviation of the ranks of each portfolio holding along the dimensions size, book-to-market and momentum over the previous 36 months. These rankings vary over time due to active decisions by the fund manager, reclassification of the securities or changes in the relative values of the securities. The return-based measure is the R^2 of a return attribution model over the previous 36 months.

2009).[288] Indeed, U. S. funds where the manager is located in financial centers, although being larger in fund size, outperform other funds. This result is especially pronounced for funds located in New York and for growth funds indicating that growth companies might be more difficult to value and that soft information plays a more important role for growth stocks. Moreover, the results are robust to alternative metrics measuring city size, education level and the density of financial information.[289] Consistent with informational advantages of financial centers fund companies are more likely to outsource management of their funds if they are located far from a financial center and if they offer a large variety of fund styles (Chen, Hong, and Kubik, 2007).

The effects of informational networks are also prevalent in the trades of individual fund managers (Hong, Kubik, and Stein, 2005). Specifically, a fund manager is more likely to buy or sell a certain stock if other fund managers located in the same city also buy or sell this stock, respectively. This effect is not restricted to local firms indicating that word-of-mouth effects exist between different fund managers rather than between local companies and local fund managers. Hong, Kubik, and Stein (2005) conjecture that in addition information derived from local press or road trips of senior executives of companies to certain cities might explain this result.

However, contrary to these results, funds located in financial centers might be further away from their portfolio companies. Thus, funds not located in financial centers might benefit from closer relations to the stocks they hold in their portfolio (Coval and Moskowitz, 1999, 2001). In fact, mutual funds investing in companies with local headquarters earn significant abnormal returns on these investments. This is particularly true for small and old funds with concentrated portfolios. A similar relationship has been documented for research analysts in an international setting covering 32 countries (Bae, Stulz, and Tan, 2008). Analysts located in the same country as the covered company provide significantly more precise earnings forecasts than foreign analysts. A similar local information advantage exists for

[288] Even though Cuthbertson, Nitzsche, and O'Sullivan (2008) also look at the funds' domiciles, their results do not provide additional insights to this question. First, they focus on the legal domicile of the fund rather than the location of the fund manager and, second, they cannot differentiate whether their results are driven by location or a relationship between the investment objective of a fund and the decision to set it up as an onshore or offshore vehicle.

[289] City size is measured by population size, education level is measured by the proportion of people with a bachelor degree or higher and financial density is measured by the ratio of all finance professionals to the total population.

hedge funds (Teo, 2009). In particular, emerging markets hedge funds and funds with illiquid portfolio securities benefit from an office in their investment region by significantly higher abnormal returns compared to hedge funds managed from a distant office. The location choice of new funds established by entrepreneurial fund managers is driven to a large degree by the origin of their founders, consistent with the informational advantages of a close relation to portfolio stocks (Parwada, 2008). These newly established funds exhibit a strong local bias in their equity holdings, presumably benefiting from asymmetric information between local and more distant investors.

Political Proximity

Chin and Parwada (2009) investigate the relationship between portfolio managers' political attitude, their portfolio composition and their investment performance during the presidential campaign in the U. S. If the employees of an investment management company lean more toward the Republican party, as measured by the financial campaign contribution via their Political Action Committees, the funds of this family tend to overweight stocks believed to benefit from a win of the Republican candidate relative to the stock that would profit by a Democratic win et vice versa. Furthermore, investment management companies tend to adjust their portfolios according to updated information about the likely outcome of the election.[290] Most interestingly, however, funds outperform in their politically motivated trades relative to their non-politically motivated trades by 4.72 percent for Republicans and 3.40 percent for Democrats, respectively. This emphasizes the importance of soft information for the generation of abnormal returns as it might be the case that portfolio managers derive superior information from networks with politically connected firms.

Information Networks

Mutual fund managers outperform on those trades when stocks are affected by information-events implying a certain informational advantage on these stocks (Da, Gao, and Jagannathan, 2008). Social networks, such as shared education networks, are an important determinant in the information transfer between mutual fund managers and corporate board members (Cohen, Frazzini, and Malloy, 2008). Fund managers overweight stocks of companies when board members of

[290] However, it cannot be ruled out completely that causality is reversed, i. e. investment management companies might support the political party which they believe is most beneficial for the stocks they hold in their funds.

these companies attended the same university. The performance of these holdings is significantly higher than the performance of other fund holdings, which is especially prevalent around news announcements. The results are independent of educational effects and are not restricted to certain funds, certain schools or certain firms. Takahashi (2010) confirms these conclusions based on a data set of Japanese mutual funds. Pareek (2009) abandons an explicit assumption about the social networks linking fund managers and corporate managers and provides evidence for network effects based on large positions in the same stock which cannot be explained by similar style or regional characteristics. This implies that mutual fund managers gain informational advantages through social networks.

Moreover, information networks seem to exist within financial conglomerates (Massa and Rehman, 2008). Mutual funds increase their holdings in companies that have a lending relationship with an affiliated bank after a deal. Those holdings outperform the other holdings of the fund. Moreover, funds decrease their holdings in companies with a lending relationship which subsequently generates negative abnormal returns. This relationship is more prevalent when the fund's office is located close to the lending bank implying that fund managers generate superior information from informal networks within financial conglomerates.

3.8.1.3 Manager Characteristics

Education

It is reasonable to believe that fund managers with a better education provide higher performance results. However, the empirical results do not unambiguously support this hypothesis (Chevalier and Ellison, 1999a). Variables used to measure education and experience by Chevalier and Ellison (1999a) are the average student SAT score of the institution where the manager received his undergraduate degree and whether he holds an MBA degree. Managers who obtained their undergraduate degree from universities with higher average SAT scores generate higher performance. However, information networks cannot be ruled out completely as an explanation for this result. Also, managers from more prestigious universities might be hired by investment management companies that provide better research and trading services and more efficient back offices translating into lower costs and higher net returns. Having obtained an MBA or not, however, does not have an impact on performance.

Experience

Also personal investment experience affects fund performance. For example, mutual fund managers simultaneously managing a hedge fund benefit from this constellation and improve mutual fund returns (Nohel, Wang, and Zheng, 2010). Moreover, managers of hedged mutual funds, a special type of investment fund, who at the same time manage a hedge fund generate 1.31 to 1.97 percent higher performance than those who do not (Agarwal, Boyson, and Naik, 2009). Performance persistence is also stronger among these funds. Investment experience seems to be an important determinant of fund performance. In contrast, experience in the form of higher manager age or tenure does not lead to higher performance (Chevalier and Ellison, 1999a). Tenure is not related to fund performance at all while younger managers even slightly outperform older managers on a risk-adjusted basis. This might be explained by more effort from younger managers due to career concerns. For hedge funds, Boyson and Cooper (2004) also report a negative relationship between manager tenure and performance indicating that hedge fund managers tend to outperform their peers at the beginning of their career. This return differential quickly disappears as managers gain in experience. At the same time, young managers tend to manage smaller funds with higher failure rates. The spread of 9 percent annual excess return between a portfolio of young winner hedge funds and experienced loser funds mainly stems from the underperformance of the latter.

Gender

If behavioral patterns play a role in investment success one might conjecture that gender explains performance. Indeed, comparing individual investors indicates that men trade significantly more than women implying that they are more overconfident when making investment decisions (Barber and Odean, 2001). Women outperform men by 0.091 percentage points per month net of trading costs controlling for differences in market risk and the SMB loading. This number increases to 0.143 percentage points if restricted to single households which are believed to be more prone to overconfidence. The trading behavior of professional fund managers is similar (Niessen and Rünzi, 2005). Female managers follow more consistent and less extreme trading strategies involving lower risk and turnover. However, based on risk-adjusted returns this does not translate into an outperformance of female managers compared to their male peers.

Management Structure

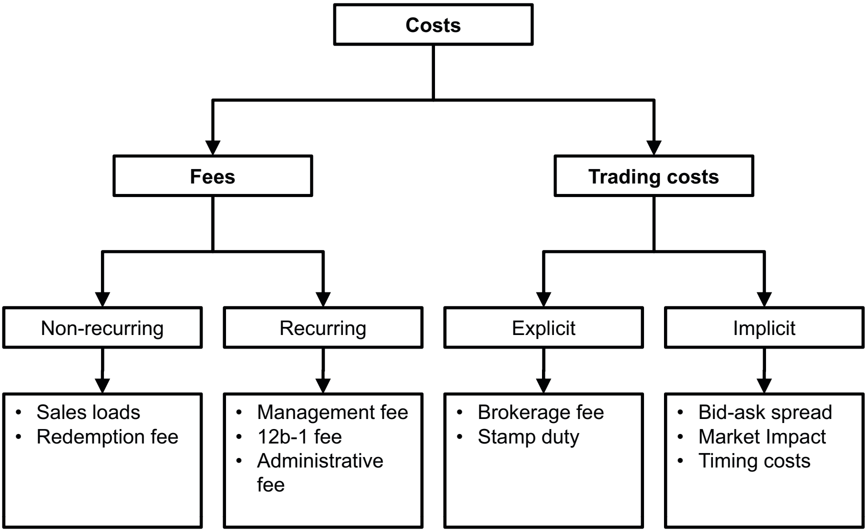
Classical decision making theory predicts that the optimal performance outcome should be achieved irrespective of whether the decision is made by an individual or a team. Behavioral decision making theory, in contrast, argues that team members correct each other's errors by pooling resources. This should lead to superior outcomes as compared to decisions made by individuals. Empirical tests of both theories based on Australian mutual fund managers, however, reveal no significant performance differences between team-managed and single-managed mutual funds (Prather, Middleton, and Cusack, 2001; Prather and Middleton, 2006). However, the result that large funds tend to underperform small funds might be interpreted as a result of hierarchy costs because large funds more often are managed by teams (Chen, Hong, Huang, and Kubik, 2004). These hierarchy costs in turn put a drag on performance. Bär, Kempf, and Rünzi (2010) and Bär, Ciccotello, and Rünzi (2008) report weak support for this by documenting slightly smaller alphas for team-managed funds. However, team-managed funds more consistently follow their style and exhibit stronger signs of performance persistence (Bär, Ciccotello, and Rünzi, 2008). Moreover, it seems that the performance of teams is not in general superior or inferior (Bär, Niessen, and Rünzi, 2008). Rather, specific team characteristics are related to performance. Social categorization, leading to less communication within the team, might result in lower performance while broader access to information of different team members might have a positive effect on innovation and performance. In fact, informational diversity, such as having team members with different education or tenure, has a positive impact on performance whereas social diversity, such as age or gender, has a negative impact.

3.8.2 Cost-Related Determinants

While the previous section has presented evidence on cross-sectional determinants of managerial skill this section focuses on costs as the other side of the coin. The primary types of costs are advisory fees for the management of the portfolio, transfer agent fees for servicing the fund's shareholders and 12b-1 fees for the distribution of the fund's shares (Figure 3.3). Additionally, transaction costs for trading securities are paid directly from the fund's assets. Lower costs should, ceteris paribus, lead to higher investor returns. However, skilled managers might earn higher fees and exploiting investment ideas involves transaction costs. Therefore, it is an empirical question how different cost components affect net returns in the cross-section. An advantage of using costs as predictor of performance instead of the skill determinants is that most of the costs are relatively easy to observe and stable over time.

Figure 3.3: Costs of fund investments

This figure presents costs associated with fund investments. Fees are explicitly mentioned in the fund prospectus while trading costs are usually deducted from the fund's assets and are not separately reported.



Fees

Fees reduce net performance but might also signal managerial skills. Several studies conclude, however, that investors' returns are negatively correlated with expense ratios implying that higher costs are not associated with better investment advice (e. g. Elton, Gruber, Sanjiv, and Hvlaka, 1993; Malkiel, 1995; Carhart, 1997). Similar conclusions have been presented for international markets (Otten and Bams, 2002; Bessler, Drobetz, and Zimmermann, 2009) or other asset classes such as bond funds (Blake, Elton, and Gruber, 1993). Even more, funds with lower before-fee performance tend to charge higher fees (Gil-Bazo and Ruiz-Verdú, 2009). Mutual funds seem to set fees strategically according to the performance sensitivity of their clientele exploiting the reluctance of some investors to withdraw money from underperforming funds. On an aggregate scale, U. S. investors could save on average 0.67 percent per year by switching from active management to passive management (French, 2008).

However, fees represented by the total expense ratio are not the only direct costs born by fund investors. Usually, investment management companies charge front-end and back-end loads, part of which are used to compensate the distribution network. Again, it might be argued that higher loads signal superior fund selection by skilled brokers or financial advisors. Empirical evidence, however, suggests that broker-sold funds cannot outperform direct-sold funds which do not charge loads (Bergstresser, Chalmers, and Tufano, 2009). Furthermore, funds with high loads, which should indicate better advice by brokers, do not outperform funds with low loads (Morey, 2003). A comparison of no-load funds with load funds suggests that the former even outperform the latter before load charges are deducted. Thus, the service of brokers does not directly translate into higher performance implying a negative relationship between sales loads and performance.

These results imply that mutual fund sponsors and brokers collect all of the abnormal returns they generate by superior investment skill or the selection of certain mutual funds. Net of these costs, investors' returns tend to be close to zero, or even negative, and expenses and loads cannot reveal any information about net abnormal returns even though they seem to be weakly related to skills. This is consistent with an equilibrium in the sense of Grossman and Stiglitz (1980). In a similar fashion, funds domiciled in offshore locations, which benefit from favorable tax treatment, tend to charge higher fees (Khorana, Servaes, and Tufano, 2009). Thus, part of the tax benefit of offshore funds is collected by the fund sponsor offering these funds. In general, competition among investment management companies should drive fees down. However, as a large number of mutual fund investors are in 401(k) plans, they are essentially locked in hindering competition.

Transaction Costs

In addition to fees (direct costs) mutual fund investments involve indirect costs that are not disclosed in the prospectus but still paid from the fund's assets. These include transaction costs for trades by the portfolio manager such as commissions and market impact. In general, estimates of average transaction costs on the fund level vary widely in the literature depending on specific criteria such as trade size, market capitalization, investment strategy and exchange listing. Estimates of average transaction costs for institutional orders are around 0.5 percent for exchange listed stocks and around 1.3 percent for Nasdaq stocks and can be even higher than 2 percent for large trades in small stocks (Keim and Madhavan, 1997). Interestingly, a reduction in tick size, which took place in the U. S. in 1997 and 2000 / 2001, increased transaction costs for large investors such as mutual funds on average (Bollen and Busse, 2006). This result is most likely driven by lower market depth because market makers exited the business due to lower profit opportunities. Specifically, the need for trade immediacy, which is probably high for liquidity-induced trades and index funds, increases transaction costs (Keim and Madhavan, 1997; Frino, Gallagher, and Oetomo, 2006). In particular, forced sales of mutual funds due to excessive redemptions result in high transaction costs (Coval and Stafford, 2007; Christoffersen, Keim, and Musto, 2007). Some hedge funds even strategically exploit these situations when mutual funds are in distress by providing liquidity or front-running the forced trades of mutual funds (Chen, Hanson, Hong, and Stein, 2008).

Transaction costs vary considerably across funds because fund managers have a significant impact on costs by trading patiently and avoiding assets with very low liquidity (Keim, 1999). Moreover, passive funds could signal that they do not trade based on private information potentially lowering their transaction costs because other market participants do not face the risk of trading against a better informed counterparty. This strategy cannot be replicated by a fund publicly known as active. However, empirically active fund managers seem to trade at lower costs than index funds (Christoffersen, Keim, and Musto, 2007). For individual trades of active funds, higher transaction costs are related to higher subsequent performance of these holdings (Christoffersen, Keim, and Musto, 2007). This implies that expensive trades, most likely, are trades based on private information requiring high trade immediacy.

On aggregate fund level, Livingston and O'Neal (1996) document average (median) commissions paid by mutual funds of 0.28 (0.21) percent of total net assets based on a sample of equity mutual funds for the period from 1989 to 1993. This translates into 0.14 percent commission costs when scaled by traded volume.[291]

[291] Note that traded volume, other than the CRSP definition of turnover, includes liquidity-

However, transaction costs born by mutual funds not only include directly paid commissions but also indirect costs such as market impact. Including indirect components, the average U. S. equity fund has annual trading expenses of 0.75 percent of assets under management, spread costs of 0.46 percent and brokerage commissions of 0.28 percent (Chalmers, Edelen, and Kadlec, 2001a). These costs vary significantly across funds from 0.28 percent trading costs (spread plus commission) for the 10th percentile to 1.29 percent for the 90th percentile. Variation is greater within investment objectives than between investment objectives implying that differences in trading costs go beyond the standard classification of funds' investment objectives (Chalmers, Edelen, and Kadlec, 1999). They may rather be affected by individual skills of managers or buy-side trading desks.

A comparison of funds with different levels of average transaction costs reveals a significant spread in four-factor alphas of 3.2 percentage points between the lowest and highest trading expense quintiles (Chalmers, Edelen, and Kadlec, 2001a). Quintile portfolios formed on turnover yield only a spread of insignificant 0.89 percentage points. Thus, turnover is not an adequate proxy for transaction costs because of the high cross-sectional variation of the costs per trade. Moreover, these results imply two conclusions: (1) fund managers might not possess enough skill to cover their trading expenses or are not aware of the level of these expenses ex ante; (2) excessive fund flows result in a high volume of inpatient trading and the resulting transaction costs constitute a significant drag on fund performance.

Taxes

As argued above, investors care about net returns after taxes. In general, tax effects vary considerably across different funds (Dickson, Shoven, and Sialm, 2000). Some fund managers seem to actively manage their portfolios in an attempt to minimize tax liabilities for investors (Fong, Gallagher, Lau, and Swan, 2009). For example, high turnover funds generate higher tax burdens than funds trading less (Bergstresser and Poterba, 2002). Moreover, after a manager change the new manager often realizes capital gains when realigning the portfolio composition imposing large tax liabilities on continuing investors. Fund investors seem to be aware of these differences as fund flows are more sensitive to after-tax returns than to pre-tax returns according to Bergstresser and Poterba (2002). However, not only the manager but also the behavior of other investors determines the tax

induced and valuation-induced trades.

burden that mutual funds impose on their investors. In particular, according to the treatment of taxes in the U. S. creations of new fund shares, i. e. inflows, dilute unrealized capital gains of existing shareholders because tax liabilities are equally born by all investors when the capital gain is realized irrespective of when the investor actually bought the fund shares. Similarly, when fund managers have to sell stocks in order to meet redemptions by existing investors, i. e. outflows, they might realize capital gains which results in a distribution of taxable capital gains to remaining fund investors. It is worth mentioning in this context that creation and redemption in kind, which is a particular feature of exchange-traded funds, can significantly reduce unrealized capital gains and improve the tax efficiency of funds (Poterba and Shoven, 2002). Not only capital gains but also dividend payments are taxed. Thus, mutual funds usually do not receive the full dividend payment but a certain fraction is deducted as tax payment. For a set of passively investing European exchange-traded funds, Blitz, Joop, and Swinkels (2010) document that dividend withholding taxes account for on average 0.48 percentage points return deviation from the (total return) benchmark index. In this respect, internationally investing mutual funds that can rely on a network of custodians in several countries can significantly reduce these dividend withholding taxes by holding stocks at a custodian in their home country.

3.8.3 Fund-Related Determinants

Fund Size and Fund Family Size

Fund performance seems to be negatively related to fund size (Chen, Hong, Huang, and Kubik, 2004). Specifically, a two standard deviation increase in the log of the fund's total net assets results in a decrease in performance of between 0.054 and 0.077 percentage points the following month depending on the benchmark used. However, it is questionable if the fund size effect documented by Chen, Hong, Huang, and Kubik (2004) can be exploited by investors as funds in their two smallest size groups have an average fund size of only 4.7 and 22.2 million USD, respectively. Consistent with lower returns of large funds, the average value-weighted fund returns, i. e. the average return of each fund weighted by the money invested in the fund (TNA), are 0.27 and 0.39 percentage points below equal-weighted returns per month for the two sub-samples of Braverman, Kandel, and Wohl (2005), respectively.[292] Also in the study of Zheng (1999) the value-weighted returns are lower than the equal-weighted fund returns, though the difference is insignificant. In contrast to these results, a positive relationship has been documented between total net assets and performance for the major European markets (Otten and Bams, 2002). However, the results of Otten and Bams (2002) might be biased because they do not control for the impact of fund family size which has been shown to be relevant when analyzing the impact of fund size on performance (Chen, Hong, Huang, and Kubik, 2004).

According to Chen, Hong, Huang, and Kubik (2004) larger funds tend to be managed by several portfolio managers competing for capital and complicating the decision making process. This leads to a focus on hard information such as fundamental company data in contrast to soft information such as information from personal interaction with the companies' management even if the latter is important for outperforming the benchmark.[293] These "hierarchy costs" reduce the performance of large funds compared to small funds with leaner management structures. However, liquidity is also an important issue explaining the relationship between fund size and performance (Chen, Hong, Huang, and Kubik, 2004; Yan, 2008). The negative impact of fund size on performance is more pronounced among funds holding illiquid assets, irrespective of the liquidity measure used, and among funds having higher turnover and investing in growth stocks (Yan, 2008).[294] This suggests that the negative relationship between fund size and performance is partially explained by transaction costs and the difficulty in executing large trades efficiently. Moreover, larger funds seem to be less active and are managed more closely to the benchmark (Cremers and Petajisto, 2009).

In contrast to fund size, the size of the fund family has a positive impact on performance (Chen, Hong, Huang, and Kubik, 2004). Large fund families can offer better resources and more efficient trading services as well as higher lending fees. Hierarchy costs do not play an important role for fund families as the individual funds do not compete internally for capital but rather are managed rel-

[292] Braverman, Kandel, and Wohl (2005) do not provide test statistics on the significance of the differences.

[293] Hard information is information that can be easily reduced to numbers such as financial statements, past returns or a credit history (Petersen, 2004). Examples for soft information are opinions and rumors. Hong, Kubik, and Stein (2005) analyze the relationship between information type and performance in more detail.

[294] These results are based on a two-way sort on fund size and the liquidity of a fund's assets into 25 quintile portfolios as well as a cross-sectional regression approach in the fashion of Fama and MacBeth (1973).

atively independently by the different managers. Thus, according to these results it appears that one fund with a size of 1 billion USD has inferior performance compared to two funds from the same family and both with a size of 500 million USD.

Fund Age

Fund performance is higher among young funds (Huij and Verbeek, 2007; Karoui and Meier, 2009). This result also holds for funds of the major European markets even after controlling for fund size (Blake and Timmermann, 1998; Otten and Bams, 2002). Cuthbertson, Nitzsche, and O'Sullivan (2008) indirectly confirm these findings by reporting a decreasing alpha when young funds are excluded from their sample of U. K. funds. However, the outperformance of young funds is usually restricted to a relatively short period of up to 36 months and is strongest for the first year after a fund's inception (Blake and Timmermann, 1998; Karoui and Meier, 2009).[295] For example, Blake and Timmermann (1998) report abnormal returns of 0.8 percent for the first year. The monthly spread in risk-adjusted returns between young and old funds is 0.09 percentage points over 12 months and 0.12 percentage points over 36 months (Karoui and Meier, 2009). Moreover, performance persistence is more pronounced among young funds compared to older funds (Huij and Verbeek, 2007; Karoui and Meier, 2009).

However, part of the superior performance of young funds might be explained by the very first years of a fund's life cycle and corresponding activities of mutual fund companies to push fund performance of newly launched products. However, the results of Gaspar, Massa, and Matos (2006) do not seem to support this conjecture. An alternative explanation is that young funds are more likely to be managed by younger managers who face stronger performance incentives and, as a result, tend to outperform older managers (Chevalier and Ellison, 1999a). Indeed, young funds tend to hold more concentrated and riskier portfolios and face a higher risk of dropping from the top performance deciles to the bottom deciles in the subsequent years consistent with young managers exploiting the option-like payoff of their contracts (Karoui and Meier, 2009). Moreover, young funds tend to receive high inflows and these inflows, according to Berk and Green (2004), reduce the potential to generate alpha. However, it cannot be ruled out that young funds outperform old funds due to an incubation bias in the data set

[295] Note that Blake and Timmermann (1998) report negative returns for the first months because they deduct the front-end load from the return.

(Evans, 2010; Karoui and Meier, 2009).[296] In summary, a negative relationship between age and performance seems to exist. It cannot be ruled out, however, that age is just picking up some of the performance determinants discussed above.

Regulatory Environment

In addition to the performance determinants discussed above, the regulation and the resulting restrictions of funds' investment strategies appears to be an important explanation for fund performance. However, as all mutual funds of the same country tend to be subject to the same legal rules this conjecture is difficult to test. Only different fund types allow meaningful comparisons. For example, Agarwal, Boyson, and Naik (2009) compare the returns of traditional hedge funds with traditional mutual funds and with new and innovative hedged mutual funds which are funds that employ hedge fund like strategies but are regulated under the rules of mutual funds and sold to retail investors.[297] The empirical results of Agarwal, Boyson, and Naik (2009) reveal that higher freedom in investment strategies, the protection from daily liquidity supply and demand by investors, lower regulation and higher incentives increase the performance of funds. Hedge funds outperform hedged mutual funds by 5.99 to 6.72 percent per year based on a Carhart (1997) four-factor model and a Fung and Hsieh (2004) seven-factor model, respectively. Hedged mutual funds outperform traditional mutual funds by 1.33 to 3.93 percent per year. Interestingly, managers of hedged mutual funds who at the same time manage a hedge fund generate 1.31 to 1.97 percent higher performance than those who do not.[298] Based on the four-factor and the seven-factor model the difference

[296] See also the discussion of an incubation bias in section 2.1.2.2.

[297] These three investment products differ in their investment strategy. Hedge funds are largely unrestricted with respect to investment strategies. Hedged mutual funds are also allowed to use short selling and leverage but their short positions must be covered and borrowing is limited to one third of their assets. Furthermore, their investment in illiquid assets is restricted to 15 percent of total assets as they are, like traditional mutual funds, obliged to report daily net asset values and offer the possibility of daily redemptions to their investors. Traditional mutual funds usually rule out the use of derivatives for investment purposes in their prospectuses even though some allow it for risk management and handling fund flows. To align incentives of management and investors hedge funds rely heavily on performance-based fee contracts that reward the management for superior performance. This is very rarely the case among hedged mutual funds or traditional mutual funds as in these cases only symmetric ("fulcrum") fees are allowed following the 1970 amendment to the Investment Company Act of 1940. Because symmetric fee contracts are not very attractive to the fund's management Elton, Gruber, and Blake (2003) report that only 108 out of 6,716 funds in their sample use performance fees.

[298] Controlling for differences in fund size, age, expenses and flows the numbers are as follows: hedge funds outperform hedged mutual funds by 3.3 percent, hedged mutual funds outperform traditional mutual funds by 4.8 percent and hedge mutual funds with a manager having experience in managing hedge funds outperform those who do not by 4.1 percent

in mangers having hedge fund experience or not explains all or half of the difference between the performance of hedged mutual funds and traditional mutual funds, respectively. Additionally, Agarwal, Boyson, and Naik (2009) show that persistence exists among the winners in hedged mutual funds and that this persistence is stronger for hedged mutual funds with managers simultaneously managing hedge funds. However, due to the very small sample size these results can only be seen as indications and have to be interpreted very carefully. Moreover, not only the regulatory environment but also other aspects, most importantly the incentive contracts, differ between these investment products. Therefore, the difference in returns between hedged mutual funds and traditional mutual funds can only be partially attributed to differences in fund design.

3.9 Discussion

This chapter has provided a comprehensive review of methodological aspects of performance evaluation. Moreover, a framework for the choice of the correct performance measure has been derived. The decision of which specific measure to choose depends on the investment strategy of the fund, the investor's portfolio, the chronological focus and intended use of the performance result, i. e. ex-post evaluation versus ex-ante performance prediction, as well as the level of delegation exercised by the fund investors, i. e. whether the fund is highly focused or broadly investing in several asset classes.

Moreover, it is argued in this chapter that in particular the time variability of the investment strategies of funds, which implies time-varying factor loadings, the correct benchmark model specification and a potential estimation error due to the large random component in fund return series are the major obstacles in a precise evaluation of investment performance. The time variability can best be accounted for by parametric methods such a conditional models or by rolling-window regressions, which are a non-parametric approach. With respect to the specification of the benchmark model, it is concluded, based on a comprehensive discussion of recent developments in the asset pricing literature, that the four-factor model of Carhart (1997) is still a reasonable representation of return factors compared to alternative specifications even though its empirical performance in explaining stock returns is still far from satisfactory. Yet, an extension of this model in order

based on the seven-factor model.

to account for some of the aspects with respect to the behavior and investment strategies of mutual fund managers is recommended. Specifically, the four-factor model could be augmented by factors controlling for liquidity risk, stock-return mean reversion and higher moments.[299] With respect to an efficient estimation procedure, this chapter proposes the Bayesian approach as a promising alternative to conventional OLS estimation. This approach incorporates not only information from the data but also additional information (prior) into the estimation in order to derive more efficient parameter estimates. This methodology is applied in the empirical section.

Based on a review of empirical studies on mutual fund performance, this chapter concludes that fund managers are able to generate abnormal returns based on gross returns, not taking into account transaction costs or other expenses. Net of these costs, however, mutual funds tend to underperform their benchmarks on average by an amount that roughly corresponds to their fee levels. Average investor returns are even below average fund returns due to poor timing decisions of fund investors, i. e. they tend to participate more in bear markets than in bull markets. In the cross section more active funds that follow a concentrated and time-consistent investment strategy provide the highest investment results. Moreover, soft factors such as access to certain information networks also contribute to good performance results. Fund managers who are located in financial centers, who have certain ties to local companies, who attended the same universities as CEOs of the corporations they invest in, who are politically connected or who are part of a financial conglomerate with a lending relationship to the companies they invest in tend to outperform their peers in these holdings. Results for manager characteristics, such as education or tenure, or characteristics of the management team are less clear cut. However, young and small funds with low fees and high operational efficiency, i. e. low transaction costs, clearly outperform large, old and expensive funds.

Based on these results, it is an intriguing question of why, if some managers perform better than others, these managers cannot be identified ex ante and why their superior skills do not translate into superior performance net of costs. The following chapter goes on to investigate potential economic explanations for this relationship.

[299] The former two factors are applied in the empirical part while the third factor based on higher moments is unfortunately not available but also of less importance for this study.

4 Dynamic Aspects of Mutual Fund Performance

The previous chapters have argued on a theoretical basis that on average the investment performance of active mutual funds is negative net of costs and empirical results are consistent with this view.[300] However, it is still possible that some fund managers are able to outperform their benchmark. If some managers are good at picking stocks, then it is reasonable to believe that such talents persist over time. The literature on performance persistence aims to test this conjecture.[301] Interestingly, over periods of one year or longer, no persistence in fund performance can be documented.

This lack of persistence in fund performance has several potential interpretations: (1) fund managers do not possess true investment skills in selecting securities or timing markets;[302] (2) the statistical methods applied are unable to detect real skills and attribute skills misleadingly to luck; (3) systematic factors hinder successful fund managers to continually outperform the market and contribute to a mean reversion of fund performance. All of these potential explanations are discussed below. The finding of more recent studies, that performance persists over horizons as short as one month or one quarter, is consistent with the third explanation, namely systematic factors driving away performance persistence over longer horizons.

In particular, investors, the investment management company as well as the fund manager might respond to past performance. Rational investors update their beliefs about managerial skill based on previous performance (Berk and Green, 2004). They should withdraw money from poorly performing funds, thereby exercising external governance, and invest it in previous winner funds if investment skills are persistent. The investment management company has an incentive to promote the last year's winner funds, inflating their asset base through inflows,

[300] See for empirical results section 3.7.1 and for theoretical arguments section 3.7.3.

[301] Tests on performance persistence are a stronger test for managerial skill than the conventional tests of funds' alphas because three hypotheses are jointly tested: (1) the measure used is able to detect real skills; (2) the manager possesses real skills; (3) these skills are persistent over time.

[302] Earlier studies have interpreted these findings as a sign of market efficiency (Lerbinger, 1984; Malkiel, 1995).

P. Lückoff, *Mutual Fund Performance and Performance Persistence,*
DOI 10.1007/ 978-3-8349-6527-1_5,

and to increase fees. In the case of loser funds, investment management companies might exercise internal governance and decide to fire the underperforming manager in an attempt to stop outflows. The fund manager of a successful fund might be lured away by a competing investment management company while in case he ends up at the lower end of the last year's performance ranking he might start gambling. All of these actions may affect future performance. For example, at the end of 1995, the fund manager of Fidelity's Magellan fund, Jeffrey N. Vinik, allocated almost 20 percent of the fund's assets to fixed income securities. As a result, the fund lagged behind the performance of its peers in the subsequent months and lost a significant fraction of its assets due to outflows. In the end, Fidelity decided to replace Jeffrey N. Vinik in June 1996.[303]

The objective of this chapter is to explain the dynamics of fund performance based on the actions of the parties involved, which strongly depend on the past ranking of a fund. A theoretical life cycle of mutual funds and their performance can be developed according to these arguments.[304] The life of a fund is characterized by both periods of favoritism and neglect by investors. The last year's winner funds with high performance rankings receive a lot of attention, eventually resulting in strong inflows and the manager leaving the fund. It is most likely that performance subsequently deteriorates. Thus, a period of neglect follows when investors punish the poor performance and the investment management company eventually brings in a new manager, both of which should help to improve investment performance. Thus, fund flows and manager changes, being detrimental to persistent outperformance of winner funds, are at the same time beneficial for loser funds. An efficient product market, which is facilitated by the open-end structure, and an efficient labor market for portfolio managers are important mechanisms in this context. Consequently, finding potential solutions for sheltering outperforming funds from the negative consequences of excessive inflows and a manager change needs to account for their beneficial positive effects among recent underperformers.

The ultimate aim of this chapter is to identify economic relationships between fund flows, manager changes and performance that help to predict fund performance. This chapter starts with a discussion of performance persistence in sec-

[303] See also Walter (1999, p. 20).
[304] A similar Momentum Life Cycle (MLC) for stocks has been put forward by Lee and Swaminathan (2000).

tion 4.1. Section 4.2 discusses the response of investors to past performance as one of the most important equilibrium mechanisms while section 4.3 provides a discussion of how fund managers might respond to inflows and outflows and how this affects performance. Section 4.4 presents additional equilibrium mechanisms such as manager replacements. Finally, section 4.5 discusses which measures could be used to mitigate the negative impact of fund flows on performance while still allowing for effective external governance.

4.1 Performance Persistence and Predictability

4.1.1 Performance Persistence

Mutual fund performance does not seem to persist in a way that investors can benefit from an ex-ante identification of real investment skill by observing past performance.[305] Recent outperformers produce insignificantly higher returns than the benchmark in the subsequent period (e. g. Hendricks, Patel, and Zeckhauser, 1993; Brown and Goetzmann, 1995; Carhart, 1997).[306] Persistent outperformance can only be found for the pre 1980 period (Malkiel, 1995).[307] In contrast, the same studies document that recent underperformers continue to significantly underperform the benchmarks which should at least trigger loser-fund investors to withdraw their money. Thus, even though fund performance of winner and loser funds strongly reverts to the mean, the spread between previous winner and loser funds remains positive and, in some studies, significant in the period subsequent to portfolio formation (e. g. Bessler, Blake, Lückoff, and Tonks, 2010). European evidence confirms the general findings with respect to performance persistence based on U. S. data (Blake and Timmermann, 1998; Otten and Bams, 2002). Also for institutional funds, only weak signs of performance persistence have been doc-

[305] Note that early studies reporting the existence of performance persistence, such as e. g. Goetzmann and Ibbotson (1994), who document for the period from 1976 to 1988 that past returns and past risk-adjusted returns predict future performance, were prone to survivorship bias as discussed below (Brown, Goetzmann, Ibbotson, and Ross, 1992; Elton, Gruber, and Blake, 1996b).

[306] A similar relationship has been documented for financial analysts (Emery and Li, 2009). The recommendations of analysts who have been ranked at the top positions in the last year's Wall Street Journal analyst rankings are significantly worse than those of analysts not ranked as stars while there is no significant difference in the earnings forecasts between both groups.

[307] Specifically, Malkiel (1995) reports significant persistence for seven out of nine periods in the 70s but only for four out of nine periods in the 80s (1981 / 1982, 1985 / 1986, 1986 / 1987, 1989 / 1990). However, in three periods during the 80s there is statistically significant evidence of return reversals (1980 / 1981, 1987 / 1988, 1988 / 1989).

umented (Busse, Goyal, and Wahal, 2010). Performance persistence seems to be stronger among young funds, small-cap growth funds and no-load funds.[308] In the short run, however, fund performance seems to persist (e. g. Hendricks, Patel, and Zeckhauser, 1993; Elton, Gruber, and Blake, 1996a; Huij and Verbeek, 2007). Part of the observed persistence may be explained by flow-induced price pressure on the stocks mainly held by recent winner funds rather than persistent managerial skill (Wermers, 2003). For Canadian funds, very similar results on performance persistence have been reported (Deaves, 2004b). For pension funds, the empirical results are more in favor of the existence of persistent manager skills (Tonks, 2005) while the results for other active investment products such as hedge funds is rather controversial (Agarwal and Naik, 2000; Boyson and Cooper, 2004).[309]

Fees

Part of the spread between winner and loser funds might be explained by persistent differences in fee levels and transaction costs rather than persistent skill (Carhart, 1997). Indeed, removing the 10 percent of funds with the highest expense ratios improves the performance of the bottom decile by 2 percentage points annually (Elton, Gruber, and Blake, 1996a). However, the difference between the top and bottom decile is still highly significant indicating that fees alone cannot account for the difference in performance. Transaction costs are difficult to measure because they are paid directly from the funds' assets and are not disclosed to fund investors. Moreover, they are believed to vary widely across funds (Chalmers, Edelen, and Kadlec, 2001a). Thus, they are a natural candidate for explaining the observed persistence even though no study has yet attempted to analyze this relationship.

Stock Return Momentum

Moreover, it appears to be important to consider stock return momentum when analyzing the dynamics of mutual fund performance in order to distinguish between persistence in stock returns and persistence in managerial skill. In a comprehensive study Carhart (1997) shows that the return spread between the winner and loser portfolios can be explained to a large degree by the four-factor model,

[308] Gruber (1996), Blake and Timmermann (1998), Bollen and Busse (2005), and Huij and Verbeek (2007).

[309] Agarwal and Naik (2000) report persistence among hedge funds, which is, similar to open-end mutual funds, only short lived. Contrary, Boyson and Cooper (2004) report no performance persistence among hedge funds after controlling for common risk and style factors in the short and in the long run. However, taking into account the tenure of the manager they are able to develop a trading strategy that results in superior returns at short horizons.

which augments the three-factor model of Fama and French (1993) by a momentum factor.[310] This suggests that winner funds merely happen by luck to hold the last year's winner stocks which continue to outperform due to stock return momentum. His results reveal a spread of 0.67 percentage points in returns between the top and bottom decile in the year after portfolio formation which cannot be explained by the Jensen one-factor model. However, the four-factor model explains 0.38 percent of this spread, leaving a difference in the four-factor alpha between the top and bottom decile of 0.29 percent.[311] Most of this difference, 0.20 percent, is accounted for by the spread between the worst and the second worst decile portfolio. In other words the four-factor model explains all but 0.09 percent difference in returns between the top and the second worst decile. Differences in expense ratios and to a lesser extent in transaction costs resulting from turnover explain part of this remaining spread. This implies that before fees and transaction costs the difference between the top decile and the second worst decile is almost zero and that the winner minus loser spread is almost entirely due to the bad performance of the lowest decile.[312] Thus, performance persistence of individual fund managers is usually centered around losing funds after accounting for stock return momentum (Carhart, 1997).

Competition

Drawing on results from the industrial organizational literature, abnormal returns should be lower in sectors with higher competition. This reasoning can be translated to funds: high competition in a specific investment style results in more effort of competing funds to close the gap to the top performers, faster learning by imitation and even stronger competition for the managers with the highest talent. All of this should reduce performance persistence. However, an alternative view is

[310] For a detailed discussion see section 3.3.2.

[311] This result can mainly be explained by the extremely high loading on the momentum factor of top-decile funds during the evaluation period as compared to the period before and after evaluation which suggests that top-decile funds merely happen by chance to hold the last year's winner stocks.

[312] In annual terms, the return spread on buying the last year's winner funds and selling the last year's loser funds is 8 percent. Thereof, 4.6 percent are explained by different loadings on the market, value, size and momentum factor. Another 0.7 percent are explained by differences in expense ratios and 1 percent by transaction costs leaving 1.7 percent to differences in managerial skills. Looking at the spread between the top decile and the second worst decile of funds shows that of the 5.4 percent spread the four-factor model explains 4.4 percent and expense ratios and transaction costs another 0.9 percent, leaving only 0.1 percent unexplained. This implies that 1.7 percentage points spread between top and bottom-decile funds is almost entirely attributable to the bad performance of the loser decile.

that competition increases performance and performance persistence at the cost of the investment management companies' profitability. Empirical results support the former hypothesis; persistence is higher the lower the competition in a specific sector (Keswani and Stolin, 2006).[313]

Other Predictable Patterns

At first glance, the results on long-term persistence do not seem to imply the existence of a high level of managerial skill. However, several studies document the predictability of future performance differentials when additional information is taken into account. A natural candidate that should contain information on future performance is fund ratings because fund rating companies condense a broad set of data into a mark. Early empirical evidence on the value of mutual fund ratings is rather mixed (Blake and Morey, 2000; Morey, 2005).[314] The new rating methodology of Morningstar introduced in June 2002 has some predictive power with respect to future outperformance (Gottesman and Morey, 2007). Moreover, Bechmann and Rangvid (2007) construct an atpRating, which primarily uses costs as input in contrast to Morningstar's rating which relies a lot on more volatile performance data. Specifically, a weighted sum of operating expenses and the front- and back-end loads are used as a cost indicator that determines the relative ranking of the fund. Therefore, the atpRating acts more like a cost ranking than a ranking on skills. It can be used to predict differentials in future fund performance with low cost funds outperforming high cost funds. In a similar vein, funds with a high level of operational efficiency, defined as the efficiency of trading by the fund manager measured as the actual transaction costs incurred, outperform funds with lower levels of operational efficiency because of persistent differences in operational efficiency (Chalmers, Edelen, and Kadlec, 2001a). The return gap, which measures the performance contribution of short-term trading between two portfolio disclosure dates, also seems to be persistent over time but varies cross-sectionally such that it can be used to predict future performance of funds (Kacperczyk, Sialm, and Zheng, 2008). Lastly, the active share, which measures the degree of benchmark deviation of a manager, is also related to fund performance and persistence over time (Cremers and Petajisto, 2009).

[313] Competition is measured by asset concentration, the number of funds in a sector or the proportion of mature funds.

[314] The results of Blake and Morey (2000) indicate that at least downgrades according to the old Morningstar methodology can be used to identify future poor performers.

4.1.2 Potential Data Biases

Survivorship Bias

Sample selection and the characteristics of the data set can have a considerable impact on the results of performance persistence studies. Brown, Goetzmann, Ibbotson, and Ross (1992) and Malkiel (1995) suggest that survivorship bias in the data might produce results that indicate the predictability of future performance based on past performance even though this predictability is not true. A survivorship bias potentially arises when only those mutual funds are considered which survived until the end of the sample period.[315] Specifically, a set of existing funds represents a heterogeneous mix of different management styles, each represented by a certain vector of risk exposures. By examining only surviving funds those strategies that proved to be unsuccessful ex post are excluded from the analysis. Strategies that produced high returns just by luck tend to survive and, thus, average fund returns in the database are biased upwards.[316] Malkiel (1995) considers survivorship bias by including all funds in existence in the period from 1971 to 1991 based on Lipper data. The estimated impact of survivorship bias on average fund returns is 1.4 percent. More recent studies provide slightly lower estimates. According to Elton, Gruber, and Blake (1996b), the survivorship bias, measured as the difference in three-factor alphas between the surviving funds and all funds, is around 0.4 percentage points for studies with 10 years of data and goes up to around 1.0 percentage point for studies with 20 years of data. Consistent with this, Carhart, Carpenter, Lynch, and Musto (2002) document a bias of 1.0 percentage point for studies using data longer than 15 years.

The impact of a survivorship bias in the data set on persistence results, however, is not trivial and depends on the survival condition.[317] If survival depends on only one period, then funds moving from good to bad performance are removed while funds consistently providing high abnormal return remain in the data set. This leads to upward-biased persistence results (Brown, Goetzmann, Ibbotson,

[315] This may either be a sample selection criterion by the researcher or due to a limitation of data availability at commercial data vendors.

[316] In addition, a selection bias may arise when only funds that existed at the beginning of the sample period are selected. However, the direction of a selection bias is ambiguous and, thus, it has no systematic impact on average fund returns.

[317] A single-period survival rule implies that a fund disappears when its performance over one period is below a certain threshold level; a multi-period survival rule implies, instead, that a fund disappears when its performance over n periods is below a certain threshold level.

and Ross, 1992). In contrast, when survival depends on performance over several periods, survivorship bias creates spurious performance reversals rather than spurious performance persistence (Hendricks, Patel, and Zeckhauser, 1993; Carpenter and Lynch, 1999; Carhart, Carpenter, Lynch, and Musto, 2002). This is consistent with the empirical results of Carhart (1997) and Hendricks, Patel, and Zeckhauser (1993) who document strongest persistence for the full sample and weakest for the survivorship-biased sample. Also, Tonks (2005) documents stronger signs of persistence when controlling for survivorship bias as compared to earlier studies that potentially suffered from that bias. Moreover, the multi-period survival restriction seems to be stronger in simulation studies than the single-period survival effect such that the persistence results of studies not accounting properly for survival are biased downwards rather than upwards, i. e. true persistence is stronger than documented.[318] Simulating fund returns with no persistence but using realistic death rates, survivorship bias cannot explain the persistence results documented by earlier studies even if a single-period survival restriction is used (Carpenter and Lynch, 1999). For example, using three-year formation and one-year evaluation periods yields a winner-minus-loser spread in the simulated data of 0.14 percentage points annually, well below the 0.36 percentage points reported by Carhart (1997). Thus, the documented persistence does not seem to be spurious.

Look-Ahead Bias

While survivorship-bias is a property of the sample selection (or the available data set), a potential look-ahead bias might arise as a property of the test methodology. Specifically, requiring funds to survive a minimum period of time after the portfolio formation introduces a look-ahead bias, especially when final period returns are missing in the database or excluded from the sample due to minimum fund size requirements (Carpenter and Lynch, 1999).[319] This applies even if all funds are included in the data set. The direction of this bias depends on the nature of the persistence in the data: if attrition removes funds with low means, it reduces the cross-sectional dispersion in fund performance resulting in lower persistence; however, if attrition removes funds with high volatility, true skill can be measured more precisely in the formation period resulting in stronger persistence.

[318] Note that this finding also has implications for studies on stock returns when firms disappear or delist (Eisdorfer, 2008).

[319] Missing return series are more prevalent in hedge funds databases as compared to mutual fund databases.

Potential Treatment

To mitigate both, a survivorship bias and a look-ahead bias, Elton, Gruber, and Blake (1996b) propose to "follow the money" by tracing a fund after its disappearance. They assume that if a fund is merged with another fund the money is invested in the acquiring funds according to the merger terms. A similar methodology is applied to funds that change their investment objective. They conclude that if researcher fail to take these potential biases into account, results might be misleading. However, based on empirical results neither a survivorship bias nor a look-ahead bias seem to be affecting the results of recent studies (Carhart, 1997; ter Horst, Nijman, and Verbeek, 2001).

4.1.3 Methodological Aspects

Test Methodologies

From the methodological perspective, different approaches have been applied to analyze performance persistence. The most common are autocorrelation tests for performance measures, the Spearman rank correlation test, contingency tables as well as ranked portfolio tests for decile as well as for spread portfolios (Hendricks, Patel, and Zeckhauser, 1993; Brown and Goetzmann, 1995; Malkiel, 1995). The latter involves ranking all funds based on their performance over the previous period (formation or ranking period) and then forming portfolios of these funds according to their portfolio rank (Carhart, 1997). Most studies apply decile portfolios. Then, the performance of these portfolios is evaluated over the subsequent period (evaluation period). Extensive simulations have indicated that ranked portfolio tests are the most powerful test for detecting performance persistence (Carpenter and Lynch, 1999). Additionally, Elton, Gruber, and Blake (1996a) and Huij and Derwall (2008) show that if portfolio weights in the fund deciles are optimized based on modern portfolio theory rather than taken as equal among all funds the performance of the top-decile portfolio increases significantly.

Ranking Measures

Different performance measures have been used for portfolio formation. The simplest measure that can be applied is cumulated raw returns. This not only has the advantage of enabling short ranking periods but also avoids the estimation error inherent in a sorting based on risk-adjusted returns (Carhart, 1997). However, raw returns might not be an adequate measure of real investment skill. For example, being a growth fund manager during periods when growth stocks outperform value stocks increases the likelihood of ending up in the top decile, even if the manager has no skill.[320] More importantly, some managers might take on excessive risks and end up in the top decile by luck rather than by skill. Thus, ranking mutual funds based on raw returns might result in a noisy separation between skilled and unskilled fund managers.

In contrast, portfolio formation based on risk-adjusted returns should provide a much more reliable separation of skilled and unskilled but lucky fund managers (Elton, Gruber, and Blake, 1996a; Bollen and Busse, 2005). It not only controls for risk but, in the case of multifactor models, also for differences in style exposures. Carhart (1997) performs a sorting based on past three-year four-factor alphas in addition to a sorting on raw returns over the past year. The spread in returns between the resulting top and bottom-decile portfolio is smaller than the spread from a ranking based on past 12-month returns. However, the spread in four-factor alphas is larger indicating that a sorting on risk-adjusted returns rather identifies superior management skill as measured by alpha.[321] Furthermore, the spread between top and bottom funds from a sorting on alphas seems to be longer-lived in that top-decile alphas are still higher than the alphas of the other deciles five years after the portfolio formation. This implies that alpha is a better predictor of true skill than raw returns.

Brown, Goetzmann, Ibbotson, and Ross (1992) suggest using the appraisal ratio, defined as alpha scaled by residual standard deviation, due to the positive relationship between idiosyncratic risk and ex-post performance in the presence of survivorship bias. Kosowski, Timmermann, Wermers, and White (2006) provide evidence for the superior characteristics of the t-value of alpha as the ranking measure.[322] Heterogeneity in risk-takings in the cross section of funds, which results in non-normalities in conventional alpha estimates, does not result in non-normalities in the cross section of alpha t-values.[323] Indeed, rankings on the t-values of alpha carry the most information on subsequent three-year alphas in the evaluation period as compared to rankings on one- and three-year alphas or raw returns (Elton, Gruber, and Blake, 1996a).

[320] This assumes that managers do not actively attempt to time the style exposures.
[321] Note that an alternative explanation for this result is a model bias because the same model is used for ranking an evaluation.
[322] Note that the t-value of alpha scales alpha by its standard deviation.
[323] However, non-normalities in the cross section of individual fund residuals still imply non-normality in the cross section of t-statistics.

The problem with using alphas for ranking is that, usually, short ranking periods such as one year contain the most explanatory power for subsequent fund performance. But based on only 12 months of data a multifactor model cannot be efficiently estimated. Thus, a trade off between using short ranking periods and estimation error is evident. Based on rank correlations Elton, Gruber, and Blake (1996a) show that three-year alphas are best predicted by three-year alphas as compared to the t-value of the three-year alpha, one-year alphas, and one-year raw returns. However, one-year alphas in the evaluation period have the highest rank correlation with one-year rankings on raw returns. This indicates that the cost of risk-adjusting in the form of estimation error is higher than the benefit for short periods such as one year but that risk adjustment improves the sorting over longer periods when estimation error is less of a concern. Consequently, several attempts have been made to improve the estimation efficiency over short periods.

Elton, Gruber, and Blake (1996a) propose calculating one year alphas based on OLS regressions over three years as the three year alpha of this regression plus the mean of the residuals during the ranking year. Alternatively, daily data can be used for rankings on risk-adjusted returns over short periods (Bollen and Busse, 2005). This approach results in an economically and statistically significant outperformance of the top funds over quarterly periods which vanishes over longer periods. In a similar vein, Busse and Irvine (2006) use daily fund returns and adopt the Bayesian methodology of Pástor and Stambaugh (2002b) incorporating information from non-benchmark assets and longer histories into the estimation. This approach also improves the predictability of future performance. Huij and Verbeek (2007) employ an empirical Bayes approach that enables them to study short-term performance persistence using monthly data which is still more widely available than daily fund returns. Their methodology extracts information from the cross-sectional distribution of factor sensitivities to enhance estimation efficiency. Based on a 12 months ranking period and monthly rebalancing of the portfolio they document a statistically significant outperformance of the top fund portfolio.[324] Lengthening the ranking period or using a one month lagged ranking period removes significance.

Additionally, Bollen and Busse (2005) suggest sorting funds not only based on a pure selectivity measure such as alpha but on a combination of selectiv-

[324] Note that this result is based on estimating the alpha of a concatenated time series of decile fund portfolios in the fashion of Carhart (1997).

ity and timing skills because some managers might produce superior returns by applying timing strategies rather than pure stock picking. They do not find significant differences between mixed models and pure selection models. In contrast, Christopherson, Ferson, and Glassman (1998) document that time-varying, i. e. conditional, alpha measures are superior in predicting future performance as compared to unconditional alphas or raw returns, even though none of both allows the ex-ante detection of real investment skill. Mamaysky, Spiegel, and Zhang (2008) apply a similar methodology as but allow the coefficients to depend on an unobservable variable which itself follows an AR(1) process instead of relying on macroeconomic variables to explain the variation of the coefficients over time. They document that, based on this approach, the spread between winner and loser funds is an impressive 4 percentage points per year. Therefore, the choice of the ranking measure is important for the success of the investment strategy.

Evaluation Measures

The standard approach for performance evaluation is to construct a concatenated time series of decile portfolio returns (e. g. Carhart, 1997). In the first step, the cross-sectional average return of all funds in a specific decile is computed for each period separately and then these average returns are stacked over the whole sample period. In the second step, these concatenated vectors of decile portfolio returns are regressed on a set of indexes or benchmark factors. However, Elton, Gruber, and Blake (1996a) criticize this approach because the characteristics and composition of these portfolios change significantly over time. The time-series estimates of the intercept might be temporally unstable and potentially biased. To mitigate this bias, Elton, Gruber, and Blake (1996a) suggest, to use the whole return history of the fund for estimation of the coefficients and computing alpha as the sum of the alpha over the entire history plus the residuals during the evaluation period. However, this approach assumes constant coefficients over time for each fund instead of constant coefficients for each time period while a fund belongs to a certain decile. It is not clear which assumption more closely matches the empirical return series.

Moreover, Bollen and Busse (2005) stress the importance of individually estimating the performance for each evaluation period instead of using a concatenated time series of post ranking returns. This allows for time variation in factor risk loadings and can be viewed as a non-parametric version of conditional performance evaluation models (Ferson and Schadt, 1996). Individually estimating each fund's performance in the evaluation period and the use of risk-adjusted returns for ranking differs from the methodology used by Carhart (1997) as a consequence of him using monthly data. Changing either one toward Carhart's methodology leads to a disappearance of persistence in the study of Bollen and Busse (2005). Furthermore, the correlation between factor loadings and factor returns for the concatenated time series of top funds turns out to be negative implying perverse factor timing by the changing composition of the top fund portfolio. Not accounting for this correlation biases alpha estimates of the top fund portfolio toward zero. The perverse timing result might well be an effect of money flowing into funds when returns are high.

4.1.4 Potential Model Biases

Investment Style

Brown and Goetzmann (1995) indicate that persistence is correlated across managers suggesting that persistence might be due to similar strategies used by fund managers that outperform common benchmarks for a certain period. This is especially evident in the years 1980 / 1981, 1987 / 1988 and 1988 / 1989 when persistence even reverses, i. e. past winner funds become loser funds and vice versa (Brown and Goetzmann, 1995; Malkiel, 1995). These observations can be interpreted as a reversal of successful styles which are consistently followed by fund managers rather than a reversal of manager-specific skills. This indicates that to a certain degree persistence might be driven by the functioning of certain investment styles over periods of more than one year rather than by persistent stock picking talent. Interestingly, restricting the analysis to funds that belong to the same style deteriorates the performance of the winner-fund portfolios and underlines the importance of being in the right style at the right time (Huij and Verbeek, 2007). Combining the predictability of sector returns with the predictability of manager skills, Avramov and Wermers (2006) develop a trading strategy in mutual funds that yields significantly abnormal returns.

The results on the impact of investment style on performance persistence demonstrate the importance of risk-adjusting when analyzing performance persistence. However, neither the common risk-adjustment methodologies nor conventional fund style classifications seem to sufficiently control for this effect (Brown and Goetzmann, 1995). Previous returns are explained by style rather than managerial skill even if rankings on alpha are used (Teo and Woo, 2001; Ibbotson and Patel, 2002).[325] Consequently, the top decile contains funds with skilled managers and funds with unskilled managers who, by chance, were in the right investment style during the ranking period.

Therefore, more sophisticated methods of style adjusting might be required to analyze performance persistence. Teo and Woo (2001) propose using returns in excess of the average returns of all funds in the same investment objective using the Morningstar style box classifications.[326] Alternatively, Ibbotson and Patel (2002) apply the alpha from a return-based style analysis as a ranking measure. This approach allows for a fund-specific and style-adjusted benchmark for the estimation of ranking period performance. However, because the style of a fund is determined over a rolling 36-month window lagged by one month, this approach might also suffer from a style bias for funds that do not consistently follow one style as defined by the benchmark. Indeed, a significant portion of funds does not consistently follow one style (Brown, Harlow, and Zhang, 2009). Both studies, however, reveal that performance persistence is stronger if style-adjusted returns are used for ranking (Teo and Woo, 2001; Ibbotson and Patel, 2002).

Omitted Factors

Moreover, using risk-adjusted returns poses the risk of a model bias due to using a possibly misspecified model for both ranking and evaluation, which would otherwise be avoided by using raw returns (Scholz and Schnusenberg, 2008). A model bias might be especially relevant when a risk factor is omitted and funds have loadings on this risk factor that are relatively constant over time but vary cross-sectionally. In this case, funds with a relatively high loading on the omitted factor might appear to persistently outperform even though they only persistently earn a risk premium on the omitted factor. In particular, these funds have persistence in their beta loading on the omitted factor but not in alpha.

[325] See especially Figure 3 in Teo and Woo (2001).
[326] The Morningstar style box assigns funds based on their disclosed portfolio holdings to one of nine styles according to an independent sort along the two dimensions small-cap / mid-cap / large-cap and value / blend / growth.

4.1.5 Discussion

Some conclusions can be drawn from these studies. First, persistence seems to be clustered around losing funds rather than winner funds, which can partially be explained by higher fees and transaction costs. Second, persistence is a short lived phenomenon usually not lasting longer than one year. Third, ranking based on risk-adjusted returns and improved statistical methodologies improves persistence as compared to ranking based on simple raw returns. Fourth, it is important to account for time-variability in the composition of the decile fund portfolios. Fifth, the persistence results might partially be explained by the functioning of certain investment styles in certain periods. Sixth, conditioning on further fund characteristics can improve the predictability of fund performance.

However, the tendency of fund performance to revert to the mean seems to be stronger than the tendency to persist (Bessler, Blake, Lückoff, and Tonks, 2010). Even more noticeably, Hendricks, Patel, and Zeckhauser (1993) report that, even if performance of the past four quarters is positively related to next quarter's performance, the performance of quarters $t-5$ to $t-8$ is negatively related. This highlights that past success is not only unrelated to future success in the long-term but even seems to negatively affect funds managers' abilities to maintain abnormal returns. Hendricks, Patel, and Zeckhauser (1993, p. 102) point out the following reasons for finding short-term persistence but no signs of persistence in the longer run:

1. Superior analysts get bid away once they build a track record,[327]
2. new funds flow excessively to successful performers, which then leads to a bloated organization and fewer good investment ideas per managed dollar,[328]
3. urgency and drive are diminished once reputation is established,[329]
4. market feel of managers is limited to evanescent market conditions, and
5. salaries and fees rise to capitalize on demands arising from recent successes.[330]

[327] This has also been suggested by Tonks (2005).
[328] See also Berk and Green (2004).
[329] See also Chevalier and Ellison (1999a)
[330] See also Casavecchia and Scotti (2009) and Bris, Gulen, Kadiyala, and Rau (2007).

All of these arguments are related to how fund managers or investors respond to a good track record. Thus, it is important to consider the dynamic response of all agents inducing endogeneity into the analysis of performance persistence. As managerial effort cannot be measured and adjustments to the fee level are rather limited in extent, the fund flows and potential changes in the management of the fund appear to be the most important aspect in this context. Consequently, these factors are analyzed in more detail in the following sections.

4.2 Performance-Flow Relationship

This section discusses how fund investors respond to past performance in an attempt to analyze whether these actions have an impact on future performance and, thus, might help to explain the empirical results on a lack of long-term performance persistence. In the first step, determinants of fund flows are investigated.

4.2.1 Characteristics of Fund Flows

Open-end funds are obliged to report daily net asset values of their portfolios and to allow daily creations and redemptions to this net asset value making fund shares very liquid. This allows mutual fund investors to react quickly on personal liquidity shocks and to adjust their investments according to individual beliefs about the health of the economy on a timely basis. Moreover, investors reallocate money between different funds depending on their beliefs about future fund performance. Managerial skill is the most important determinant and thus, investors aim to infer from past performance the relative skill levels of different fund managers. If a fund manager is replaced or promoted to another fund, this should be taken into account. Moreover, fees are an important determinant of fund performance and relatively stable over time, making them a good predictor. Governance mechanisms such as board characteristics also affect performance and might be helpful for updating investors' beliefs about future performance. Fund ratings and rankings in the media usually make performance comparisons relatively easy for fund investors. When fund investors are unsatisfied with the investment results of their funds they can easily identify an alternative fund to invest in based on published rankings. Thus, reallocation decisions among different funds should involve lower costs than reallocation decisions among individual stocks because relative performance information is readily available.

There is a large amount of research attempting to identify the determinants of mutual fund flows and the relationship between past performance and subsequent flows, known as "performance-flow relationship" (e. g. Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lynch and Musto, 2003).[331] However, gross fund flows, i. e. inflows and outflows separately, are usually not observable to the researcher such that most studies rely on an indirect measure of monthly net inflows:

$$\text{flow}_{it} = \text{TNA}_{it} - \text{TNA}_{it-1}(1 + r_{it}) \tag{4.1}$$

where TNA_{it} refers to the total net assets of fund i at the end of period t and r_{it} is the return of fund i between $t - 1$ and t assuming that all distributions are reinvested and net of fund expenses.[332]

To obtain relative fund flows, which should be more comparable across funds of different fund size, absolute flows can be scaled by $\text{TNA}_{it-1}(1 + r_{it})$ in order to obtain relative flows (Berk and Tonks, 2007):[333]

$$\text{rel\_flow}_{it} = \frac{\text{TNA}_{it} - \text{TNA}_{it-1}(1 + r_{it})}{\text{TNA}_{it-1}(1 + r_{it})} \ . \tag{4.2}$$

Based on German data, where mutual funds report their net fund flows to BVI Bundesverband Investment und Asset Management e. V., the German association of investment management companies, Ber and Rünzi (2006) provide empirical evidence that fund flows measured according to equations 4.1 and 4.2 are a sufficient proxy for net fund flows and that they do not bias the results. This is also consistent with the findings of Keswani and Stolin (2008c) based on a very detailed data set of gross fund flows of U. K. mutual funds.

Net inflows into U. S. mutual funds averaged at 322 million USD in the 15-year period between 1994 and 2008 (ICI Investment Company Factbook 2009).

331 Note that, following e. g. Sirri and Tufano (1998) and Kempf and Rünzi (2008a), the impact of past performance on current fund flows is referred to as "performance-flow relationship" while the relationship between past fund flows on current performance is referred to as "flow-performance relationship". In the literature, this terminology is not always consistent (e. g. Chevalier and Ellison, 1997; Berk and Green, 2004).

332 Additionally, fund flows should be adjusted for asset growth due to fund mergers because they do not reflect voluntary investment decisions by fund investors (Zheng, 1999).

333 Other studies use TNA_{it-1} for scaling (e. g. Gruber, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Zheng, 1999; Del Guercio and Tkac, 2002). However, in this case fund flows are not restricted to -100 percent and incorrectly assigns some fund flows of young funds to internal growth instead of external growth (Berk and Tonks, 2007).

Investors appear to react cyclically: they still invested 504 billion USD in mutual funds in 2001 when the Dow Jones oscillated around an index level of 10,000 and withdrew 43 billion USD in 2003 after the burst of the technology bubble when the Dow Jones had fallen below 8,000. The maximum inflow of 878 million USD has been recorded in 2007. There is also seasonality of fund flows with a year. In the fall, investors tend to allocate more toward bond funds and less risky investments while in the spring they increase their allocation toward equity funds (Kamstra, Kramer, Levi, and Wermers, 2008). This can be explained by seasonal affective disorder (SAD) which claims that people suffer from depression when the hours of daylight shrink. Moreover, there is seasonal behavior of fund flows within one month. Daily net inflows are negative at the beginning of the month and positive over the mid- and end-month period (Rakowski, 2010).

4.2.2 Performance-Flow Relationship

On an individual fund level an efficient reaction of consumers (investors) to product quality (fund performance) ensures that high-quality (high-performance) products are offered (Ippolito, 1992). Moreover, this mechanism should not allow badly-performing funds to survive.[334] Thus, past performance should be the most important determinant of funds flows. However, in practice investors might require a relatively longer time period to update their beliefs because the performance signal is only measured with a significant amount of noise, especially among young funds (Ippolito, 1992). For the early period of 1964 to 1985, Ippolito (1992) documents that investors react to both, good and bad past performance by investing additional money or withdrawing money, respectively. Though, the withdrawals are smaller in magnitude for a negative performance surprise compared to a positive surprise of equal size. Several follow-up studies confirm this finding: investors chase recent winner funds but are reluctant to withdraw significant amounts of money from loser funds, resulting in a positive but convex performance-flow relationship (e. g. Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lynch and Musto, 2003).

This pattern is even more pronounced among younger and smaller funds (Chevalier and Ellison, 1997; Sawicki and Finn, 2002) and performance becomes more

[334] Specifically, with no new funds entering the market, perfectly persistent performance and no transaction costs, this mechanism would lead to a fund market with high-quality funds having a market share of one which, at the same time, implies a probability to detect a high-quality funds based on past performance of one (Ippolito, 1992).

important in explaining fund flows during bear markets (Shrider, 2009). In addition, investors seem to avoid funds prone to conflicts of interest. They are more sensitive to past performance of namesake funds and these funds, in general, attract higher levels of cash inflows (Ferris and Yan, 2007a).[335] Similarly, investors seem to value more frequent portfolio disclosure resulting in a positive relationship between portfolio disclosure frequency and net inflows (Ge and Zheng, 2005). Interestingly, for more recent periods in the 1990s and 2000s it seems that investors do indeed respond to poor performance by withdrawing money which might be explained by differences in the sample periods (O'Neal, 2004; Cashman, Deli, Nardari, and Villupuram, 2006; Ivković and Weisbenner, 2009).[336] A potential interpretation is that investors have become more sophisticated over the recent years. Consequently, investors clearly chase past winner funds but the conclusions on selling loser funds remain mixed.[337]

Family Effects

The relative ranking within the fund family also has an important impact on subsequent inflows beyond that of the peer-group ranking (Kempf and Rünzi, 2008a). This effect is more pronounced in large families where the intra-family competition is stronger. Some investors only choose from the funds offered by one fund family as they can freely move capital around within the family without incurring transaction costs. Furthermore, the availability in pension plans such as 401(k) schemes might be restricted. In addition, mutual fund families might put more marketing effort on a few funds that rank well within the family, intensifying the performance-flow relationship for these funds. Moreover, good performance of other funds in the family relative to their peer group have positive spill-over effects in attracting fund flows to other funds from the same family (Nanda, Wang, and Zheng, 2004). However, extremely bad performance of one fund does not translate into outflows from other family funds. This implies that

[335] At namesake funds the fund manager is usually the owner of the investment management company, sits on the board of the fund and has significant investments of personal wealth in the fund. Ferris and Yan (2007a) argue that these measures reduce potential conflicts of interest.

[336] Specifically, the earlier studies not finding a relationship between below average performance and withdrawals analyzed the periods from 1982 to 1992 (Chevalier and Ellison, 1997), from 1971 to 1990 (Sirri and Tufano, 1998) and from 1985 to 1995 (Lynch and Musto, 2003) while the more recent studies finding a reaction on bad performance used samples from 1995 to 1999 (O'Neal, 2004), from 1991 to 1996 (Ivković and Weisbenner, 2009) and from 1997 to 2003 (Cashman, Deli, Nardari, and Villupuram, 2006).

[337] A more detailed discussion follows below.

investment management companies strongly exploit the performance of star funds in their marketing and advertising but are successful in hiding underperformers. Furthermore, fund families documenting innovation by starting a large number of funds or offering a greater number of investment objectives can also generate higher inflows into their funds (Khorana and Servaes, 2007; Zhao, 2008).

Evidence from Other Investment Products

Evidence from other investment products is, in general, consistent with the results for mutual funds. However, some product-specific determinants of flows also play a role. Fund flows into bond funds (Zhao, 2005a) and international equity funds (Zhao, 2008) also exhibit an asymmetric relationship to past performance even though investors are more sensitive to risk-adjusted performance than to raw returns. Among international funds investors tend to prefer funds that are less correlated with the U. S. market and funds that provide a regionally more diversified portfolio (Zhao, 2008). Fund flows into socially-responsible investment (SRI) funds are more sensitive to past positive abnormal returns and less sensitive to past negative abnormal returns compared to conventional funds (Bollen, 2007; Benson and Humphrey, 2008). This is consistent with a clientele effect and SRI investors valuing not only abnormal performance but also the possibility of investing in stocks under socially responsible considerations.

Results for fund choices by index fund investors point toward an irrationality of mutual fund investors. Investors fail to incorporate fund characteristics, such as fees, risk and tax efficiency, which have strong predictable power for future fund performance, into their investment decisions (Elton, Gruber, and Busse, 2004).[338] Though this has improved in recent years the costs of suboptimal index fund choices remain significant Boldin and Cici (2010). Forgone returns are 0.13 percentage points per year for the whole period from 1996 to 2006 compared to an optimal strategy taking cost differentials into account. This number has fallen to 0.08 percentage points in 2006 but remains significant.

Results for hedge funds are inconsistent. On the one hand, investors seem to chase recent outperformers but do not redeem underperformers to the same degree (Agarwal, Daniel, and Naik, 2004). This would be consistent with the behavior of mutual fund investors. Moreover, hedge fund investors prefer funds with stronger incentive contracts and lower redemption restrictions. Redemption restrictions

[338] Choi, Laibson, and Madrian (2010) confirm the irrational choices of investors among index funds based on experimental evidence.

might impose higher costs on investors willing to withdraw their money or even make a withdrawal impossible altogether which provides a rational explanation for the convex shape of the performance-flow relationship in the case of hedge funds. On the other hand, Baquero and Verbeek (2005) report an immediate response of outflows to poor performance of hedge fund whereas inflows only react with a time lag and are better explained by past long-run performance.[339] The delayed reaction of inflows might be a result of hedge fund investments requiring a more complex due diligence process before an initial investment.

International evidence is not unambiguously in favor of a convex performance-flow relationship. For example, Canadian investors seem to avoid irrational decisions when investing in mutual funds: they neither chase past winner funds to a large degree nor do they stick to underperforming funds too long (Jog and Sinha, 2007). Rather, they rationally sell recent underperformers. German mutual fund investors do not seem to respond to past performance at all based on an analysis of the early period from 1987 to 1998, which was characterized by a dominant role of local banks owning both the investment management companies and the major market share in the distribution of mutual fund shares (Krahnen, Schmid, and Theissen, 2006). In later periods (1991 to 2003), German investors began to react on past performance, though the performance-flow relationship remains weaker as compared to that in the U. S. (Ber, Kempf, and Rünzi, 2007).

4.2.3 Shape of the Performance-Flow Relationship

According to a majority of studies, the performance-flow relationship seems to be convex: poor performance is not followed by outflows to the same degree as abnormal performance is followed by inflows. At first sight this seems puzzling because investors systematically act in an irrational manner. Even though more recent studies question these results based on more disaggregated data sets of fund flows, several potential explanations have been proposed in the literature to explain the convexity.[340] Some authors apply behavioral models while others propose rational models of investor behavior. Lastly, several studies point toward the relevance of frictions such as participation and monitoring costs and asymmetric information in explaining the observed convexity.

[339] The results of Baquero and Verbeek (2005) are based only on TASS data while Agarwal, Daniel, and Naik (2004) apply a combined data set from HFR, TASS, and ZCM / MAR.

[340] For a discussion of these more recent studies see below.

Behavioral Issues

Goetzmann and Peles (1997) apply cognitive dissonance to explain the investor behavior with respect to fund flows. In order to feel good about the previous decisions, investors tend to neglect bad information regarding fund performance. Thus, investors' perception about the past performance of their mutual funds is systematically biased upwards.

An alternative explanation for the asymmetry might be prospect theory: people simply do not realize their losses in underperforming funds because the disutility from further losses is decreasing (Kahneman and Tversky, 1979). Consistent with this, also a disposition affect, defined as investors selling winners too early but holding on to losers for too long, might affect the behavior of investors (Shefrin and Statman, 1985). Even sophisticated hedge fund investors seem to suffer from a behavioral bias known as hot-hand fallacy (Baquero and Verbeek, 2008). Specifically, the relationship between the lengths of a performance streak and subsequent inflows is stronger than warranted by the explanatory power of the performance streak for future investment performance. Investors might be too sensitive to good performance which also results in a convex performance-flow relationship. However, empirical evidence on trades of mutual fund investors shows that behavioral issues do not seem to play a major role in the direction and extent of mutual fund flows (Ivković and Weisbenner, 2009). The likelihood of selling a fund is even higher after losses as compared to after gains which is contrary to the behavior implied by a disposition affect.

As an alternative explanation, investors might be differently involved in buying and selling decisions (Johnson, 2010). Outflows can only come from old investors whereas inflows may come from old investors increasing their existing investments or from new investors establishing an initial stake. Based on a proprietary panel of all shareholder transactions in one no-load mutual fund family Johnson (2010) shows that both types of investors respond to past outperformance to a similar degree by buying new shares of the fund. However, outflows of funds are not sensitive to their own past performance but rather to the past performance of funds in which the money is afterwards channeled. This implies that investors actively buy funds but do not actively monitor the funds they hold which can be interpreted as a product market failure.

Internal Governance and Strategy Changes

Additionally, rational explanations for the convex shape of the performance-flow relationship have been proposed. Investors of loser funds might assume that a strategy change occurs at the fund level or that the investment management company brings in a new fund manager. Thus, it might be rational not to sell losing funds because future performance of loser funds is less predictable by past performance than winner-fund performance (Lynch and Musto, 2003). Loser funds benefit from a replacement of their manager and to a lesser extent from outflows in the subsequent year (Khorana, 1996; Bessler, Blake, Lückoff, and Tonks, 2010). Thus, investors who do not sell loser funds might in fact wait for this mean reversion to work for them. Indeed, fund flows seem to be less sensitive to past performance if the investment strategy has been altered (Sirri and Tufano, 1998). Moreover, firing a manager who has performed poorly reduces the outflows by about one half (Chevalier and Ellison, 1999b).[341]

Similarly, investors pay attention to strategy changes among winner funds. For example, the departure of a named manager reduces inflows, especially if past performance of the fund was high (Massa, Reuter, and Zitzewitz, 2010). However, there is usually less incentive for winner funds to change their winning strategy. This explains why, on average, future fund performance should be more predictable among winner funds compared to loser funds which provides a rational for fund investors being more sensitive to past superior performance compared to past inferior performance.

4.2.4 Impact of Costs and Brokers on Fund Flows

Costs

Market frictions might significantly distort the decisions of fund investors contributing to the convex shape of the performance-flow relationship. For example, investors might be constrained in their decisions by rules of their pension plans which results in suboptimal allocation decisions if judged based on performance considerations (Bergstresser and Poterba, 2002). Moreover, investors tend to avoid funds with high total expenses (Sirri and Tufano, 1998; Barber, Odean,

[341] Note that the results of Bessler, Blake, Lückoff, and Tonks (2010) using a larger data set cannot confirm this finding.

and Zheng, 2005).[342] This result also applies to other asset classes such as bond funds (Zhao, 2005a). Interestingly, a disaggregation of total costs reveals that higher annual expenses increase both, inflows and outflows (Ivković and Weisbenner, 2009). Higher expenses attract more inflows, potentially because they are partly used for distribution efforts, while, at the same time, result in more outflows because they are perceived by investors as higher costs of maintaining the investment. Indeed, decomposing annual fees into marketing expenses (12b-1 fees) and operating expenses reveals that net inflows are negatively related to operating expenses but that higher marketing expenses can attract higher net inflows (Zhao, 2005c; Barber, Odean, and Zheng, 2005; Khorana and Servaes, 2007). Consequently, investors are not free of biases when selecting mutual funds. Many studies reveal a negative relationship between costs and fund performance (e. g. Carhart, 1997). Moreover, higher fees are not related to higher operational efficiency, which could offset higher fees by lowering trading costs of the fund (Boldin and Cici, 2010). Thus, fund investors would greatly benefit from a better understanding of the relationship between mutual fund fees and performance.[343]

Another cost component affecting the choices of investors are taxes (Bergstresser and Poterba, 2002). General conclusions are not easy to draw because the tax treatment of mutual fund returns differs considerably between individual investors but also between different countries and over time due to new legislation.[344] U. S. investors seem to be concerned with after-tax returns rather than before-tax returns when choosing mutual funds (Bergstresser and Poterba, 2002). Moreover, U. S. investors avoid funds with high unrealized capital gains which represent a tax duty for them even though their fund shares may have been created after the fund accrued the gains. A capital-gains overhang, however, is a U. S.-specific issue but does not apply to other important mutual fund markets such as the U. K. or Germany. A comparison of funds held in taxable and tax-deferred accounts reveals that tax-loss selling is an important determinant of why investors redeem shares of loser funds (Ivković and Weisbenner, 2009). Specifically, there is

[342] Total expenses are defined in the study of Sirri and Tufano (1998) as the sum of the total expense ratio and one seventh of the front-end load.

[343] The SEC tried to improve the cost awareness of fund investors in 2004 by the requirement to disclose a dollar amount of costs associated with an 1,000 USD investment into a mutual fund. Indeed, U. S. equity funds with below average expense ratios received 102 percent of all net inflows during the period from 1999 to 2008 while funds with above average expense ratios lost 2 percent of all net inflows (p. 63, ICI Investment Company Factbook 2009)

[344] For example, Germany introduced a new tax scheme in 2009.

no relationship between performance since purchase and redemption decisions in tax-deferred accounts. In the case of funds held in taxable accounts, redemptions are even higher when fund characteristics, such as turnover capital gains overhang and the fraction of fund returns distributed to investors, predict high future taxable distributions. Furthermore, investors are reluctant to sell funds that recently increased in value to postpone tax payments. Specifically, a 10 percentage points price increase over the past year decreases outflows over the subsequent month by 0.5 percent of assets.

In addition to annual expenses, investors face one-time transaction costs involved with switching between funds (Ippolito, 1992; Sirri and Tufano, 1998; Huang, Wei, and Yan, 2007). The relationship between load charges and net inflows is unambiguously negative (Barber, Odean, and Zheng, 2005; Ivković and Weisbenner, 2009). This implies that investors are highly aware of visible costs such as loads. The negative relationship between costs and net inflows has also been documented for commissions charged by brokers (Barber, Odean, and Zheng, 2005). However, investors reallocating their money face not only direct costs but also indirect costs such as search costs when choosing a new fund, also attenuating the performance-flow relationship (Sirri and Tufano, 1998). However, higher distribution costs might also improve the availability of fund information and reduce investors' participation and monitoring costs (Sirri and Tufano, 1998).[345] Comparable to the role of disclosure requirements for listed companies the relevant question is whether aggregate information costs of investors are reduced, i. e. whether reduced participation compensate for higher annual fees.

Clientele Effects

Fund investors are not a homogenous group where each individual behaves the same way. Rather, it is reasonable to believe they differ across countries, across funds and even within the investor base of one fund across different clienteles. Investor clienteles are differently affected by the costs involved in the process of selecting new funds (participation or search costs) and with the monitoring of existing fund holdings (monitoring costs) (Huang, Wei, and Yan, 2007). These differences influence investors' timing of their buying and selling decisions and are important determinants of the performance-flow relationship (Gruber, 1996). Important differences relate to characteristics such as their level of sophistication,

[345] See discussion below.

financial education, investment experience, knowledge and access to information. The level of delegation is usually negatively related to investors' sophistication, i. e. hybrid funds (highest level of delegation) have the least sophisticated investors and country or sector funds (lowest level of delegation) have the most sophisticated investors. Thus, more focused funds tend to have more sophisticated investors, consistent with empirical evidence (Cashman, Deli, Nardari, and Villupuram, 2007). Moreover, unsophisticated and less well educated investors often do not independently choose their allocation but are subject to the influence of advertising and the advice of brokers.

Participation and monitoring costs also depend on fund characteristics and are negatively related to their visibility. In general, funds with higher visibility are more sensitive to past performance (Sirri and Tufano, 1998). However, the relationship is non-linear. Specifically, funds with lower participation costs have a relatively higher sensitivity to medium performance and a relatively lower sensitivity to high performance while funds with higher participation costs are more sensitive to performance at high levels (Huang, Wei, and Yan, 2007). Due to relatively high costs involved with an in-depth investigation of all funds at offer, investors usually pre-select a set of funds which they assess as promising based on past performance that can be observed at minimal cost (winner-picking effect). Funds with higher past performance are, therefore, researched by a larger fraction of investors. Moreover, the higher the average sophistication level of investors and the more information about the fund is cheaply available the lower the performance hurdle for a fund to be investigated by a larger number of potential investors. As a result, funds with lower participation costs are more sensitive to flows already at lower performance levels (participation effect). Lastly, in the case of high participation costs investors only trade a fund once its past performance is sufficiently high or low (no-trading effect). The combination of these effects results in a convex shape of the performance-flow relationship.

The visibility of a fund is affected by country-specific characteristics of the mutual fund market as well as fund-specific characteristics. In a cross-country study covering 28 different markets, Ferreira, Keswani, Miguel, and Ramos (2009) reveal that the performance-flow relationship is less convex in countries with higher economic, financial and mutual fund market development. Investors in more developed countries face lower costs and presumably are better educated financially. Costs and investor sophistication seem to affect the shape of the performance-flow relationship. Moreover, in countries where fund managers tend to take on higher risks, the performance-flow relationship is more convex.

The visibility of a specific fund is related to the size and popularity of the fund family, its affiliation with a star-fund family, such as Fidelity, marketing efforts as proxied by marketing expenses and media coverage (Sirri and Tufano, 1998; Huang, Wei, and Yan, 2007). With respect to monitoring costs of existing fund holdings, private investors might not have access to information about their funds on a timely basis. Mutual fund rating companies such as Morningstar or Lipper can significantly reduce both participation and monitoring costs by offering timely information on rating upgrades and downgrades (Del Guercio and Tkac, 2008). Fund ratings can be provided at relatively low costs because they benefit from economies of scale in information production.[346]

Empirical evidence confirms that mutual fund ratings and rankings in the media increase the sensitivity of fund flows to performance. Mutual funds listed in the Barron's or Money Magazine have significantly higher fund flows than a control group not mentioned in the media despite the fact that the future performance of listed funds is not higher compared to unlisted funds (Jain and Wu, 2000). Media coverage in three personal finance publications and two national newspapers are correlated with money inflows of between 6 and 15 percent of total net assets in the years between 1996 and 2002 (Reuter and Zitzewitz, 2006). Moreover, net inflows react significantly to new information provided by rating upgrades or downgrades beyond their reaction on underlying past performance (Del Guercio and Tkac, 2008).[347] In particular, downgrades seem to arouse investors of badly performing funds. Some of the outflows following downgrades occur immediately in the month of the rating change. However, investment management companies strongly refer to top performance, and eventually corresponding rating upgrades, in their marketing material but try to disguise the bad performance of their loser funds (Sirri and Tufano, 1998). Thus, participation costs are further reduced for higher performing funds through information distributed by the investment management company leading to an even more convex shape of the performance flow relationship.

[346] Usually, investment management companies pay for the ratings of their funds such that this service does not involve direct costs for investors.

[347] When rating agencies use risk-adjusted performance measures for their ratings, the incentives from ratings might be different from the incentives resulting from the performance-flow relationship (Bagnoli and Watts, 2000).

Participation and monitoring costs even vary across fund investors of the same fund due to the existence of different investor clienteles (Keswani and Stolin, 2008b). Consequently, investor characteristics are important determinants of participation and monitoring costs in addition to fund and country characteristics. In recent years, the size of the institutional segment of the mutual fund market has grown dramatically, both in the number of funds and assets under management. Specifically, the number of funds (fund share classes) classified as institutional increased from 22 in 1986 to 873 in 1998, the assets under management even increased over the same period from 3.2 billion USD to over 302 billion USD (James and Karceski, 2006). Professional trustees of institutional funds, both in the U. S. (Del Guercio and Tkac, 2002) and Australia (Sawicki, 2001), seem to behave more rationally: they dismiss poorly performing fund managers and avoid chasing recent winner funds. Furthermore, institutional management clients apply risk-adjustment methods such as tracking error while retail fund investors use less sophisticated performance measures (Del Guercio and Tkac, 2002). Consistent with this result, retail investors even respond to return components not explained by real investment skill implying that they do not appropriately take investment risk into account (Keswani and Stolin, 2008b). However, the magnitude of the response on past risk-adjusted returns of retail investors is higher than that of institutional investors. Berk and Tonks (2007) report that a fraction of investors irrationally sticks with underperforming funds and compare this behavior with the reluctance of some mortgage holders to refinance in the case of lower interest rates.

In the case of index funds, institutional investors tend to make slightly worse investment decisions than retail investors when comparing their fund choice to an optimal choice based on cost considerations (Boldin and Cici, 2010). The forgone return of institutional investors compared to the optimal choice is higher than that of retail investors. However, this result stems from the better opportunities in the form of some institutional index fund share classes with extremely low costs rather than from absolutely inferior choices of institutional investors compared to retail investors.

Broker Advice

Further differentiating between individual investor clienteles reveals that the behavior is different not only between retail and institutional investors but also within these groups (Keswani and Stolin, 2008b). The results of Keswani and Stolin (2008b) imply that the sales channel through which a fund is traded is an important determinant of the response to past performance. In general, brokered funds have a higher sensitivity to past performance than non-brokered funds (Zhao, 2005c; Bergstresser, Chalmers, and Tufano, 2009). This is especially true for the independent advisor channel (Keswani and Stolin, 2008b). Consistent with this, funds with higher loads are more sensitive to past performance (O'Neal, 2004).

However, there also seems to be some role for brokers to "wake up" investors of badly performing funds in the sense that the redemptions by investors who are advised by brokers are more sensitive to past underperformance than those of no-load investors who do not receive additional advice (Christoffersen, Evans, and Musto, 2007). This result is even stronger for unaffiliated brokers as compared to captive brokers. Indeed, in the case of poorly performing funds, the sensitivity of redemptions to past underperformance is much stronger for those share classes of funds sold by unaffiliated brokers as compared to share classes sold by brokers associated with the mutual fund company (Bergstresser, Chalmers, and Tufano, 2009). This indicates that affiliated advisors act in their self-interest rather than in their clients' interest. The results of Keswani and Stolin (2008b) imply that, compared to unaided retail investors, those buying through independent intermediaries or in-house private client discretionary portfolio management services are even more sensitive to performance components unrelated to managerial skill. Inflows and outflows react only modestly to past performance when the fund order is placed through the direct sales force of the investment management company or tied agents of other banks.

An analysis of index funds provides an even cleaner estimate of the influence of advisors because differences in costs are highly visible and the primary determinant of different performance between these commodity-like products (Boldin and Cici, 2010). However, a significant fraction of investors fail to correctly account for cost differences in their fund allocation. The explanation for this apparent paradox seems to be the influence of financial advisors and brokers. Almost all of the suboptimal choices are restricted to funds with 12b-1 fees and broker-sold funds. Thus, financial advisors and brokers seem to systematically channel index fund investors into those funds that pay higher distribution fees.

4.2.5 Speed of Reaction

The level of sophistication of the investors base affects both the rationality and the extent of the response as well as the speed of the reaction. In recent years it appears that at least some investors react more quickly to past performance than previous studies concluded (Cashman, Deli, Nardari, and Villupuram, 2007; Goriaev, Nijman, and Werker, 2008). The higher the sophistication of a fund's investor base the higher the speed of their reaction to past performance. Goriaev, Nijman, and Werker (2008) find empirical evidence for two types of investor clienteles: (1) sophisticated institutional investors who evaluate fund performance up to date based on short term performance during the previous three months; (2) private investors who evaluate fund performance with an average lag of three months taking into account longer evaluation periods of up to 12 months.

The finding of short-term evaluation is supported by Benson, Faff, and Smith (2007). They argue that existing studies failed to account for endogeneity between flows and performance. Current and lagged returns positively affect current net inflows when controlling for the endogeneity between both variables consistent with the view of some investors quickly responding to actual performance (Benson, Faff, and Smith, 2007). The effect of current returns on fund flows, however, is primarily driven by an immediate response of institutional funds while the impact of current returns on retail fund flows is not significant. Lagged returns display a significant impact on fund flows up to a lag of 5 months.[348] Controlling for persistence in fund flows reveals that investors react more quickly to performance than previously documented (Cashman, Deli, Nardari, and Villupuram, 2007). This finding is especially apparent in specialized funds focusing on single sectors or countries as compared to funds with broader investment objectives which provides evidence for the conjecture that the level of delegation is negatively related to investors' sophistication.

In the very-short run, focusing on daily data, net inflows are negatively related to returns over the previous two days implying a contrarian behavior of fund investors (Rakowski and Wang, 2009). Moreover, daily fund flows are mean reverting in the sense that high past inflows negatively affect current flows for up to a two-day lag. This effect is strong with about 74 percent of funds having a significantly negative coefficient on the first lag and 55 percent on the second lag.

[348] With one exception at a lag of 4 months.

These empirical results reveal that several investor clienteles follow a diverse set of investment strategies in mutual funds.

4.2.6 Evidence from Gross Flows

In recent years, several studies have started to question the earlier results of a convex shape of the performance-flow relationship based on more detailed data sets on gross flows instead of net-inflow estimates. Considering only net inflows can mask a considerable amount of mutual fund trading. For example, in 2005 136 billion USD net inflows into U. S. equity funds were a result of 1,210 billion USD gross inflows and 1,074 billion USD gross outflows in that year (Cashman, Deli, Nardari, and Villupuram, 2007).[349] However, the empirical results of these studies are not easy to reconcile.

Gross Inflows

For gross inflows, the results appear to be relatively consistent with the results based on net inflows. The relationship between inflows and relative returns is positive and convex implying that investors use relative performance rankings to select funds (O'Neal, 2004; Christoffersen, Evans, and Musto, 2007; Ivković and Weisbenner, 2009). This relationship is evident for current and past returns O'Neal (2004). Funds with the highest return rank receive disproportionately high inflows. This result also holds for abnormal returns (Cashman, Deli, Nardari, and Villupuram, 2007). Gross inflows are significantly related to past risk-adjusted performance, as measured by four-factor alphas over trailing 36 months windows, for up to a lag of five months. Moreover, inflows are more sensitive to the positive levels of risk-adjusted returns, again measured by four-factor alphas, than to negative levels, i. e. they increase more after high abnormal returns than they decrease after low abnormal returns (Keswani and Stolin, 2008b). The relationship between absolute raw returns is relatively flat (Ivković, Sialm, and Weisbenner, 2008). Moreover, investors do not actively rebalance into funds that depreciated in value in order to keep their allocation stable over time (Christoffersen, Evans, and Musto, 2007). Rather, current and potential investors reduce inflows as a response to poor performance (Cashman, Deli, Nardari, and Villupuram, 2006).

In contrast, O'Neal (2004) argues that fund flows are not sensitive to abnormal returns beyond the impact of the relative return rank. However, gross fund flows

[349] Part of this may by explained by reinvested distributions.

are highly persistent, potentially because investors move streams of fund flows such as monthly savings schemes instead of single flows or due to the delayed reaction of some investor clienteles (Cashman, Deli, Nardari, and Villupuram, 2007). Not accounting for fund-flow persistence might bias the empirical results on the performance-flow relationship and the study of O'Neal (2004) might suffer from exactly this bias.

Gross Outflows

Christoffersen, Evans, and Musto (2007) document that redemptions are insensitive to the performance rank of the fund relative to the investment objective based on trailing one-year returns. Only in the case of broker-sold funds, investors seem to withdraw money from poor performers while no-load fund investors show the strongest signs of a disposition effect. Ivković and Weisbenner (2009) confirm that outflows are not related to relative performance but document that gross outflows respond to absolute returns. Specifically, gross outflows increase after negative raw returns while investors are reluctant to sell winner funds that have recently appreciated in price. Both might be a result of tax considerations, realizing capital losses but postponing capital gains taxes.

Other studies document that redemption rates are slightly higher for winner funds than for loser funds, consistent with the rebalancing out of funds with relatively higher performance, especially for no-load funds (O'Neal, 2004; Christoffersen, Evans, and Musto, 2007; Cashman, Deli, Nardari, and Villupuram, 2006). This behavior results in a U-shaped performance-outflow relationship. Combined with strong inflows into winner funds, these results indicate that investors tend to quickly trade current winner funds.[350] A high correlation between gross inflows and gross outflows supports this conjecture (O'Neal, 2004). High frequency trades in and out of winner funds are more pronounced among riskier funds and the fraction of fund flows explained by these trades has dramatically increased in recent years. Keswani and Stolin (2008b) suggest that high frequency trades in and out of funds are primarily driven by the retail channel, at least for their U. K. data set.

With respect to risk-adjusted returns, Cashman, Deli, Nardari, and Villupuram (2006) report that current investors respond to low performance ranks based on four-factor alphas by redemptions. O'Neal (2004) confirms these results based on

[350] Note that part of these trades might be related to late trading as discussed in section 2.1.3.3.

relative market-adjusted returns for the current and prior year.[351] However, this negative relationship is not statistically significant within the worst performing quintile of funds. According to Keswani and Stolin (2008b), outflows are only sensitive to negative four-factor alphas but relatively flat over positive values of alpha. This implies that also gross flows, both inflows and outflows, follow a non-linear pattern similar to that observed for net inflows in previous studies. In combination with outflows in general being less responsive to performance than inflows this explains the convexity of the performance-flow relationship.[352]

However, gross outflows exhibit even higher persistence than gross inflows (Cashman, Deli, Nardari, and Villupuram, 2007). Accounting for this, the negative relationship between past risk-adjusted returns and gross outflows brakes down: gross outflows are not related to lagged four-factor alphas for lags of 1 to 12 months.[353] Consistent with these results, but not controlling for persistence, O'Neal (2004) reports that risk-adjusted performance does not seem to have an impact on redemption decisions after relative performance is included in the regression.

Time Period

The partially conflicting results of more recent studies on fund flows might be a result of different data sets and more importantly different time periods covered by the studies.[354] Ivković and Weisbenner (2009) cover the period from 1991 to 1996 and O'Neal (2004) from 1995 to 1999, which are mainly bull markets. Keswani and Stolin (2008b) analyze the period from 1992 to 2001 which is also dominated by positive market returns. Instead, Cashman, Deli, Nardari, and Villupuram (2006, 2007) analyze the period from 1997 to 2003 and Christoffersen, Evans, and

[351] Note that O'Neal (2004) uses returns over fiscal years of funds. To account for differences of fiscal year ends across funds he first adjusts annual fund returns for market returns.

[352] The lower sensitivity of outflows to performance is consistent with both, a behavioral explanation and the conjecture that outflows are more often driven by non-performance related reasons such as liquidity needs (Keswani and Stolin, 2008c).

[353] With the exception of weak significance at a lag of eight months.

[354] With respect to data sets, Ivković and Weisbenner (2009) study the individual accounts of a large discount broker covering more than 1,100 funds of more than 40 investment objectives which might represent a non-random sample of investors and funds. Cashman, Deli, Nardari, and Villupuram (2006, 2007), instead, focus only on equity funds and analyze gross-flow data from N-SAR filings to the SEC for a total of 2,619 funds. A similar data set is used by Christoffersen, Evans, and Musto (2007) for a total of 1,665 equity funds. O'Neal (2004) only includes the 200 largest equity funds in his sample, which are almost equally distributed between load and no-load funds, and uses 485-B forms to obtain gross flow data. Keswani and Stolin (2008b) are the only study providing international evidence based on 470 U. K. funds.

Musto (2007) use data from 1996 to 2003, periods characterized by positive and negative returns. Taking the differences between market environments into account, Shrider (2009) confirms that during rising markets, relative performance is more relevant in explaining the extent of redemptions while in down markets absolute performance matters more. Thus, during a period in which market returns are high and large sums of money are flowing into the fund management industry, relative performance matters more for redemptions. Eventually, this is a result of investors selling the laggards in their portfolio in order to finance the purchase of relative winner funds, consistent with the model of Johnson (2010). During market turmoil, however, investors seem to panic and sell those funds with the highest absolute losses.

4.2.7 Discussion

In summary, the new evidence for investors' reactions to past performance based on more disaggregated data sets still does not provide a clear picture of how investors behave. It appears that inflows respond to relative returns while outflows are more sensitive to absolute returns (Ivković, Sialm, and Weisbenner, 2008). However, several determinants are important to account for. The sophistication of investors, investor-specific participation and monitoring costs and the channel through which funds are traded, especially the question of whether or not investors receive professional advice, determine the speed and extent of the reaction and whether risk-adjusted or raw returns are used to judge the fund manager's skills. Moreover, tax considerations and the current market phase affect behavior. Conflicts of interest between the distribution channel and investors might further bias the results.

In addition, the strategic behavior of investors is relevant. For example, the risk of other investors withdrawing money from funds and the liquidity-induced transaction costs associated with this action might force other investors in this fund to withdraw first (Chen, Goldstein, and Jiang, 2010). Thus, the effect of fundamentals, i. e. past performance, on the incentive of investors to take action, i. e. to withdraw money, might be amplified if other investors are expected to take the same action. Liquidity-induced transaction costs are higher in less liquid securities and therefore this incentive to withdraw first is stronger for funds holding less liquid portfolios.

From a methodological perspective endogeneity between flows and performance and the persistence of fund flows are important determinants to consider. Moreover, because the same fund can have several investor clienteles with changing composition over time, the determinants of fund flows not only differ across funds but also over time. Therefore, a venue for further research might be to analyze differences across funds in greater detail rather than focusing on an explanation of average fund flows.

4.3 Fund Flows as Equilibrium Mechanism

If investors respond to past performance, as has been previously shown in section 4.2, it is interesting to analyze what implications follow from these actions for the relationship between past and future investment performance. Specifically, the resulting fund flows might affect the actions of fund managers and translate into a performance impact. To analyze this question in detail, this section takes the opposite view as compared to the previous section by asking how fund flows affect fund performance. The determinants of performance from section 3.8 are combined with the actions of fund investors from section 4.2 in order to derive the implications for performance persistence.

Several studies have attempted to measure the drag on performance resulting from distortions due to fund flows (e. g. Edelen, 1999; Alexander, Cici, and Gibson, 2007; Rakowski, 2010).[355] In an influential theoretical contribution Berk and Green (2004) argue that fund flows are a potential equilibrium mechanism for mutual funds. Even if different skill levels exist across fund managers a rational response of investors to observed performance prevents performance persistence among both, winner and loser funds.[356] They assume that investors learn about managerial skill by observing past performance and allocate their capital accordingly. Specifically, investors withdraw money from poorly performing funds and invest it into recent winner funds. A key assumption in the model of Berk and Green (2004) is that performance is not only a positive function of investment skills but at the same time negatively related to fund size:

[355] For a similar argument in the context of private equity funds see Diller and Kaserer (2009).

[356] A similar idea was already put forward by Lerbinger (1984) who suggests that the Peter's principle of Peter and Hull (1969) also applies to mutual funds: fund size adjusts to the individual level of incompetence of the fund manager erasing abnormal returns. This is expected to happen quickly because investment performance is easy to observe.

$$\text{performance}_i = f(\underbrace{\text{managerial skill}_i}_{(+)};\ \underbrace{\text{fund size}_i}_{(-)}). \tag{4.3}$$

The decreasing returns to scale in active management are explained by a positive relationship between fund size and transaction costs. Indeed, Chen, Hong, Huang, and Kubik (2004) and Yan (2008) document that small funds significantly outperform large funds, a finding which is consistent with decreasing returns to scale in active management. In combination with investors' response to past performance this prevents persistent abnormal returns. Recent winner funds grow in size up to the level that the transaction costs a manager faces balance his superior skill. Loser funds shrink in size such that decreased transaction costs bring them back to a neutral performance. Dangl, Wu, and Zechner (2008) interpret fund flows as an external governance mechanism which is based on the disciplining effect of the product market.[357] In short, inflows reduce future performance because fund size increases relative to managerial skill and outflows improve future performance because fund size decreases relative to managerial skill.

The higher the sensitivity of fund flows to past performance the higher the tendency to revert to the mean. For example, mutual fund ratings might be destructive for recent winner funds, which is termed "kiss of death" by Morey (2005). In particular, rating upgrades imply high skill of the fund manager but at the same time trigger high inflows. According to Berk and Green (2004) this potentially reduces the fund manager's ability to provide superior returns in the future. Instead downgrades, if they trigger outflows, might be beneficial for the future performance of perviously underperforming funds.

In comparison to the equity market, equilibrium on the mutual fund market is attained through fund flows rather than through price changes according to the model of Berk and Green (2004).[358] This is in contrast to the mechanisms of the equity market. If investors receive positive information about the skills of a manager of an industrial company the stock price is expected to adjust imme-

[357] Note that the negative impact of inflows on performance described above can be interpreted as a lack of governance. Driven by the fee interest of the investment management company funds are allowed to grow in size over and above the threshold that allows them to generate superior returns.

[358] Also, product market equilibrium is attained differently. For example, if a producer sells a certain good with a profit, competitors will enter the market and copy the successful strategy driving away the producer rents.

diately in an efficient market. However, the price of fund shares is determined by the stock prices of its underlying securities and managerial skill is not priced. Because the prize channel is not available fund size adjusts instead. In equilibrium, skilled fund managers maximize their salary by managing larger funds than their unskilled peers while expected abnormal returns are zero for all managers.[359] Thus, it is fund managers who earn the rents from their superior investment skills through higher fees, which are proportional to fund size, rather than investors through abnormal net returns. Moreover, the findings of Chen, Hong, Huang, and Kubik (2004) and Yan (2008) that small funds outperform large funds indicates that a significant fraction of funds are off their equilibrium size in the sense of Berk and Green (2004) because investors do not respond fully rationally to past performance.

Despite its theoretical appeal, the model of Berk and Green (2004) lacks an explanation of how exactly decreasing returns to scale set in. They basically assume a positive relationship between fund size and average transaction costs which are a drag on alpha. However, if funds add new stocks to the portfolio rather than upscaling existing holdings, why should average transaction costs increase? Moreover, it is important to distinguish between short-term and long-term effects of fund flows which, in some cases, are in the opposite direction. In the short term, fund flows itself have an immediate impact on performance because money has to be invested in the case of positive net inflows or assets have to be sold in the case of negative net inflows (liquidity-induced trades). Over longer periods the change in fund size which results from earlier fund flows is more relevant. The model of Berk and Green (2004) focuses on the latter effect but it seems important for a comprehensive understanding of how flows affect performance to consider both short-term and long-term effects. To analyze the impact of flows on performance in detail and the different choices a fund manager has as response to inflows or outflows, fund size, as measured by total net assets (TNA_{it} of fund i in period t), can be disaggregated into its components:

[359] Fama and French (2010) argue that the model of Berk and Green (2004) violates equilibrium accounting because active investors can only earn zero alphas before the costs of active management are deducted (this gross active return is equal to the net return of passive investors) and negative alphas after the costs of active management are taken into account.

$$\mathrm{TNA}_{it} = \mathrm{cash}_{it} + \sum_{j=1}^{m_{it}} \mathrm{own}_{ijt}\ \mathrm{mcap}_{jt} \tag{4.4}$$

where cash_{it} is the value of the cash position in period t, m_{it} is the number of risky assets in the fund's portfolio in period t, own_{ijt} is the ownership of fund i in asset j as measured by the fraction of total shares outstanding of asset j held by the fund in period t and mcap_{jt} is the market capitalization of asset j in period t.

In the case of positive or negative net inflows, the first option a fund manager has is to adjust the cash position and leave the composition of the risky assets untouched.[360] However, this option is usually limited to lower levels of inflows or outflows. In the case of larger net inflows, the manager can upscale or downscale existing investments according to the level of net inflows. That is, he proportionately buys or sells all assets in the portfolio altering the ownership share of each stock. As an alternative, in the case of inflows, he could replace small companies with low market capitalizations by larger companies which allows him to increase the fund size while keeping the ownership share and the number of stocks in the portfolio constant. In the case of outflows, he can accordingly replace large cap stocks by small cap stocks. This has an impact on the size tilt of the portfolio. As a last option to respond to non-zero net inflows, the fund manager could adjust the number of stocks in the portfolio by diversifying or concentrating. Diversification means adding new stocks to the portfolio which have previously not been held, while concentration refers to selling off existing holdings. Even though fund managers tend to respond to non-zero net inflows by a combination of these choices it becomes evident from Table 4.1 that each of the choices has a distinct impact on fund performance.[361] In the following, each of these mechanisms is analyzed in detail and the question of whether some of these mechanisms might contribute to the observed short-term persistence and long-term mean reversion in fund performance is discussed.

[360] Note that net inflows are the difference between gross inflows and gross outflows.

[361] This section focuses on the general impact of fund flows on fund performance. In the empirical part it is further distinguished between different performance measures based on multifactor models and a more detailed analysis of how performance is affected by fund flows is provided, see Table 7.2.

Table 4.1: Expected response of fund performance to fund flows

This table presents the potential response of fund performance to inflows (left panel) and outflows (right panel), respectively. A black triangle (▼) indicates a decrease and a white triangle (△) indicates an increase in performance. The potential response of the fund manager to fund flows can be summarized by Equation (4.4): $\text{TNA}_{it} = \text{cash}_{it} + \sum_{j=1}^{m_{it}} \text{own}_{ijt}\ \text{mcap}_{jt}$. Panel (a) refers to a variation of the cash position (variation of cash_{it}), panel (b) refers to all trades in risky securities, irrespective of the specific type of trade, panel (b1) refers to an adjustment of the ownership as measured by the fraction of total shares outstanding held by the fund for each holding (variation of own_{ijt}), panel (b2) refers to an adjustment of the market capitalization of each holding (variation of mcap_{jt}) and panel (b3) refers to the concentration of the portfolio as measured by the number of stocks (variation of m_{it}).

Inflows		Outflows	
Description	Perf.	Description	Perf.
(a) Cash position			
Cash drag	▼	Cash drag	▼
Beta decreases	▼	Beta increases	△
(b) All trades in risky assets			
Transaction costs	▼	Transaction costs	▼
Distorted security selection	▼	Distorted security selection	▼
(b1) Ownership ratio (upscale / downscale)			
Price pressure (short term)	△	Price pressure (short term)	▼
Price pressure (long term)	▼	Price pressure (long term)	△
Position liquidity decreases	▼	Position liquidity increases	△
(b2) Market capitalization (adjust size tilt)			
Average market cap increases	▼	Average market cap decreases	△
Asset liquidity increases	▼	Asset liquidity decreases	△
Information advantage decreases	▼	Information advantage increases	△
(b3) Portfolio concentration (diversify / concentrate)			
More best ideas required	▼	Fewer best ideas required	△
Hierarchy costs increase	▼	Hierarchy costs decrease	△

4.3.1 Cash Position

Cash Drag

A fund's cash position usually serves two objectives. First, fund managers actively alter the fraction of their portfolio held in the risk-free asset as a simple mechanism to time the market exposure. Second, and even more importantly, it serves as a buffer for fund flows because mutual fund shares are traded in a cash transaction.[362] Immediate and rapid investment of fund flows is costly in terms of adverse selection and transaction costs, which ultimately reduces the fund's alpha. In order to avoid that each dollar of inflows or outflows leads to a trade at the fund level, funds usually try to adjust the share of their portfolio in the risk-free asset to the level of expected fund flows and unexpected deviations from that level (Chordia, 1996). Fund managers aim to identify the optimal cash position as a trade-off between transaction costs of liquidity-induced trading and a cash drag (Connor and Leland, 1995).[363] Cash drag refers to the costs of a suboptimal cash position. The average return on risky assets is higher than that of the risk-free asset. The portfolio alpha is the weighted average of the individual portfolio holdings' alpha. Thus, the higher the cash position the lower the average return and the closer the portfolio alpha is to zero. However, in times of negative market returns, funds can benefit from a large cash position. Yan (2006) finds that the actual cash level is usually above the level which would be optimal without unexpected fund flows reducing average fund performance. Because both large inflows and outflows induce a higher level of cash holdings, a cash drag cannot be an explanation for mean reversion in fund performance because it even reduces the performance of loser funds when they experience large outflows rather than improving it as predicted by Berk and Green (2004).[364] Rather, absolute fund flows or fund-flow volatility determine the level of the cash drag.

Unintentional Beta Variation

However, there might still be an important role for the cash position in explaining mean reversion in fund returns. In the case of inflows, the cash position increases

[362] Moreover, the cash position is a buffer for cash inflows from dividends and rights issues (Connor and Leland, 1995).

[363] Additionally, index funds aim to minimize a potential increase in tracking error due to fund flows (Connor and Leland, 1995).

[364] This can also be seen in Table 4.1 because in both cases of inflows and outflows, the arrows point in the same direction.

and the overall portfolio beta decreases if the fund manager is not willing to trade at this point in time. This allows the manager to trade patiently and to avoid excessive transaction costs but results in sub-optimal portfolio betas and negative market timing skills. Average raw returns are negatively affected while risk-adjusted returns control for the beta shift and are not affected.[365] In the case of outflows, the cash position is reduced leading to an upward shift in the portfolio beta and a corresponding increase in raw returns while risk-adjusted returns, again, remain unaffected. Because fund inflows tend to be stronger in rising markets, et vice versa, this results in unintentional beta variation sometimes referred to as "perverse timing" (Ferson and Schadt, 1996). The empirical results of Coval and Stafford (2007) are consistent with a positive relationship between lagged net inflows and the current cash ratio of the portfolio implying a negative relationship between net inflows and the portfolio beta. Moreover, Ferson and Warther (1996) document evidence of a significant negative relationship between changes in net sales of funds and changes in beta on an aggregate basis.

4.3.2 Transaction Costs and Distorted Security Selection

Transaction Costs

When inflows drive the cash level significantly above the desired level or it decreases below that level due to outflows, fund managers need to trade in the underlying assets. Irrespective of which approach the manager chooses according to equation (4.4), upscaling existing positions, diversifying into additional stocks and swapping into larger stocks in the case of inflows or downscaling, concentrating the portfolio and swapping positions into smaller stocks in the case of outflows, this induces transaction costs. Commissions and market impact reduce fund performance in the short term irrespective of the direction of flows.[366] Empirical results support this view. Funds with more volatile daily flows tend to

[365] This assumes that the time-varying beta can be precisely observed or estimated. In empirical applications beta can only be estimated with estimation error which results from the actions of the fund manager. In this case, the alpha is also biased and it becomes empirically impossible to distinguish between the different effects on raw returns and risk-adjusted returns.

[366] Transaction costs for liquidity-induced trades are usually higher than those of information-based trades (Edelen, 1999). However, if the fund manager can successfully signal that his trade motive is not private information, he might be able to trade more cheaply (Keim, 1999). For a general discussion of the relevance of transaction costs for the generation of abnormal returns see Madhavan and Coppejans (2008).

underperform their peers with less volatile flows (Rakowski, 2010).[367] Daily gross inflows can only be balanced by gross outflows of the same day resulting in the need to invest (divest) the remaining positive (negative) daily net inflow. Johnson (2004) argues that these indirect costs are economically significant compared to direct costs such as management fees.[368]

Edelen (1999) estimates that on average between 63 and 67 percent of inflows result in purchases (depending on whether he uses a time-series or cross-sectional regression specification). The corresponding numbers for outflows are 76 and 68 percent. Thus, about two thirds of inflows or outflows result in trading in underlying stocks. Dubofsky (2010) applies a broader sample of funds and reports slightly lower estimates of liquidity-induced trading compared to Edelen (1999).[369] Based on the time-series specification, on average only 12 percent of inflows and 47 percent of outflows result in trading for domestic non-index equity funds.[370] However, the results based on the cross-sectional regression approach are more in line with Edelen (1999): 77 percent of inflows and 65 percent of outflows lead to portfolio trades. For the entire sample including international and bond funds, Dubofsky (2010) reports that, respectively, between 30 and 68 percent of inflows and between 51 and 52 percent of outflows induce purchases and sales. Liquidity-induced trading is lowest among international funds, presumably because of higher trading costs in international equities, and highest among index funds which follow the most restricted investment strategy and face the additional risk of an increased tracking error if they do not immediately adjust their portfolio.[371] Again, inflows

[367] Note that net inflows clearly understate the amount of money funds have to deal with. Net inflows into equity mutual funds were 136 billion USD in 2005. The corresponding gross-flow figures are 1,210 inflows and 1,074 billion USD outflows (Cashman, Deli, Nardari, and Villupuram, 2007).

[368] Moreover, they are caused disproportionately by heterogeneous investor clienteles who demand liquidity to a different extent. Specifically, transaction costs are positively related to the trading frequency of each individual fund investor but are born equally by all fund investors. Thus, a wealth transfer from long-term investors to actively trading short-term investors occurs. It seems reasonable to belief that retail investors have a long-term investment horizon whereas at least some institutional investors aim at short-term gains (e. g. Goetzmann, Ivković, and Rouwenhorst, 2001; Greene and Hodges, 2002; Zitzewitz, 2003, 2006). Thus, the composition of a fund's investment clientele determines the level of liquidity-induced transaction costs.

[369] Specifically, Edelen (1999) employs 166 randomly chosen U. S. equity funds between 1985 and 1990 while Dubofsky (2010) uses 2680 domestic and international equity and bond funds for the period from 1999 to 2003.

[370] Note that median estimates are 57 and 32 percent respectively.

[371] Moreover, international equity funds were the primary targets of fund timing strategies (see section 2.1.3.3). Because of these high frequency trades in and out of the fund, they tend to have the longest cash accumulation period (Dubofsky, 2010).

and outflows increase transaction costs and the absolute level of fund flows or flow volatility seems to be the better determinant of the performance drag.

Distorted Security Selection

However, these liquidity-induced trades might occur at inopportune times and force mutual fund managers to select stocks they are willing to buy or sell, respectively, which they might not optimally choose (Edelen, 1999; Alexander, Cici, and Gibson, 2007).[372] Moreover, Stein (2005) argues that the open-end structure of mutual funds prevents fund managers from pursuing successful long-term investment strategies because they face the risk of outflows when convergence to fundamentals is unlikely to be smooth or rapid. But a focus on short-term gains is not optimal from the perspective of most investors and induces high trading expenses.

Dividing a fund's alpha into a part resulting from liquidity-induced trading volume and discretionary trading volume shows that the former has a negative impact on performance in the long run (Edelen, 1999). One unit of liquidity-based trading (purchases or sales), equal to the fund's total net assets in size, reduces abnormal performance by 1.74 percent, 0.63 percent of which can be explained by administrative expenses and commissions while the remainder is an idiosyncratic component due to losses to informed investors. Frino, Lepone, and Wong (2009) report that 1.5 percent of fund flows is lost in trading and market timing measures are also negatively affected by fund flows.

In a similar vein, Alexander, Cici, and Gibson (2007) provide more direct evidence based on individual trades of fund managers conditioned on their trading motive. The trading motive is measured by the level of fund flows during the month the trade was made and the trade size. Purchases concurrent with outflows, classified as valuation-induced, outperform stock investments made in periods with concurrent inflows, which are classified as liquidity-induced, by 2.81 percentage points the following year.[373] Additionally conditioning on trade size reveals even stronger results. Large purchases concurrent with high outflows are interpreted as most informative buying decisions and outperform small purchases

[372] However, fund flows might also be used to cheaply rebalance the portfolio in case it has become misaligned due to different relative price changes of portfolio stocks (Johnson, 2004).

[373] Only trades in the first three quarters of a year are considered to avoid a bias from year-end window dressing and tax-induced trading. However, including the fourth quarter only marginally affects the results.

during inflows which are believed to be predominantly liquidity-induced. Indeed, large information-induced buys outperform small liquidity-induced transactions even by 3.20 percentage points in the subsequent year. Consequently, even ignoring trading expenses, liquidity-induced purchases and sales reduce the funds' performance relative to a characteristics-based benchmark compared to a situation without liquidity-induced trading, i. e. only with information-induced trades.

A complimentary explanation for this effect might be the endogenous response of corporate managers to a temporary overvaluation of their company's shares by initiating an SEO or selling their own shares (Frazzini and Lamont, 2008; Khan, Kogan, and Serafeim, 2009). Frazzini and Lamont (2008) report that stocks held by funds with large inflows, which is interpreted as an indicator for high sentiment stocks, underperform in the following months partly because they respond to high investor sentiment by issuing additional capital.

Consistent with the results for inflows, stocks sold during periods with outflows (liquidity-induced) subsequently exhibit 1.70 percentage points higher performance than stocks that are sold during periods with inflows (valuation-induced). Following a similar argument with respect to trade size in the case of purchases, large sales during inflows significantly underperform small sales during outflows. Small liquidity-induced sales outperform large valuation-induced sales by 2.21 percentage points. It would have been better from the fund's perspective to keep the stocks which have been sold due to liquidity demand from redemptions. Similar to the arguments of Frazzini and Lamont (2008) one might expect that corporate managers respond to the low sentiment of investors by initiating share repurchase programs or the like which would also contribute to performance reversals (Bessler, Drobetz, and Seim, 2009). Although, based on this argument, fund performance would not revert to the mean because fund flows are affecting managerial skill as described by Berk and Green (2004) but rather because of an endogenous reaction from corporate managers on fund flows.

Liquidity-induced trades, both buys and sells, are detrimental to fund performance because of distorted trading decisions and associated trading costs. Even though this relationship might explain why winner funds that receive high inflows tend to revert to average performance it falls short of providing a rationale for mean reversion among loser funds. Quite to the contrary, according to the above argument "liquidity-motivated trading should be associated with negative abnormal returns, whether the trade is a sale or a purchase" (Edelen, 1999, p. 457). If outflows distort selling decisions and cause higher transaction costs and administrative expenses, then loser funds with outflows should face an even more difficult task in bringing performance back to the mean.

4.3.3 Ownership

Price Pressure

In the case that a successful fund manager uses inflows to upscale existing positions, the resulting price pressure might be beneficial and boost fund performance in the short run but might also contribute to mean reversion over longer time periods. Specifically, recent winner funds that receive high inflows might drive up the prices of stocks held in their portfolio if their ownership share is already relatively high.[374] Wermers (2003) suggests that winner funds have similar holdings, i. e. recent winner stocks, which enforces the price pressure triggering even more inflows and initiating a feedback loop.

The empirical results of Wermers (2003) and Coval and Stafford (2007) are consistent with this view. Price pressure may contribute to performance persistence over shorter horizons and, at the same time, explain why winner-fund performance reverses some time after a positive streak because the price impact from uninformed trading is usually only transitory (Bernhardt and Davies, 2009). Controlling for the flow-induced price pressure Wermers (2003) cannot document a large spread between past winner and loser funds implying that performance persistence is explained by flow-induced price effects rather than by persistent management skill. Thus, after a longer period of persistent inflows, upscaling has a negative effect on performance once the price pressure discussed above dies out. However, the results of Rakowski and Wang (2009) for the very-short run are inconsistent with this argument. They find that past net inflows have a permanent

[374] Other studies confirm the price pressure effect resulting from fund flows on an aggregate market level. For the period from 1984 to 1993 Warther (1995) documents strong evidence that monthly fund flows are positively correlated with current returns of the stocks held by these funds. However, investors do not seem to follow positive-feedback trading strategies. Using daily data, Edelen and Warner (2001) report a positive concurrent relationship between fund flows and market returns. This concurrent relationship seems to be driven mainly by a response of returns to fund flows as indicated by an analysis of intraday data. The response of fund flows to market returns, however, is lagged one day implying that mutual fund investors respond to common news or just follow positive-feedback trading strategies. Goetzmann and Massa (2003) support the result that aggregate fund flows affect market returns based on an analysis of daily data on index funds. Oh and Parwada (2007) provide recent support for these findings for the Korean market.

positive impact on performance over three days which does not revert back over longer horizons.

In the case of excessive outflows, the choice of which stocks to sell is naturally restricted to the portfolio holdings. Thus, price pressure is also a matter when redemption rates are high.[375] This is especially severe when several funds become losers due to overlapping holdings and simultaneous outflows. Several of these distressed funds are then forced to sell the same stocks while no natural buyers are present. Indeed, funds in the bottom decile of net inflows are about twice as likely to sell stocks compared to funds experiencing normal flow. The higher the overlap in holdings of funds with large outflows, the more prices are temporarily driven away from fundamental values. Coval and Stafford (2007) report that in the two quarters (quarter $t-1$ and event quarter) with the strongest selling pressure for stocks sold by funds with the highest outflows cumulative abnormal returns are highly significant -7.9 percent, almost all of which is reversed in the 12 months following the sale. These forced sales are particularly expensive when at the same time market liquidity dries up, as in the case of market turmoil. Usually, in these scenarios investors tend to withdraw money from mutual funds that invest in risky assets such as bonds and stocks while market volatility and spreads increase, making transactions more expensive. Open-end funds do not have any mechanism to hedge against this scenario because the money flows to other types of mutual funds, such as money market funds, and bank deposits.[376]

Because these transactions are predictable, other investors can benefit at the expense of funds suffering from immediate liquidity needs by providing liquidity or even front-running these trades. Indeed, hedge funds show higher returns during months when a large fraction of mutual funds are in distress as defined by fund outflows exceeding four percent of total net assets (Chen, Hanson, Hong, and Stein, 2008). Furthermore, short interest is higher in the stocks heavily sold by mutual funds in distress. Both findings indicate that hedge funds profit from extreme fund flows out of mutual funds by front-running their trades and by providing liquidity.[377]

[375] Note that the full effects of price pressure only unfold fully over time when the fund manager retains a fraction of the asset in the portfolio, i. e. only downscales the holding.

[376] For example, Gatev and Strahan (2006) argue that banks offer a unique mechanism to hedge against an increase in loan demand due to market-wide liquidity shocks on the commercial paper market because usually deposits increase when market-wide liquidity shocks occur and can be used to finance the increased demand for loans.

[377] However, the data set of Chen, Hanson, Hong, and Stein (2008) does not allow them to

Price pressure when selling stock due to outflows is an important determinant of fund performance in distressed situations. Similarly to winner funds, it might explain why poor performance persists (or even magnifies) over the short run but reverses after some time when the transitory effect of price pressure reverses. This is consistent with the predicted negative relationship between net inflows and performance, i. e. an improvement in performance when net inflows are negative, in the model of Berk and Green (2004).

Position Liquidity

In the long run, in particular previously outperforming funds suffer from an increased asset base due to inflows. Most fund managers respond to inflows by upscaling existing positions (Coval and Stafford, 2007; Pollet and Wilson, 2008). Coval and Stafford (2007) report an almost linear increase in the change in ownership from the lowest to the highest net inflow decile.[378] In a frictionless world, this should not have an impact on average fund performance or alpha because all portfolio weights are adjusted proportionately. However, in a world with frictions, the position liquidity is reduced because the fund owns an ever larger fraction of total shares outstanding for each company in its portfolio.[379] Average transaction costs increase with fund size and trading flexibility of the fund manager is significantly reduced (Chan, Faff, Gallagher, and Looi, 2009). Furthermore, large trades are more expensive and difficult to hide. Other investors can easily front-run and exploit the information contained in the trading behavior of large funds. Indeed, Chen, Hong, Huang, and Kubik (2004) provide empirical evidence that transaction costs increase with fund size and report a negative relationship between lagged fund size and performance. Yan (2008) confirms this finding and

distinguish whether the trading signals for hedge funds are generated from public information of whether private information is used, which might potentially be illegal if this information comes from brokers that serve as the prime broker for the hedge fund but at the same time execute the trades of the mutual funds.

[378] Specifically, the lowest decile funds experience outflows of on average −12.5 percent per quarter and decrease their holdings by on average −20.5 percent while the highest inflow decile receives 23.7 percent of the previous month's total net asset as new money and increases the number of shares in the average position by 0.8 percent. These numbers clearly are biased downward because portfolio turnover is positive, i. e. the average fund reduces the number of shares in its average position by roughly 10 percent each quarter. Thus, the correct interpretation is that the ownership ratio strongly responds to inflows (Coval and Stafford, 2007).

[379] Position liquidity refers to the liquidity of the total position a fund holds in a certain stock. It depends on the asset liquidity of the stock, e. g. large-cap stocks tend to be more liquid than small-cap stocks, and is negatively related to the ownership ratio, i. e. the fraction of shares outstanding held by the fund.

strongly relates the negative impact of fund size on performance to liquidity aspects. These negative effects are larger the lower the operational efficiency of the fund (Chalmers, Edelen, and Kadlec, 2001a). Additionally, if the number of stocks in the portfolio increases the time and resources of the portfolio manager spend on research are reduced per stock. Even though Johnson (2004) points out that fund investors might also benefit from cost reductions due to economics of scale in large funds the negative impact of higher transaction costs seems to dominate.

The opposite occurs when a fund has a longer streak of outflows. The average ownership share decreases and position liquidity is improved with beneficial effects for average transaction costs. Consequently, position liquidity is a potential mechanism through which positive net inflows reduce subsequent performance and negative net inflows help to improve performance. Because the effect is translated into performance through higher transaction costs it affects all performance metrics net of transaction costs such as raw returns and all alpha measures.

4.3.4 Market Capitalization

Upscaling or downscaling existing holdings is not the only choice for fund managers as a response to inflows. In order to avoid the negative side-effects associated with a proportionate increase or decrease in the ownership of each position they can alternatively alter the average market capitalization of stocks in their portfolio. In the case of inflows, small-cap stocks are replaced by large-cap stocks and the opposite transaction is done in the case of outflows.[380] This allows the manager to accommodate the fund flows without altering the ownership or the number of stocks in the portfolio.

Investment Style

If the fund managers respond to fund flows by adjusting the average market capitalization of their portfolio stocks the long-term investment style of the fund depends on past fund flows. For example, positions in very small companies become unavailable for funds that received high amounts of new money. This would imply a negative relationship between lagged net inflows and the small-cap tilt of the portfolio as measured by the loading on the SMB factor for example. Performance

[380] Note that altering the average market capitalization of the portfolio might also have unintentional effects on the portfolio beta because the composition of the portfolio changes. However, it depends on the individual stocks' beta whether this increases or decreases the portfolio beta and, thus, the impact on performance is ambiguous.

metrics not controlling for the size exposure are negatively related to past inflows through this mechanism while performance measures that take size into account, such as the four-factor model of Carhart (1997), remain unaffected. Consistent with this, persistence is stronger among small-cap funds because those with high inflows eventually become large-cap funds over time (Blake and Timmermann, 1998; Huij and Verbeek, 2007).

Asset Liquidity

Another result from tilting the portfolio toward large-cap stocks after inflows is that the average asset liquidity of the portfolio holdings increases. In general, this has the beneficial effect of lowering transaction costs. However, several authors argue that illiquidity bears a risk premium, especially if it systematically varies with market-wide liquidity (e. g. Chan and Faff, 2005; Acharya and Pedersen, 2005; Amihud and Mendelson, 2006).[381] Thus, tilting toward more liquid stocks prevents the fund from earning a liquidity premium which would show up as positive abnormal returns in most performance metrics.[382] Only once a liquidity factor is specifically added to the performance model, alpha remains unaffected. A similar relationship holds true in the case of outflows. Fund managers have a preference of selling liquid stocks first when exposed to redemptions (Clarke, Grant, and Gasbarro, 2007). Moreover, they tilt their portfolio holdings toward liquid stocks when they expect more volatile markets and more volatile fund flows (Huang, 2008; Chan, Faff, Gallagher, and Looi, 2009). Thus, in the case of outflows, the average portfolio liquidity is reduced which translates into positive abnormal returns for all but the liquidity-augmented measures. Consequently, the open-end feature of mutual funds limits the flexibility of investment strategies. On average, mutual funds tend to hold more liquid stocks reducing the potential to outperform (Chordia, 1996). Massa and Phalippou (2005), however, argue that funds which are restricted by higher higher liquidity needs make up for this performance drag using a variety of measures such as lower fees, higher skills or even cross-fund subsidization. Funds that cannot do so and consistently underperform because of their higher liquidity needs would disappear from an efficient mutual fund market in the long run. However, over the medium term variation in the funds' liquidity

[381] See section 3.4.1.4 for a more detailed discussion.
[382] The aggregate effect on performance is a function of portfolio turnover and the level of the liquidity premium which depends on the marginal investor's portfolio turnover and the sensitivity of the asset's liquidity to market liquidity.

over time, which is to a large extent driven by fund flows, might explain mean reversion in mutual fund performance.

Information Advantage

Moreover, analyst coverage is usually positively related to company size (Hong, Lim, and Stein, 2000). Thus, it is harder for managers to gain an informational advantage in large-cap stocks. The segment of large-cap stocks appears to be more efficient as compared to small-cap stocks. Tilting the portfolio toward large caps also increases the tendency to become a closet indexer (Cremers and Petajisto, 2009). These funds closely follow their benchmark and have low alphas as a result. All of these effects might explain why funds which previously received high inflows subsequently generate lower abnormal returns. Additionally, funds that experienced large outflows may benefit from a reversal of these effects.

4.3.5 Portfolio Concentration

Rather than upscaling or swapping small for large stocks existing holdings fund managers might respond to positive net inflows by initiating new positions in stocks.[383] This seems to be beneficial for performance relative to the other choices. Initiating buys subsequently outperform their characteristics-based benchmark according to the methodology of Daniel, Grinblatt, Titman, and Wermers (1997) by 0.80 percentage points in the following year (Alexander, Cici, and Gibson, 2007). These results are complimentary to the evidence in Pollet and Wilson (2008) who document that fund performance benefits from diversification, especially in the case of illiquid investment objectives such as small-cap funds. Increasing the number of stocks in the portfolio from 50 to 100 increases annualized performance by 0.37 to 0.51 percentage points depending on the model specification. This effect is much stronger for funds investing in the smallest quintile of stocks at 0.76 to 0.92 percentage points. It decreases almost monotonically from small-cap to large-cap funds. Excluding all funds smaller than 100 million USD from the analysis roughly doubles all estimated coefficients.[384] Capacity constraints are most severe for large funds and benefits from diversification are positively related to a

[383] Note that also diversifying or concentrating the portfolio might have unintentional effects on the portfolio beta because the composition of the portfolio changes. However, it depends on the individual stocks' beta whether this increases or decreases the portfolio beta and, thus, the impact on performance is ambiguous.

[384] These funds account for approximately 10 percent of total assets under management in 1980 and for less than 2 percent in 2000.

fund's total net assets and negatively related to the average market capitalization of stocks held by the fund.

Best Ideas

Even though diversification seems to be the best choice for fund performance when exposed to significant inflows, this cannot avoid a negative relationship between inflows and fund performance over the longer term because diversification is not sustainable over the longer run. Usually, fund managers have a limited list of best ideas and invest in those companies in a descending order with lower positions yielding lower abnormal returns (Cohen, Polk, and Silli, 2009; Pomorski, 2009). After a significant increase in fund size, good investment opportunities vanish and funds literally meet the capacity constraints of their formerly successful investment strategies. Similarly, when fund size decreases, fund managers' best ideas make up a larger fraction of overall fund performance which should help to enhance performance. However, this beneficial effect depends on the ability of the fund manager to generate best ideas in the first place. If he was unable to do so before and ended up in the bottom decile due to a lack of investment skills, why should a smaller fund size help?

Consistent with capacity constraints, Morey (2005) documents that fund performance subsequently suffers from a five star rating by Morningstar, which usually entails large inflows. Capacity constraints have also been documented for hedge fund strategies by Naik, Ramadorai, and Stromqvist (2007) for the recent period of 2000 to 2004 when hedge funds received large amounts of new money. Performance deterioration is strongest for those hedge fund strategies that attracted the highest inflows because many managers follow the same investment ideas. The results are economically significant: a 10 percent increase in annual flows deteriorates performance by 0.36 to 0.94 percentage points in the following months compared to an average alpha across all funds of 0.25 percent. However, this relationship cannot be confirmed for all strategies indicating heterogeneity between those strategies in the ability of coping with new money from investors. In particular, strategies relying heavily on the liquidity of the underlying markets, such as relative value, fixed income and emerging markets, suffer from significant inflows. This implies that not only a lack of best ideas but also an increase in average trading expenses, as discussed above, might be relevant for capacity constraints. However, this research does not provide an answer for whether fund performance can benefit from outflows to the same degree. For individual hedge funds, Fung, Hsieh, Naik, and Ramadorai (2008) provide empirical evidence that high net inflows attenuate the ability of hedge funds to generate persistent abnormal returns. However, subsequent differences between the subgroups of hedge funds with high and low net inflows are statistically significant only for t-values of alphas (1.47 versus 1.84) but not for differences in levels of alphas themselves (4.7 versus 3.5 percent annual performance), due to the high variance in the level of alpha in the cross-section.

Hierarchy Costs

Fund management companies might try to increase the generation of best ideas by hiring additional managers for a fund. However, team-managed funds, in general, are unable to outperform single-managed funds.[385] Even worse, hiring new managers bloats the fund's organization and eventually leads to increased hierarchy costs because individual managers in the team internally compete for capital (Chen, Hong, Huang, and Kubik, 2004). Indeed, empirical results support this hypothesis. Large funds tend to underperform small funds because hierarchy costs outweigh the benefits from a management team (Chen, Hong, Huang, and Kubik, 2004; Yan, 2008). Moreover, Kempf and Rünzi (2008b) provide evidence that individual fund managers in the same fund family compete with each other in tournaments. Thus, fast growth of a fund's total net assets results in performance deterioration through capacity constraints and hierarchy costs.

In the opposite case of outflows, fund managers can completely sell off existing holdings which increases the portfolio concentration. Performance usually benefits from this, as outflows are used to dispose of momentum losers. A complementary explanation is that outflows mitigate behavioral biases such as a disposition effect of fund managers (Shefrin and Statman, 1985). It may be easier for fund managers to break up with momentum losers when forced to sell something through outflows as compared to situations where they do not necessarily have to sell stocks. Terminating sells underperform their characteristics-based benchmark by -0.98 percentage points in the subsequent year which implies that is was the correct decision to sell (Alexander, Cici, and Gibson, 2007). Thus, outflows seem to improve performance when they are used to concentrate the portfolio. First, it appears that fund managers have some skills when selecting the right stocks to

[385] Prather, Middleton, and Cusack (2001), Prather and Middleton (2006), Bär, Ciccotello, and Rünzi (2008), Bär, Kempf, and Rünzi (2010), and Bär, Niessen, and Rünzi (2008).

sell and, second, outflows reduce capacity constraints and hierarchy costs. After a smaller fund size is reached, the fund can be single-managed and this manager can focus on his best ideas.

Fund Family Response

In addition to a response at the fund levels, fund families might also respond to asset growth. Indeed, fund families tend to establish new funds when they receive large inflows (Pollet and Wilson, 2008), an effect which is even more pronounced among large families (Khorana and Servaes, 1999). The number of stocks held by all funds of one family increases even more than the number of funds. Hence, family growth is strongly associated with the generation of additional investment ideas which mitigates capacity constraints. This result is consistent with a positive impact of fund family size on performance (Chen, Hong, Huang, and Kubik, 2004; Yan, 2008). On the contrary, the individual funds of large fund families are even more reluctant to diversify their holdings as a response to inflows as compared to the average fund (Pollet and Wilson, 2008). Pollet and Wilson (2008) suggest that this behavior is partly explained by the ability of large fund families to lower overall transaction costs in combined holdings alleviating liquidity constraints for each individual fund. This implies that one fund family with two funds each of 500 million USD in size is not the same as a fund family with one fund of 1 billion USD total net assets. It seems important for the generation of successful investment ideas to employ more fund managers while at the same time equipping them with discretionary decision making power.

4.3.6 Discussion

The analysis above reveals that the open-end feature imposes certain risks and liquidity costs on fund investors and prevents mutual funds from pursuing certain investment strategies and persistently outperforming the market. These effects are stronger in narrow markets and if the investment objective is more illiquid. Thus, asset growth due to fund flows contributes to performance reversals of previous winner funds.[386] The level of performance sensitivity of investors determines the

[386] In addition, fund flows are an important determinant of after-tax returns. Specifically, outflows might force the manager to sell appreciated stocks in order to satisfy the liquidity demand by investors imposing a tax burden through the distribution of capital gains on the remaining investors (Dickson, Shoven, and Sialm, 2000). These negative effects can be partly mitigated if active managers consider these aspects in their investment decisions (Dickson, Shoven, and Sialm, 2000; Johnson, 2004).[387] On the other hand, large inflows

speed and extent of this mean reversion.[388] With respect to the underlying mechanisms of performance reversals, all mechanisms imply a negative relationship between positive net inflows and subsequent performance (Table 4.1).[389] Consistent with this, most empirical studies offer potential explanations for why it is so difficult to persistently outperform (e. g. Edelen, 1999; Alexander, Cici, and Gibson, 2007; Rakowski, 2010).

However, it is important to note that not all of the mechanisms discussed above are consistent with the model of Berk and Green (2004) in the case of loser funds. Therefore, the relationship between outflows and subsequent performance is more ambiguous and empirically less well documented. In fact, fund performance is reduced if money is withdrawn by investors because of distorted security selection and transaction costs, as documented by Edelen (1999) and Alexander, Cici, and Gibson (2007), and a larger cash drag, consistent with the findings of Rakowski (2010). For loser funds, this makes performance reversals even more unlikely. Moreover, if funds end up as loser funds because of a lack of the fund manager to generate best ideas with positive abnormal returns in the first place, it might be questionable if a reduction in fund size due to outflows, which theoretically should improve the ability to concentrate on fewer and more successful best ideas, indeed results in performance reversals. If no investment skill exists, a small fund size alone might not help. In the short-run temporary price movements due to selling pressure of loser funds with similar holdings reduce performance even further. Thus, it is an empirical question which of the positive and negative effects of outflows dominate. This might strongly depend on the time period considered.

Moreover, the empirical findings of higher performance persistence among hedge funds would be consistent with the model of Berk and Green (2004) because the response of inflows to past performance is slower among hedge funds compared to mutual funds according to Baquero and Verbeek (2005).[390] This reduces the downward pressure on performance following a period of high returns. However,

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can dilute the unrealized capital gains to the benefit of existing fund investors. Thus, fund flows play an even more important role for investors who do not hold their funds in tax-exempt accounts.

[388] For example, Phalippou (2010) provides empirical evidence for venture capital funds that funds backed by less skilled investors have a non-significant performance-flow relationship and show performance persistence while fund flows of funds backed by skilled investors are sensitive to past performance and these funds do not generate persistent performance.

[389] Only over short horizons, the price-pressure effect boosts winner-fund performance. However, this effect decays over longer horizons.

[390] The more intensive due diligence process, which is required when selecting a hedge fund, is most likely the reason for the delayed reaction of inflows on past performance.

according to the empirical results of Agarwal, Daniel, and Naik (2004) hedge fund investors seem to chase recent outperformers but do not redeem underperformers to the same degree. In light of this evidence, other reasons seem to be more responsible for the performance persistence observed among hedge funds, such as more performance sensitive compensation contracts.

Furthermore, other empirical studies call the conjectures of Berk and Green (2004) into question. For example, Jog and Sinha (2007) document for their sample of Canadian funds that investors do not chase recent winner funds but that winner-fund performance still does not persist. This result can only be interpreted as evidence against the existence of managerial skill in Canadian equity fund managers. However, Jog and Sinha (2007) do not report whether loser-fund performance persists. According to them finding significant withdrawals one could expect based on Berk and Green (2004) that loser-fund performance does not persist, unlike the U. S. evidence. Accounting for endogeneity in fund flows and fund returns and especially the contemporaneous relationship between both, Benson, Faff, and Smith (2007) suggest that there is no impact of current or lagged fund flows on fund returns. Only for the subset of large funds and institutional funds, current net inflows have a significantly negative impact on performance while one-month lagged net inflows exhibit a significantly positive impact on performance. More distant fund flows do not seem to affect current performance. This would only be consistent with a price pressure effect but does not confirm the long-term implications of Berk and Green (2004). In summary, despite the theoretical appeal of the model of Berk and Green (2004) the empirical conclusions with regard to its implications for flows and performance do not yet appear to be settled.

4.4 Manager Changes as Equilibrium Mechanisms

Managerial turnover might be a complementary explanation for the lack of performance persistence.[391] Implicitly, existing studies on performance persistence

[391] Additional mechanisms that might contribute to mean reversion in (net) performance are behavioral biases or strategic fee setting. In particular, if fund managers have performed well over the past they tend to increase their trading activity due to overconfidence which subsequently has a negative impact on investment performance (Pütz and Rünzi, 2009). Poorly performing managers also tend to increase portfolio turnover, though Pütz and Rünzi (2009) do not report the impact of this behavior on performance. Moreover, winner funds might increase fees to gain a larger share of their skills, thereby reducing net performance. However, analyzing the changes in fund size and fees after funds are ranked into the winner decile Elton, Gruber, and Blake (1996a) conclude that skilled fund managers increase their salaries by increasing fund size rather than increasing fees. Loser funds

assume that fund managers and mutual funds are one intrinsically linked entity.[392] This is clearly not the case as fund managers move between funds and enter or exit the mutual fund industry due to various reasons. Indeed, it has already been suggested by Hendricks, Patel, and Zeckhauser (1993, p. 102) that "superior analysts get bid away once they build a track record." Similarly, Tonks (2005, p. 1940) argues that "over time these individuals [fund managers] move between jobs, so that over longer horizons, the persistence in fund-management-house performance weakens."

4.4.1 Winner Funds

Star fund managers have an incentive to extract a higher income from their skills. If they are unable to negotiate an acceptable compensation package related to the higher fees received by the investment management company as a result of the increase in assets under management they might either move to a larger fund within the same organization or to another investment management company altogether. In general, mutual funds have only a few measures to attract and keep skilled managers by directly rewarding them for superior performance. When the fund manager is named in the prospectus, this even increases his negotiation power (Massa, Reuter, and Zitzewitz, 2010). From this perspective, anonymously-managed funds might provide some advantages.

Empirical evidence indicates that promotions, i. e. the star fund manager subsequently manages a larger fund, are positively linked to past performance (Hu, Hall, and Harvey, 2000; Baks, 2003). Moreover, successful managers might be lured away by competing fund companies. In recent years many mutual fund managers also maximized personal wealth by quitting their jobs as mutual fund managers and starting a hedge fund.[393] It is an important responsibility of well-governed investment management companies to keep an existing manager with a good performance record. In particular, if managers anticipate poorer performance and the associated reputational damage in the next period due to excessive inflows and capacity constraints it seems rational to secure their high income by

could reduce fee levels to improve net returns. However, empirical results imply that they rather tend to increase management fees in order to benefit from investors' inertia (Casavecchia and Scotti, 2009).

392 One notable exception is Baks (2003).

393 Jeffrey N. Vinik, the former manager of Fidelity's Magellan fund, probably was one of the first to do so in 1996.

moving to another job. In this case, the decision to stay or to leave might signal the manager's own judgment of personal investment skills.

Speaking in terms of Berk and Green (2004), these star managers simply increase their fees, though not at the same fund. If investment performance depends on managerial skill, the funds previously managed by these managers no longer outperform the market but, as the managers take performance with them, the funds that hired these managers now appear among the winner funds. At the old fund, a new manager with presumably lower skills will be hired. A manager change can be interpreted in terms of equation (4.3) as an adjustment of fund size relative to managerial skill similar to the fund-flow mechanism. In this case, however, fund size relative to managerial skill adjusts immediately through a change in management rather than gradually over time as through fund flows. Thus, the effect can be expected to set in within a shorter time period. Fund size of the previously winning funds is now too large relative to the skill level of their new managers and winner funds with a manager change subsequently underperform compared to winner funds without a manager change.

4.4.2 Loser Funds

At the lower ranks of past performance, manager changes might similarly be responsible for mean reversion. Recent studies show that investors are beginning to react more quickly to past performance than earlier studies have documented (Goriaev, Nijman, and Werker, 2008). This provides an incentive to the investment management company to fire the managers of loser funds in an attempt to stop outflows.[394] Manager replacements are interpreted by Dangl, Wu, and Zechner (2008) as internal governance, which is a complimentary mechanism to the disciplining effect of the market.[395] Effective internal governance mechanisms should result in a replacement of underperforming managers by new managers with presumably higher skills. The new manager might alter the investment strategy aiming to improve subsequent performance.

394 Parrino, Sias, and Starks (2003) provide empirical evidence that in the case of corporations a reduction in institutional ownership increases the likelihood of forced CEO turnover.

395 One might expect that also fund boards are beginning to act when they observe bad performance. However, as discussed in section 2.2.3.2, fund boards cannot directly influence the manager replacement decision. However, Ding and Wermers (2006) find that the size of the board and its independence have a positive impact on the likelihood of a manager replacement suggesting some informal channel.

In terms of Berk and Green (2004) fund size and compensation of the unskilled managers is essentially reduced to zero once they are fired. Thus, manager replacements can also be interpreted as fund size adjustments. Previous loser funds that replace their unskilled manager by an average manager are now too small relative to the skill level of the new manager and, thus, subsequently outperform their peers without a change in management. The withdrawal of funds by investors and the replacement of a badly performing fund manager are two alternative control mechanisms in delegated fund management that help to end a period of inferior investment returns according to equation (4.3).

However, the functioning of the manager replacement mechanism strongly depends on assumptions about the population from which new managers are drawn. Dangl, Wu, and Zechner (2008) assume that new managers are drawn from a new population. Otherwise, if the new manager were drawn from the group of managers fired by the other investment management companies the mechanism would break down. Investment management companies face the risk that the new manager would be drawn from a position below the former manager if the performance of their loser fund is relatively good compared to the other loser funds in the same segment. Consequently, a manager one position below the median would not be fired. However, it follows that the investment management company that employs the manager two positions below the median also had no incentive to fire the manager. This argument can be carried forward such that no manager would be replaced. In practice, however, new fund managers enter the market such that the job market consists of fired and new managers. Moreover, there might be other private reasons for managers to search for a new job. Lastly, if managerial skills can only be observed with error, the above argument would no longer hold because investment management companies do not exactly know the relative position of their managers compared to their peers.

4.4.3 Empirical Results

Several empirical studies confirm the arguments from above and document an inverse relationship between fund performance and manager turnover (Khorana, 1996; Chevalier and Ellison, 1999b; Gallagher and Nadarajah, 2004). Using a sample of 339 funds that replaced their managers over the period from 1979 to 1992, and a control group of 4,830 funds that did not, Khorana (1996) reports an inverse relationship between the probability of a manager change and past performance. Moreover, demotions, i. e. the manager subsequently manages a smaller fund, are negatively linked to past performance (Hu, Hall, and Harvey, 2000; Baks, 2003). Using a similar sample of 393 domestic equity and bond fund managers that were replaced over the period from 1979 to 1991, Khorana (2001) finds in a follow-up study that a manager change in outperforming funds results in a deterioration in post-replacement performance from 1.9 percent in the pre-replacement period to 0.4 percent in the third year after replacement.[396] For underperforming funds Khorana (2001) documents that performance improves post-replacement, with abnormal performance improving from −2.40 percent in the year before replacement to 0.50 percent in the third year after replacement. Hence, manager turnover appears to place a curb on performance persistence.

4.4.4 Interaction with Fund Flows

A high relative performance ranking of a mutual fund might result in high inflows or a change in manager or both. With respect to the interaction between manager changes and fund flows as equilibrium mechanisms it might be conjectured that the combined effect among winner funds is less than the sum of individual effects. This is because if investors observe that the manager of a winner fund leaves they might rationally expect past superior performance to be less predictive for future performance. In this case, less money is flowing into recent winner funds with a manager change compared to recent winner funds without a manager change. Empirical studies should, therefore, consider both equilibrium mechanisms simultaneously in order to obtain unbiased results.

Similarly, a low relative performance ranking of a mutual fund might induce outflows, a manager replacement or both. Both mechanisms might be substitutes or complements among loser funds. In the case of substitutes, investors might be reluctant to withdraw money from poorly performing funds in expectation of an internal manager replacement and a subsequent improvement in performance. Moreover, investment management companies might fire poorly performing fund managers in order to stop outflows. Thus, if one of the internal and external governance mechanisms is already applied, the other one is less likely to be exercised.[397]

[396] For a more detailed discussion of the impact of a manager change on performance see section 2.2.3.2.

[397] See Cremers and Nair (2005) and Dittmar and Marth-Smith (2007) for a discussion of

Then, the performance improvement of loser funds with performance-sensitive investors but an investment management company that is reluctant to replace underperforming managers, eventually due to an ineffective fund board structure, should be comparable to that of loser funds with performance-insensitive investors but an investment management company that strongly enforces internal governance mechanisms. However, an alternative expectation for the interaction of both mechanisms among loser funds is that both provide a signal about managerial skill based on different sets of information, the investors' and the investment management company's, respectively. In this case, outflows occurring simultaneously to a manager replacement might be interpreted as an especially strong signal of poor managerial skills which should be followed by even stronger mean reversion. Thus, also in the case of loser funds, it seems important to consider both equilibrium mechanisms simultaneously in order to obtain unbiased results.

4.5 Approaches to Reduce the Detrimental Impact of Flows on Performance

The discussion above reveals that the response of investors, fund managers and the investment management company is an impediment to persistent fund performance. This is disadvantageous among winner funds because it seems almost impossible to achieve persistent outperformance even if managerial skill exists. It appears important to identify potential solutions which avoid or at least mitigate the negative impact of inflows and manager changes on performance. Several obstacles prevent an efficient solution. First of all, investment management companies receive fee income which is in most cases linearly related to fund size. The interests of investors, who prefer small outperforming funds, are in conflict with those of fee-maximizing investment management companies. Moreover, the same mechanisms that prevent persistent outperformance also appear to be important governance mechanisms among loser funds. Thus, in this case, fund flows out of the fund and manager replacements are beneficial for performance. It is necessary to find solutions which reduce the negative effects on performance but still allow for effective governance.

Moreover, the costs from fund-flow risk are significant in the short term because a large fraction of trading volume is liquidity-induced and these trades reduce

internal and external governance mechanisms in the context of corporations.

performance irrespective of the direction of fund flows. Thus, it is important to distinguish between the negative impact of inflows and outflows in the short term, which is primarily driven by transaction costs and distorted trading, and the longer-term impact of asset growth after a period of superior returns.

Table 4.2 presents several approaches that might help to reduce the negative impact of fund flows on performance. Some of these approaches directly aim to affect the sensitivity of fund flows to past performance and reduce fund flows or short-term volatility of fund flows, avoiding liquidity-induced trading all together. This can be achieved using explicit restrictions with respect to the creation or redemption of fund shares or implicitly by applying modified fee structures. Moreover, alternative trading and pricing mechanisms might reduce the level of fund flows. In addition to these approaches, investment management companies can try to reduce the performance impact of fund flows for a given level of flows by using derivatives to implement their investment strategies or by switching over to alternative investment strategies. However, it is important to note that several of the approaches presented below also affect the ability of investors to exercise external governance by withdrawing money from poorly performing funds.

4.5.1 Redemption Restrictions

Lock-up Periods, Redemption Notice Periods and Gates

Explicit measures to reduce short-term fund flows are redemption restrictions such as lock-up periods, redemption notice periods, minimum holding periods or gates. These are heavily used by hedge funds, yet they are less common among mutual funds. A lock-up period specifies the time horizon an investor has to hold on to the fund investment before fund shares can be sold. A redemption notice period, in contrast, requires that the investor informs the fund manager a certain period in advance before selling fund shares while a minimum holding period specifies a certain period after the initial purchase during which the investors are not allowed to sell fund shares. Gates restrict withdrawals during periods when redemptions exceed a certain fraction of total assets under management (Healy and Lo, 2009).

All of these measures are mainly used to avoid unexpected large outflows which trigger fire sales and impose liquidity costs on remaining fund investors.[398] Coval

[398] Another measure often used by hedge funds to avoid the fire sale of illiquid assets are side pockets. Illiquid assets put into these side pockets cannot be used for redemptions which avoids negative effects on long-term investors when these assets are temporarily hard to

Table 4.2: Approaches to reduce the detrimental impact of flows on performance

This table presents potential approaches to reduce the detrimental impact of fund flows on subsequent investment performance according to different categories. Columns (1) and (2) refer to the level of liquidity-induced trading volume due to inflows and outflows, respectively; column (3) refers to the level of capacity constraints; column (4) refers to the level of external governance. A black triangle (▼) indicates a decrease and a white triangle (△) indicates an increase in one of these variables. For example, a lock-up period reduces the level of liquidity-induced trading volume due to outflows, which is beneficial for fund performance, but at the same time reduces the available level of external governance, which potentially reduces fund performance.

	Liquidity trades		Capacity	External
	Inflows	Outflows	constr.	govern.
(a) Redemption restrictions				
Lock-up period	–	▼	–	▼
Redemption notice period	–	▼	–	▼
Minimum holding period	–	▼	–	▼
Gates	–	▼	–	▼
(b) Fee structure				
Redemption fee	–	▼	–	▼
Trailer fee	▼	▼	–	–
Load fee	▼	▼	–	▼
Performance fee	▼	▼	▼	▼
High-water mark	▼	▼	▼	▼
(c) Creation restrictions				
Soft closing	▼	–	▼	–
(d) Trading and pricing mechanisms				
Swing pricing	▼	▼	–	▼
Secondary market	▼	▼	–	–
Exchange-traded funds	▼	▼	–	–
(e) Investment strategy and organizational fund structure				
Derivatives	▼	▼	–	–
Quantitative / index funds	–	–	▼	–
Alternative benchmark	–	–	▼	▼
Team-managed funds	–	–	△ ▼	–
Funds of funds	▼	▼	▼	△
Closed-end funds	▼	▼	▼	▼

and Stafford (2007) and Chen, Hanson, Hong, and Stein (2008) identify high costs associated with sale transactions of mutual funds in distress. These costs can be reduced by restricting the amount which can be redeemed by investors. Moreover, in particular redemption notice periods allow fund managers to better predict future flows and to adapt the investment strategy accordingly. Indeed, the empirical findings of Aragon (2007) suggest that imposing lock-up and redemption notice periods allows hedge funds to invest in illiquid strategies and to gain 4 to 7 percent higher returns than hedge funds without redemption restrictions. He interprets the liquidity of fund shares as a priced risk factor similar to what has already been suggested for the liquidity of stocks (Amihud, 2002; Pástor and Stambaugh, 2003).

A combination of redemption restrictions with a risk overlay management based on liquid derivatives contracts still allows investors who are (at least partly) locked into a fund to manage their risk exposures according to their needs Healy and Lo (2009). Thus, if redemptions of investors are not due to liquidity needs derivatives can be used by investors as low cost instruments to adjust risk without costly trading of the underlyings. This can, at least partially, reduce the withdrawals from funds during periods of market downturns.

Alternatively, lock-up periods, redemption notice periods or gates could only be applied to certain share classes of a fund. This was proposed, for example, in the case of open-end real estate funds in Germany. These funds are especially exposed to large withdrawals of institutional investors. Thus, redemptions from retail share classes might be unrestricted because they are usually relatively low while institutional investors, who could withdraw sums large enough to force the fund into fire sales of assets, are restricted. In general, different redemption restrictions across share classes could be used to segment different investor clienteles similar to different fee structures.

Theoretically, redemption restrictions seem to be beneficial for long-term performance of mutual funds because they reduce the fund-flow risk and costs. However, Greene, Hodges, and Rakowski (2007) suggest that redemption restrictions might also be used by investment management companies to "lock in" investors' money even if fund performance is below average which would guarantee steadier

value reliably or are illiquid. However, due to accounting when investors enter or leave the fund while certain assets are put in side pockets, this measure is usually not applicable to mutual funds with a large investor base.

fee income. In this case, redemption restrictions would constitute an agency cost for investors of badly performing funds. Redemption restrictions might weaken the beneficial long-term impact on performance from market-induced discipline through outflows as predicted by Berk and Green (2004). Moreover, redemption restrictions only enable the investment management company to manage short-term fund flows. Thus, net inflows into recent winner funds might still be an impediment to long-term outperformance because of capacity constraints. Thus, redemption restrictions can smooth fund flows by attracting investors with long-term objectives and help to avoid excessive outflows in distressed periods, but they cannot reduce the mean reversion in the sense of Berk and Green (2004).

4.5.2 Fee Structure

Load Fees and Redemption Fees

In addition to explicit redemption restrictions, investment management companies have several exchange policies at their disposal which implicitly restrict the fund flows of open-end funds. Anticipating the adverse effects of liquidity on investment performance investment management companies can choose to offer specific fee structures with respect to management fees and loads.[399] According to Nanda, Narayanan, and Warther (2000) these fee structures might be endogenously chosen in order to avoid the negative externality of fund liquidity. Investors clienteles with different requirements with respect to advice and liquidity are attracted to different share classes, customized according to their specific needs. Chordia (1996) argues that load charges are an important instrument to separate long-term and short-term investors. In particular, fund managers with higher skills may be able to deter liquidity traders by charging higher fees. Investors who do not have immediate liquidity needs might be willing to pay loads in order to shelter their investments from the negative impact of short-term investors. The latter, in contrast, cluster at no-load funds.

In contrast to load fees, which are usually paid to the investment management company, redemption fees are more directly targeted at mitigating the negative impact of fund flows on long-term investors and are usually paid directly to the

[399] Loads include front-end and back-end loads which are paid when fund shares are bought or sold, respectively, to the investment management company.

fund.[400] Redemption fees compensate existing shareholders for the transaction costs the fund pays to liquidate shares of its underlying assets. The SEC, usually not in favor of fund costs, encourages mutual funds to set redemption fees according to the estimated costs that redemptions impose on the fund (Securities and Exchange Commission, 2002).[401] Compared to back-end loads, redemption fees have the additional advantage that the proceeds are used to compensate long-term investors for losses through trading expenses. Thus, they do not only reduce fund flows directly but also reduce the transaction costs per level of liquidity-induced trading borne by old investors.

The number of load funds has been increasing in recent years which might be a result of increased competition and marketing efforts (Morey, 2003). According to Greene, Hodges, and Rakowski (2007), who focus in their study on daily fund flows, the magnitude of daily flows is reduced by 58 to 78 percent, depending on the investment category, following the introduction of redemption fees.[402] They conclude that fee policy is an effective tool for controlling short-term flows and fund-flow volatility. Even though load funds seem to suffer less from liquidity-induced trading, this does not translate into superior performance of load funds compared to no-load funds (Deaves, 2004a). Furthermore, once loads are taken into account, no-load funds tend to clearly outperform load funds while within the group of load-funds there is no discernible variation between funds with high and low loads (Morey, 2003). In contrast to earlier studies, this result is derived from load-adjusted returns, assuming that the investor borrows the front-end load at the purchase date of the fund and pays this loan back over the holding period of 60 months. Back-end loads are also converted into equal monthly payments and deducted from monthly returns.

Similar to explicit redemption restrictions, fee structures that increase the costs for redeeming fund shares have the disadvantage that the efficiency of external governance is reduced. Moreover, they might also be set strategically by investment management companies to lock-in investors into poorly performing funds. Indeed, the empirical results of Greene, Hodges, and Rakowski (2007) show that

[400] An exchange fee is the corresponding fee which investors pay when they switch into another fund from the same investment management company in contrast to selling a fund.

[401] Rule 22c-2 of the Investment Company Act of 1940 outlaws redemption of fund shares within seven calendar days of purchase if the fund does not impose a redemption fee or the board of directors determines that the imposition of a redemption fee is either not necessary or not appropriate. The SEC limits redemption fees to 2 percent.

[402] Only domestic income funds showed a slight increase in the magnitude of daily flows.

redemption fees are negatively related to marketing expenses which might indeed suggest that funds shift from attracting new investors to keeping the existing investors once they have reached an optimal fund size. However, they cannot find evidence that poorly performing funds put more effort in capturing investors' money than better performing funds. Thus, the evidence on locking-in behavior of investment management companies is mixed.

Trailer Fees

Another measure to reduce short-term volatility of fund flows is abandoning front-end loads and instead using trailer fees to compensate the distribution channel. If advisors receive a fraction of the front-end load, this provides an incentive to influence investors to switch from one fund to another fund which increases fund flows between different funds. The more investors trade fund shares, the more advisors earn. Trailer fees (or trailer commissions) instead better align the time horizon of the advisors and the investor. Specifically, a trailer fee is paid to the advisor as a fraction of annual management fees as long as the investor remains invested in the fund. This should only slightly affect external governance. Advisors might be reluctant to promote a sale of an underperforming fund in the case that this fund pays a relatively high trailer fee compared to its peers.

Performance Fees and High-Water Marks

From the discussion above it appears that most measures discussed so far aim to reduce fund-flow volatility and its short-term impact on performance but cannot protect a fund from hitting its capacity constraints after a period of large inflows. The size-based fee structure, which dominates the mutual fund industry, might even prevent investment management companies from taking action against an excessive increase in fund size. However, large net inflows are not in the interest of existing fund investors who are interested in maximizing risk-adjusted performance. To better align the interests of investors and the investment management company with respect to the optimal fund size, fees could be more strongly linked to performance than to fund size. Hedge funds usually apply such fee structures, sometimes in combination with high-water marks which force fund managers to offset former losses before they can earn a performance fee on gains, intensifying the sensitivity of pay to performance.

On the one hand, the positive relationship between fees and previous performance makes chasing winner funds a less profitable investment strategy for investors and might protect existing fund investors from excessive inflows. But even in the case of hedge funds, empirical results imply that funds actually grow beyond their performance-maximizing asset base with corresponding negative effects on performance (Naik, Ramadorai, and Stromqvist, 2007; Ammann and Mörth, 2008). On the other hand, fund flows might also become less sensitive to poor performance, weakening external governance. The marginal costs of staying invested when past performance was poor is reduced when fee levels adjust to recent performance. However, the direct incentive of performance-based fees to provide superior returns might compensate for this. Aragon and Qian (2006) even argue that, in the case of hedge funds, lowering the sensitivity of outflows to past performance might be beneficial as it avoids the liquidation of assets during times when this is especially costly.

4.5.3 Creation Restrictions

Soft Closing

In addition to the implicit fee-based measures discussed above, soft-closing is an explicit measure that aims to reduce long-term asset growth. If a fund is soft-closed, it no longer accepts subscriptions from new investors. Usually, only existing investors are still allowed to invest additional funds. Redemptions, in contrast, are not restricted. Incentive structures of fund management companies prevent closing successful funds to new investors because revenues are usually linked to fund size, so fund growth is in the interest of fee-maximizing investment management companies.

An alternative strategy for the investment management company is to soft-close a recent winner fund and try to channel potential new investors into another fund from the same family by increased marketing efforts. However, the empirical results of Bris, Gulen, Kadiyala, and Rau (2007) reveal that there are no positive spillover effects on the net inflows into other funds from the same fund family following the decision to soft-close a recent winner fund. But their results also show that the fees of closed funds are increased which more than compensates for the lower asset growth. Hence, the increase in fees reduces future net performance, although potentially by less than an increase in the asset base would have affected future performance. Moreover, soft-closing a fund might impose negative tax externalizes on remaining shareholders. As long as a fund is open to new investors, inflows dilute unrealized capital gains reducing tax liabilities of existing shareholders. This mechanism no longer exists in soft-closed funds and costs are estimated to be as high as 0.18 to 0.25 percentage points lower after-tax returns per month (Dickson, Shoven, and Sialm, 2000).

With respect to mean reversion in investment performance of formerly outperforming funds, the results of Bris, Gulen, Kadiyala, and Rau (2007) suggest that even the closing of successful funds cannot avoid a decrease in performance all together. Though soft-closing significantly reduces inflows, the funds' average four-factor alpha reverts from 0.96 percent per month to 0.15 percent in the year after closing, a significant decrease of 0.81 percentage points.[403] They interpret this result as evidence against their good stewardship hypothesis which postulates that fund closures maintain good performance. However, the results of Bessler, Blake, Lückoff, and Tonks (2010) imply that funds sheltered from inflows significantly outperform those not sheltered from inflows in the subsequent year. Thus, even though the tendency of mean reversion dominates, closing successful funds might still have a significantly positive impact on their performance compared to those left open.

4.5.4 Trading and Pricing Mechanisms

Swing Pricing

Swing pricing is another measure for reducing transaction costs from liquidity-induced trading which has gained in popularity in recent years. It modifies the trading mechanism rather than imposing direct restrictions with respect to creations or redemptions. If redemptions exceed subscriptions on a given day then the net asset value of the fund will be adjusted downwards to ensure the investors trading bear a portion of the trading costs. Likewise, if subscriptions exceed redemptions, the net asset value would be adjusted upwards. Some funds only apply partial swing pricing instead of full swing pricing. The net asset value is only adjusted when inflows or outflows exceed a certain threshold, comparable to the redemption restrictions imposed by gates only when a fund-flow threshold is exceeded. This mechanism protects the interests of long-term investors by reducing fund-flow volatility and compensating for trading expenses. The economic

[403] Inflows are not reduced to zero because existing shareholders are still allowed to invest further funds.

interpretation of swing pricing is very similar to redemption fees. In both cases, investors with liquidity needs compensate remaining investors for the expected transaction costs associated with selling the underlying assets. However, swing pricing also applies the same mechanisms in the case of inflows.

Swing pricing requires the determination of expected transaction costs in order to avoid unjustified wealth transfers between existing and new fund investors (in the case of inflows) or between remaining and selling fund investors (in the case of outflows). Potential determinants include broker commissions, expected market impact and foreign exchange costs where relevant. In the case of severe outflows, the concept of NENLE (Niedrigster Erwarteter Netto-Liquidationserlös), which determines the lowest lowest expected net liquidation proceeds, might be applied (Schmidt, 1979). However, it is clear that the swing price can only be an imperfect estimate of the transaction costs involved. Moreover, even though it is likely to reduce the transaction costs which are induced by short-term investors nut born by all investors it cannot shelter successful funds from a long-term increase in funds size and resulting capacity constraints. Thus, swing pricing might be an important instrument to protect long-term investors in volatile markets but cannot increase the chances of delivering persistent outperformance over longer periods. Fund managers might be reluctant to introduce swing pricing because it increases the fund's volatility, comparable to a bid-ask bounce. This might have negative implications for rankings based on risk-adjusted return compared to peers that do not use swing pricing.

Secondary Market

Redemption restrictions inevitably reduce the high degree of liquidity of fund shares, which is one of the cornerstones of the open-end fund concept and is also important for effective external governance. Swing pricing involves the problem of precisely estimating expected transaction costs. Thus, a potential solution to combine the benefits of external governance without imposing high liquidity costs might be a combination of primary and secondary market trading of fund shares. Usually, fund shares are only traded directly with the investment management company and each transaction alters the number of outstanding fund shares (primary market). Usually, a large fraction of gross inflows can be matched by the investment management company by gross outflows.[404] However, due to the obli-

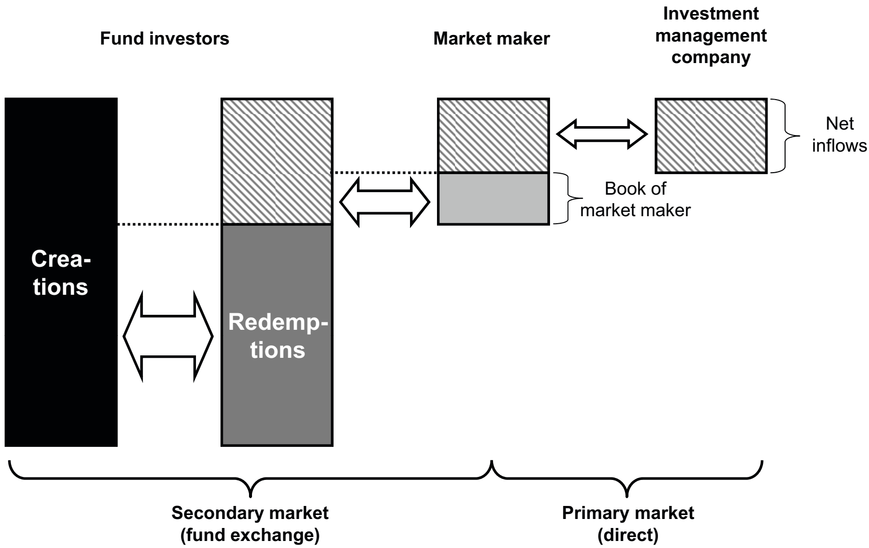
[404] Note that net inflows, which potentially lead to transactions, are the difference between gross inflows (creations) and gross outflows (redemptions).

gation to provide daily liquidity, this matching is restricted to fund flows which occur during the same trading day.

Listing fund shares at a secondary market such as a fund exchange can provide an additional channel to match inflows and outflows which would further reduce the net inflows received by the investment management company (Figure 4.1). Specifically, fund investors can trade with each other without involving the investment management company. In this case, primary market trading serves as a means of external governance which reduces the assets under management and consequently the fee income of the investment management industry if investors are dissatisfied with the investment results. At the same time, a large fraction of liquidity needs of investors can be matched on the secondary market without affecting the mutual fund. Moreover, continuous trading of fund shares allows investors to immediately react on their liquidity needs or market movements.

Figure 4.1: Secondary market trading of mutual funds

This figure presents the trading mechanism of open-end funds if fund shares are traded at a secondary market in addition to conventional primary-market trading directly with the investment management company.



However, due to the ability of the investment management company to internally match creations and redemptions of the same day, the net inflows received by the fund could only be reduced if a secondary market offers matching of liquidity demands occurring over several trading days. Thus, the existence of a market maker in the secondary market, who is willing to hold positions in fund shares overnight, is required. Therefore, the availability of derivatives on funds or certain indices usually tracked by funds can improve the efficiency of a secondary market.

The secondary market price of fund shares can deviate from the net asset value within a certain band which is determined by the front and back-end loads. If the price at the secondary market exceeds the net asset value plus any front-end loads or other transaction costs associated with buying fund shares directly from the investment management company, investors would prefer to trade in the primary market. Similarly, if the secondary market price declines below the net asset value less potential back-end loads (or additional redemption fees), investors would redeem shares directly at the investment management company. Thus, the secondary market price of the fund is usually above the net asset value minus back-end loads and below the net asset value plus front-end loads. This implies that investors are usually better off trading at the secondary market compared to the primary market. In a sense, investors pay for their liquidity needs because when buying pressure for fund shares is high, prices will usually converge to the net asset value plus front-end load and investors who provide liquidity are compensated. In the case of large selling pressure, prices converge to the net asset value minus back-end loads, again compensating liquidity providers. This is a mechanism similar to swing pricing as long as no primary market trading takes place. However, in the case of extreme fund flows, when the market maker trades excess demand or supply directly with the investment management company, the negative performance impact of fund flows remains.

Consequently, acting as market maker in a secondary market for fund shares might be lucrative because, in contrast to making a market in stocks, part of the loads otherwise earned by investment management companies can be collected. Loads are an important source of fee income for investment management companies which is the reason for why they try to hold secondary market trading at bay in most countries. For example, in Germany many open-end mutual funds can already be traded on secondary markets organized by several exchange operators. However, so far the success of these alternative trading mechanisms remains limited which can be partly explained by the dominance of banks associated with the investment management company as the main distribution channel for fund shares.[405] In the U. S., however, ReFlow has been established as a market maker in fund shares but without the listing of fund shares at a secondary market. ReFlow instead offers a non-organized secondary market: investment management companies can buy insurance against volatile fund flows by contracting with other companies to purchase or redeem fund shares in order to smooth daily net inflows (Tkac, 2004).[406] In essence, ReFlow provides cash in exchange for a position in the fund. Investment management companies can then redeem these shares within a specified period of time and have the choice to deliver cash or securities of their choosing. Even though this method imposes costs on the portfolio as the insurance premium is paid for from the fund's assets it is likely to improve fund performance by lowering short-term volatility of fund shares. However, it does not help to mitigate the negative long-term effects of an increased asset base.

Exchange-Traded Funds

Exchange-traded funds are an interesting alternative to traditional open-end funds in this context because their trading mechanism combines elements from primary and secondary market trading (Figure 4.2).[407] Usually, exchange-traded fund shares are continuously traded at an exchange, comparable to exchange trading of conventional open-end funds. However, primary market trading of exchange-traded funds only occurs as an in-kind transaction in large amounts when there is excess demand or excess supply at current prices. Thus, direct fund flows are restricted to relatively infrequent transactions which do not require trading by the fund because fund shares are exchanged for a basket of securities which represents the underlying index. Cash inflows or outflows are essentially reduced to zero. This reduces overall transaction costs of the exchange-traded fund because it avoids costly liquidity-induced trading on the fund level all together. In contrast, exchange-trading of conventional open-end funds eventually reduces net inflows

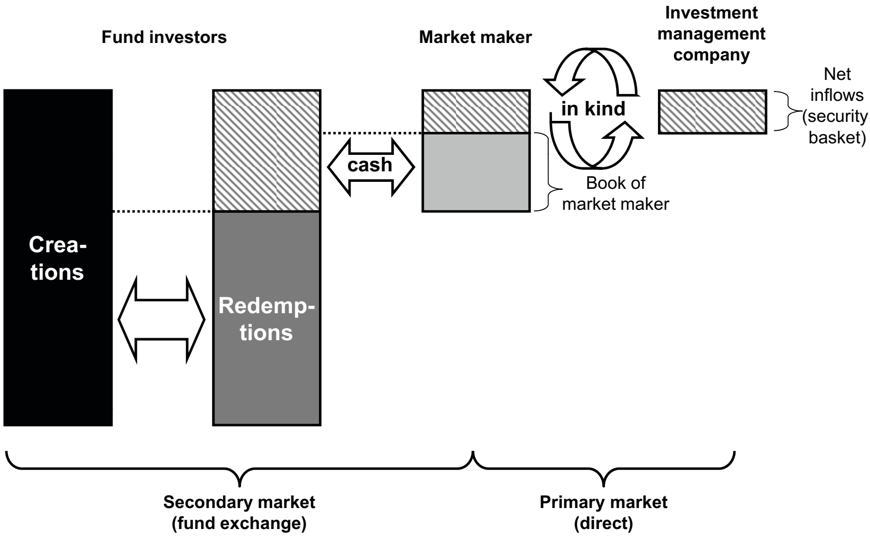
[405] In 2009, only 4 percent of German mutual fund investors purchased their funds via one of the German mutual fund exchanges according to BVI Bundesverband Investment und Asset Management e. V., the German association of investment management companies (Grit Beecken, Vor verschlossener Tür, Börse Online, 03 March 2010).

[406] By the end of 2009, ReFlow's services have been approved by the boards of 22 mutual fund families, representing more than 374 billion USD in assets, for use by 460 funds. To date, ReFlow has provided more than 2.74 billion USD in capital in over 2,166 transactions. See http://www.reflow.com for further information.

[407] See also the discussion of exchange-traded funds in section 1.4.2 in section 1.4.

Figure 4.2: Trading mechanism of exchange-traded funds

This figure presents the trading mechanism of exchange-traded funds.



received by the fund but still induces a certain amount of trading in the underlying securities.

The price of exchange-traded funds at the secondary market usually fluctuates around its iNAV. This price range is determined by the transaction costs involved with the in-kind creation-redemption process. Consequently, it is now investors directly who incur transaction costs when trading fund shares at the exchange. In the case of excess demand, the price of the exchange-traded funds is usually above its iNAV and investors who demand liquidity pay a premium. In the case of excess supply they can only sell at a discount to the iNAV. Thus, according to Guedj and Huang (2008), the exchange-traded fund structure does not reduce overall transaction costs but allocates these costs to investors with liquidity demands. In contrast to exchange trading of conventional open-end funds this still holds in the case of extreme inflows or outflows.[408] Moreover, reported performance of

[408] Note that in the case of exchange trading of conventional open-end funds, the market maker would offload excess liquidity demands through direct trades with the investment management company (Figure 4.1).

exchange-traded funds is no longer affected by liquidity-induced trading because transaction costs are not deducted from the iNAV but are directly paid for by investors.[409]

It is important to note that the exchange-traded fund structure still allows for external governance because investors can withdraw money if they are dissatisfied with the investment results. However, investors who want to withdraw money after a series of abnormally low returns might face a discount of the exchange-traded fund's price compared to its iNAV when many other investors want to sell at the same time. Similar to the secondary market trading of open-end fund shares, the exchange-traded fund structure cannot avoid an increase in the asset base resulting in performance deterioration from capacity constraints.

In the case of funds with institutional share classes, it might be reasonable to structure these institutional share classes as exchange-traded funds, only allowing in-kind transactions, while the retail share classes would also allow cash-transactions. This would reduce the amount of liquidity-induced trading and avoid the risk of large fire sales in the case of many institutional investors wanting to redeem their fund shares at the same time. Moreover, this could be combined with lock-up or redemption notice periods, allowing immediate in-kind transactions but cash withdrawals only after a certain lock-up or redemption notice period.

Another advantage of the exchange-traded fund structure is that most of these funds follow passive or rules-based investment strategies. This makes them very transparent which further reduces potential conflicts of interest between the investment management company or the fund manager and the investors. Because the investment mandate is specified within only a few degrees of freedom, i. e. the mandate usually requires to track a certain index as closely as possible implying only low costs, internal and external governance mechanisms are replaced to a certain degree by investment restrictions.

4.5.5 Investment Strategy

Derivatives

Instead of trying to control fund flows, investment management companies might use certain instruments to reduce the trading expenses from liquidity-induced

[409] However, index changes and the reinvestment of dividends still require trading on the fund level and induce some transaction costs.

trades and the drag on performance from inflows over the long term. For example, derivatives are a flexible tool for implementing investment strategies. Cash-market transactions usually involve significantly higher transaction costs compared to trading in derivatives. For example, Brown, Ozik, and Scholz (2007) show how to minimize the costs of portfolio rebalancing by using derivatives.[410] Derivatives can also be used to handle cash inflows and outflows more efficiently.[411] Essentially, the cash position is "equitized", earning the return on the benchmark index rather than the risk-free rate. Thus, liquidity-induced transaction costs are reduced by holding a larger fraction of the portfolio in cash but a cash-drag and unintentional beta variation can be avoided.

Empirical evidence on the U. S. market (Koski and Pontiff, 1999) and the Spanish market (Marín and Rangel, 2006), respectively, supports the notion that index derivatives are used by equity fund managers as a response to fund flows. Specifically, fund managers use derivatives to control risk changes that would otherwise occur due to heavy inflows or outflows which is described as unintentional beta variation above. Both, Koski and Pontiff (1999) and Marín and Rangel (2006) document that the relationship between performance and subsequent changes in fund risk is weaker for funds using derivatives and that fund managers use index derivatives rather than single stock derivatives.[412] Both results are consistent with the hypothesis that derivatives are employed as an instrument to reduce the impact of fund flows on fund risk and investment performance.

Frino, Lepone, and Wong (2009) provide complementary evidence on the beneficial use of derivatives as a tool for cash-equitization of investors. They build on a more detailed data set of Australian funds which provides the information on whether derivatives are used to manage fund flows or not. Fund performance and market timing measures of funds not using derivatives are negatively affected by fund flows while the investment performance of derivatives users is not affected by fund flows. Specifically, the performance of derivatives users in the case of fund

[410] Derivatives are also used to alter the risk-return tradeoff of specific investment strategies. See, for example, Isakov and Morard (2001) for an analysis of a covered call writing strategy on the Swiss market.

[411] Passive funds sometimes use swaps to replicate the index performance giving them more flexibility with respect to the management of liquidity. Furthermore, Stoxx Limited, an European index provider, and Source, an exchange-traded fund issuer, have launched new versions of the DJ Stoxx 600 supersector indices in July 2009 in an attempt to improve the liquidity and tradability of the indices for their use as exchange-traded fund underlying.

[412] In contrast, the hypothesis that fund managers use derivatives to game fund risk implying a stronger relationship between past performance and subsequent shifts in fund risk seems less likely (Koski and Pontiff, 1999).

flows is not significantly different from the performance of non-users in the case of no fund flows (inflows or outflows). Thus, funds which use derivatives to equitize fund flows experience the same performance as funds which are not affected by any fund flows at all. In contrast to these results, Dubofsky (2010) cannot reveal a significant relationship between a fund's usage of derivatives and its trading activity in response to investor flows indicating that derivatives are not employed to reduce liquidity-induced trading.

Based on these studies, the use of derivatives by mutual funds is a potential solution for overcoming some of the problems associated with the open-end structure. In particular, the efficient handling of excessive fund flows can be improved. Without derivatives, the costs from immediate and rapid transactions in the underlying securities have to be traded off against an unintentional beta variation when trades are executed more patiently and the cash position accommodates flows in the short term. Derivatives significantly reduce these costs. Additionally in the long term, when an increased asset base elevates average transaction costs, single stock derivatives might help to reduce trading expenses. However, the negative long-term effects of capacity constraints which are unrelated to transaction costs, such as a lack of best ideas, a shift toward more efficient market segments and hierarchy costs, cannot be reduced by the usage of derivatives.

Despite the advantages of derivatives usage, Koski and Pontiff (1999) note that only 21 percent of the 679 funds in their sample of all domestic equity funds that existed at the end of 1993 use derivatives. However, in more recent years product innovations, such as the introduction of single-stock futures, and several regulatory changes have made the use of derivatives more popular. In the U. S., the Taxpayer Relief Act of 1997 repealed the short-short rule which prevented most mutual funds from using derivatives due to unfavorable tax treatment (Koski and Pontiff, 1999).[413] Also in other jurisdictions the restrictions on the use of derivatives have been relaxed in recent years, for example in Europe according to UCITS III (Undertakings for Collective Investments in Transferable Securities).

[413] Specifically, funds that realized more than 30 percent of their capital gains from positions held less than three months were excluded from preferential pass-through tax status. Usually, trading derivatives involves short-term trading due to rolling into contracts with the next expiration date.

Quantitative and Index Funds

Instead of using only certain instruments such as derivatives, investment management companies might also modify their investment strategies altogether in an attempt to better accommodate unexpected fund flows or an increase in the asset base. In particular, the performance of rules-based investment strategies such as quantitative investing might be scalable to a larger degree than conventional active investment strategies. Moreover, computer-based investment strategies can incorporate expected transaction costs more easily into their optimization algorithm yielding higher net returns. The most extreme case of a "scalable" investment strategy is indexing. Especially in the case of broad market indices, performance should not suffer from an increase in the asset base.

Alternative Benchmark

Related to the investment strategy is the choice of the benchmark used to evaluate the fund manager's skills. A strict benchmark orientation might induce an incentive to focus on short-term gains and to herd, thereby creating capacity constraints in certain successful investment strategies.[414] Therefore, it might seem to be beneficial for investors to put more focus on long-term performance by introducing alternative benchmark concepts. This would allow funds to pursue long-term investment strategies and to exploit long-term mispricings, which also reduces asset turnover and transaction costs. Moreover, reducing the importance of relative rankings could mitigate the incentives for mutual fund managers to engage in tournament behavior which otherwise results in suboptimal risk exposures from the perspective of fund investors. Another positive aspect, successful fund managers might stay longer at their job when they have long-term incentive contracts which could also improve long-term performance persistence. However, abandoning a relative benchmark also makes investment results less transparent and performance comparisons more difficult for investors, presumably reducing the efficiency of external governance mechanisms.

[414] Scharfstein and Stein (1990), Wermers (1999), Sias (2004), Hong, Kubik, and Stein (2005), and Cohen, Polk, and Silli (2009).

4.5.6 Organizational Fund Structure

Team-Managed Funds

As discussed above, an increase in fund size requires the generation of more successful investment ideas by the fund manager because existing strategies usually cannot be scaled without limit. However, the number of investment ideas one manager can generate also seems limited. Thus, many investment management companies respond to an increase in fund size by hiring more managers (Chen, Hong, Huang, and Kubik, 2004). However, team-managed funds, in general, are unable to outperform single-managed funds.[415] Only when the team members come from diverse informational and educational backgrounds, might hiring more managers improve fund performance (Bär, Niessen, and Rünzi, 2008). In recent years, fund management companies even started to experiment with analyst-led funds.[416] In an analyst-led fund, there is no longer a manager who leads the team but all analysts who are members of the team are allowed to freely express their investment ideas. Teams of analyst-led funds can even be as large as 30 analysts specialized in specific industry sectors. Moreover, hierarchy costs increase with team size because individual members compete for the internal allocation of money and competencies (Chen, Hong, Huang, and Kubik, 2004). In sum, the results of Chen, Hong, Huang, and Kubik (2004) suggest that larger funds underperform small funds because hierarchy costs dominate the potential benefits from a larger management team.

Funds of Funds

An interesting question is how the benefits from a large investment team with respect to the selection of superior stocks can be realized without the organizational loss. Funds of funds might be a promising alternative. A fund of funds is more likely to be able to accommodate large inflows because it can resort to the investment ideas of many individual managers.[417] These managers do not com-

[415] Prather, Middleton, and Cusack (2001), Prather and Middleton (2006), Bär, Ciccotello, and Rünzi (2008), Bär, Kempf, and Rünzi (2010), and Bär, Niessen, and Rünzi (2008). However, only Bär, Niessen, and Rünzi (2008) control for fund size in this relationship but do not report whether team-managed funds tend to be larger, which would have negative effects on fund performance.

[416] Ruth Sullivan, Analyst-Led Funds Gain Momentum, Wall Street Journal, 02 November 2009.

[417] Specifically, if a fund of funds has 20 sub-funds, each of which holds 50 assets, then inflows can be spread more evenly over individual securities even if some overlap with respect to portfolio holdings exists between the individual sub-funds.

pete with each other regarding the allocation of money because each is responsible for only his own fund, avoiding hierarchy costs. On the one hand, funds of funds would also theoretically enable the pooling of the cash positions of the underlying sub-funds which would reduce their cash drag. Because fund of funds managers have better skills in evaluating the performance of sub-funds, they might also improve external governance among these funds. On the other hand, if a fund of funds decides to divest from a certain sub-fund, this might cause severe liquidity problems.[418]

The concept of funds of funds is more prominent in the hedge fund industry, where individual managers are even more specialized than their mutual fund peers.[419] The disadvantage of funds of funds is that they add a second layer of fees. For example, funds of hedge funds charge an average annual fee of 1.4 percent on top of the average fee of 1.5 percent charged by the underlying hedge funds (Ang, Rhodes-Kropf, and Zhao, 2008). Funds of hedge funds tend to underperform single hedge funds after fees (Ackermann, McEnally, and Ravenscraft, 1999; Ang, Rhodes-Kropf, and Zhao, 2008; Brown, Goetzmann, and Liang, 2004). Ang, Rhodes-Kropf, and Zhao (2008) argue, however, that most strategies of funds of hedge funds cannot be duplicated by individual investors because hedge funds are complex to evaluate and monitor, require high minimum investments and are even sometimes closed to new investors. They conclude based on certainty equivalents that funds of hedge funds are not an inferior alternative to available single hedge funds and deserve the fees they charge.

This argument usually does not apply in the mutual fund context because almost all mutual funds which funds of funds invest in would also be directly available to individual investors. However, the cost disadvantage of funds of funds might be reduced by their access to institutional share classes with lower fees. Thus, the question regarding the benefits of a fund-of-fund structure in the case of mutual funds is an empirical one which has not yet been answered by the literature.

Blake, Timmermann, Tonks, and Wermers (2009) focus on a similar issue and analyze how the recent shift to decentralized investment management in the pen-

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418 A potential measure to avoid this would be to allow only in-kind redemptions for funds of funds, at least when their withdrawals exceed a certain threshold.

419 According to the TASS hedge fund database, about one quarter of all surviving funds are classified as fund of hedge funds and this fraction is rising over time (Brown, Goetzmann, and Liang, 2004).

sion fund industry affects performance. During their sample period from 1984 to 2004, most pension fund sponsors shifted, first, from employing a single balanced manager, who invests across all asset classes, to managers who specialize in single asset classes and, second, from single managers to multiple managers within one asset class. Many of these shifts were preceded by poor performance. Moreover, plan sponsors properly anticipated diseconomies of scale when a fund became too large for a single manager and switched to multiple managers. Interestingly, performance improved after switching to decentralized management despite the higher costs of coordination of multiple managers and suboptimal diversification. This implies that changing the management structure can reduce, or in this case even reverse, the performance deterioration due to diseconomies of scale in active management.

Closed-End Funds

An extreme solution for mitigating liquidity risk and capacity constraints over both short and long horizons is to organize a fund as a closed-end structure. In fact, the liquidity of the underlyings is negatively related to the costs from fund flows (Yan, 2008), and at the same time is negatively related to the likelihood of a fund being closed-end (Deli and Varma, 2002; Cherkes, Sagi, and Stanton, 2009). Closed-end funds offer the opportunity to trade illiquid assets without facing the costs of trading at the underlying markets because closed-end funds are usually exchange listed in the U. S. Closed-end funds can invest more freely in illiquid assets and have no need to hold a cash position because they do not have to meet the liquidity supply or demand (creations or redemptions) by investors. Additionally, the pressure to report superior returns even in the short term as a result from possible withdrawals by performance sensitive investors does not exist which gives closed-end fund managers a higher flexibility to pursue long-term investment strategies (Stein, 2005).

However, Anderson, Coleman, Gropper, and Sunquist (1996) cannot support the hypothesis that closed-end funds outperform open-end funds in general. This result may be driven by severe agency costs between closed-end fund managers and investors because closed-end funds do not offer the possibility to discipline the manager by withdrawing funds (voting-by-feet). The disciplining effect of the product market according to Ippolito (1992), which guarantees that only high-quality products survive if functioning properly, fails among closed-end funds.

The market share of low-quality managers does not decrease relative to high-quality manager, in contrast to the open-end fund market. Yet, if cross-sectional differences in the skill level of closed-end fund managers exist, performance persistence should be stronger among closed-end funds compared to open-end funds because the equilibrium mechanisms of fund flows does not exist.

This is exactly what can be empirically observed, performance persistence exists for up to 36 months in a sample of closed-end funds according to Bers and Madura (2000). They analyze a sample of 384 closed-end funds over the period from 1976 to 1996.[420] A regression of current closed-end fund performance on past performance reveals that the coefficient itself as well as its t-value is much higher than what was reported in similar studies for open-end funds (e. g. Brown, Goetzmann, Ibbotson, and Ross, 1992; Goetzmann and Ibbotson, 1994). Taking into account only the periods without a manager change yields even stronger results. Yet, the results are strongest for the shorter period and decline over longer periods suggesting that also among closed-end funds some equilibrium mechanism exists. Overall, the results indicate that the higher flexibility of the management style and the absence of inflows or outflows give the managers of closed-end funds the opportunity to provide persistently superior returns.

Pension Funds

Pension funds provide an interesting fund structure to consider when analyzing different aspects of the organizational structure with respect to its impact on fund performance. The regulatory and organizational environment differs from that of mutual funds in the following aspects. Usually, pension fund consultants advice the plan sponsor in asset allocation decisions and the selection of investment management companies which, in turn, employ the fund manager. This has important implications for potential conflicts of interest and governance mechanisms. Superior managers are attracted by pension funds because they tend to be larger and the compensation is usually higher (Christopherson, Ferson, and Glassman, 1998). Interests are expected to be better aligned through the more prominent use of incentive fees in pension fund management. Additionally, unexpected fund flows do not distract performance regularly as money is invested or

[420] The sample includes 115 taxable bond funds, 64 equity funds and 202 municipal bond funds in existence at the end of 1996, which might induce a survivorship bias. However, due to the negligible number of closed-end funds that went out of business during the sample period the effect is expected to be small.

withdrawn from pension funds periodically in large amounts and these fund flows are usually known by the portfolio manager in advance. Superior performance is more likely to persist because net inflows are less sensitive to past performance such that pension funds can exploit their successful strategies without suffering from capacity constraints (Del Guercio and Tkac, 2002).

There are also reasons to believe that bad performance is less persistent among pension funds. For example, pension fund investors are likely to exercise stronger governance. They usually hold larger stakes of the funds which provides an incentive to closely monitor the fund manager and reduces such monitoring costs compared to individual investors. They are also less likely to be reluctant to sell after a period of below-average performance because pension funds are not taxed at the firm level. In contrast, private fund investors might be "locked in' by unrealized capital gains. This also implies stronger incentives for the investment management company to monitor their managers internally. Dishi, Gallagher, and Parwada (2007) provide empirical evidence that the termination of a superannuation plan mandate significantly increases the likelihood of a fund company replacing the fund manager.

On the other hand, there is a stronger client relationship between the plan sponsor and the investment management company which might result in conflicts of interest and hinder efficient governance (Christopherson, Ferson, and Glassman, 1998). For example, additional services are offered by the investment management company such as education and research reports. Furthermore, if a plan sponsor has to fire an investment manager at the same time he discloses that he might have made a bad decision when mandating this investment manager. Thus, the plan sponsor might be willing to tolerate some period of low returns before taking action which would allow for persistent underperformance.

In summary, however, empirical results indicate that stronger governance, more skilled managers and less return chasing behavior of investors results in superior performance and stronger performance persistence among pension funds compared to mutual funds (Tonks, 2005). However, the results also indicate that badly performing pension funds of the previous year continue to perform badly in the current year indicating some inefficiency in governance among poor performers. The empirical results of Christopherson, Ferson, and Glassman (1998) support this notion.

4.6 Discussion

This chapter has discussed the dynamic aspects of mutual fund performance. Based on a review of performance persistence studies it is concluded that performance persists in the short term but not in the long term. However, several methodological and data-related aspects are identified that might bias the results of existing studies. Moreover, it is argued that for a comprehensive understanding of performance persistence and the dynamics of mutual fund performance over time, the actions of investors, investment management companies and portfolio managers need to be incorporated into the analysis. Thus, this chapter goes on to investigate investor behavior and the determinants of fund flows. Fund investors seem to chase recent winner funds but are more reluctant to sell recent loser funds. However, studies based on gross flows provide evidence that at least some investor clienteles begin to sell their shares of underperforming funds on a larger scale in recent years, especially during bear markets. This relationship between past performance and current fund flows is determined by the sophistication of the investor clientele, by investor-specific participation and monitoring costs, by the channel through which funds are traded, and especially the question of whether or not investors receive professional advice, and by tax considerations.

In the next step, the perspective was reversed and it was analyzed how these fund flows affect future fund performance based on a framework derived from a decomposition of total net assets. Portfolio managers can apply one or a combination of the following strategies to respond to fund flows: (1) alter the cash position; (2) upscale or downscale existing holdings, i. e. alter the ownership ratio defined as the fraction of shares outstanding held by the fund; (3) alter the average market capitalization of stocks held by the fund; (4) alter the portfolio concentration, i. e. build up positions in new stocks not previously held in the case of inflows or sell off existing positions completely in the case of outflows. The impact of fund flows on performance depends on which specific action the portfolio manager is going to take. However, in general performance should suffer from inflows both in the short and long term and performance should benefit from outflows, at least over the longer term, while in the short term the benefits from a reduced asset base might be balanced out by transaction costs associated with liquidity-induced selling pressure. Combining the evidence of how fund flows respond to past performance and how performance is subsequently affected by these flows helps to understand how these effects contribute to mean reversion in mutual fund performance. In fact, fund flows qualify as an equilibrium mechanism.

However, not only investors but also portfolio managers might respond to past performance. It is derived that manager changes can also be interpreted as an equilibrium mechanism explaining mean reversion in mutual fund performance. Recent winner-fund managers might be lured away by competing investment management companies and replaced by some mediocre manager, resulting in subsequent performance deterioration. Similarly, underperforming managers might be replaced and the newly appointed manager might bring performance back to average levels. In the last step, this chapter presents different approaches for reducing the detrimental impact of the equilibrium mechanisms on performance persistence. These include different forms of redemption and creation restrictions, different fee structures, alternative pricing and trading mechanisms as well as changes in the investment strategy and organizational fund structure. However, a critical discussion reveals that some of these measures not only shelter the fund from equilibrium forces but also reduce the efficiency of the external governance mechanism, which might result in higher agency costs. Thus, to quantify the benefits of these measures remains an empirical question, which is addressed in the empirical part of this study.

Part III Empirical Study

5 Objectives, Data and Methodology

5.1 Objectives

It is now widely recognized in the literature that equity mutual fund performance net of costs does not persist in the long run among both winner (recent outperformers) and loser funds (recent underperformers), once survivorship bias and stock return momentum are taken into account.[421] For outperformers, the traditional explanation for this phenomenon is the absence of genuine management skill, apart from slight cross-sectional differences in fee levels. Rather, winner-fund managers happened by luck to hold the last year's winner stocks benefiting from stock return momentum but cannot successfully pick this year's winner stocks. Although the majority of loser funds continue to significantly underperform their benchmarks, indicating that any persistence is clustered around loser funds, their performance over time still improves significantly the following year and is also dominated by a strong tendency to revert to the mean (Brown and Goetzmann, 1995; Carhart, 1997).[422] This can be interpreted as evidence that loser-fund managers ended up in a low ranking in the previous year mainly due to bad luck and only to a smaller degree due to bad skills. These findings are consistent with the view that the dominant determinant of fund performance is luck, which per se is not persistent, rather than skill.

Recent studies, however, point toward the persistence and predictability of short-term fund performance (Bollen and Busse, 2005; Busse and Irvine, 2006; Huij and Verbeek, 2007). These studies challenge the traditional explanations for a lack of performance persistence. If the lack of long-term performance persistence is explained by a lack of managerial skill then there should not be any persistence in the short run either. Furthermore, fees are fairly stable and cannot explain why persistence exists in the short run, but vanishes over longer horizons. The objective of this empirical part is to further investigate potential explanations to

[421] Hendricks, Patel, and Zeckhauser (1993), Carhart (1997), Elton, Gruber, and Blake (1996a), and Elton, Gruber, and Blake (1996b), and section 4.1.
[422] This is especially evident in Figures 6.1 and 6.4. See also Figure 2 of Carhart (1997).

P. Lückoff, *Mutual Fund Performance and Performance Persistence*,
DOI 10.1007/ 978-3-8349-6527-1_6,

reconcile these findings, which at first glance appear to be contradicting. In finding explanations for the empirical results on short-term versus long-term performance persistence, two separate routes are taken: (1) it is analyzed whether differences in the methodologies applied in short-term and long-term studies are responsible for the different conclusions; (2) economic explanations for these empirical findings are investigated.

In chapter 6, this study provides new empirical results that contribute to the performance-persistence debate. These effects are analyzed for a comprehensive sample of all 3,946 actively managed U. S. equity mutual funds that existed for at least 12 months at any point in time period from 1992 to 2007. Compared to existing studies such as Carhart (1997) or Huij and Verbeek (2007), one innovation of this data set is that individual share classes of the same fund are aggregated to one observation which could otherwise potentially bias the conclusions and is especially relevant for recent periods during which a lot of investment management companies initiated the offering of several share classes on the same underlying fund portfolio. The performance of decile portfolios formed on the basis of past performance is evaluated, concentrating on the winner (top-decile) and loser (bottom-decile) portfolios. Different performance measures as well as estimation techniques are used for portfolio formation and evaluation and the impact of the length of the formation and evaluation periods is analyzed. Furthermore, winner and loser portfolios are split into subgroups based on fund flows and manager changes, and the individual and joint contributions of these alternative equilibrium mechanisms on performance are examined.[423]

The innovations with respect to the methodology are the use of the Bayesian approach to enhance the efficiency of parameter estimates, which is especially relevant for persistence studies that rely on short subperiods of return data to estimate performance. Moreover, two new specifications of the multifactor models used as benchmarks are introduced. The first model is augmented by a stock-return mean-reversion factor that allows a differentiation between mean reversion of managerial skill and mean reversion in the underlying stock returns. The second model is augmented by a liquidity factor in order to take into account recent empirical findings that illiquid securities seem to pay an illiquidity premium, yielding a higher return than liquid securities that are otherwise identical. Moreover, the analysis in chapter 6 focuses on the methodological explanation for the con-

[423] For details on the data and methodology see below.

tradicting conclusions of short-term and long-term studies. Existing studies do not use a consistent framework but the methods differ between short-term and long-term studies. On the one hand, performance persistence is analyzed over various time horizons, combining different lengths of the formation and evaluation periods but using the identical methodology to estimate and aggregate performance in order to make short-term and long-term results comparable. On the other hand, different methodologies for estimating and aggregating the performance of funds are compared over identical time horizons. This allows tracing the source of short-term persistence documented in the literature. In addition, as a byproduct of this analysis, empirical evidence is provided on the question of whether improved ranking methodologies can be used by investors to generate abnormal returns under the assumption of realistic and implementable holding periods. Existing studies use 1-month holding periods implying frequent portfolio rebalancing (Huij and Verbeek, 2007). Lastly, the comparison of different estimation and aggregation methodologies serves as a robustness test on the conclusions regarding performance persistence. At the two extremes of these methodologies are Bayesian alphas, which allow for variations of factor loadings over time and across individual funds, and the generalized calendar time approach, which assumes constant factor loadings over time and across all funds of the same decile but provides inferences that are robust to very general forms of cross-sectional and temporal dependence.

In chapter 7, this study goes on to investigate economic explanations for the observed short-term persistence but the lack of long-term persistence. In particular, the theoretical arguments of section 4.3 and 4.4 are empirically analyzed. Specifically, the question is whether fund flows and manager changes act as "equilibriating mechanisms", as defined by Berk and Green (2004, p. 1271), to explain mean reversion in mutual fund returns and, if so, how both mechanisms interact. This brings together the evidence on how investors respond to past performance from section 4.2 and the determinants of fund performance from section 3.8. Empirical evidence on these two mechanisms is provided separately for winner and loser funds by conditioning in the first step on past performance and it is analyzed whether the mechanisms differ between both groups. Existing studies on capacity constraints have rather focused on average fund performance (Chen, Hong, Huang, and Kubik, 2004; Yan, 2008). In addition, potential differences between absolute capacity constraints and capacity constraints relative to the current asset base are investigated. A major innovation in this chapter is, however, an analysis of the interaction effects between both equilibrium mechanisms, fund flows and manager changes. With respect to winner funds, the results can be interpreted as an attempt to predict future winner-fund performance. However, in contrast to existing studies that try to improve the statistical methodologies in order to generate more precise estimates of future fund performance, such as Busse and Irvine (2006) and Mamaysky, Spiegel, and Zhang (2008), the approach proposed here relies on economic reasoning that helps to improve forecasts. With respect to loser funds, the relevant question is about the efficient form of governance, internal governance in the form of manager replacements and external or market-based governance in the form of outflows, and whether both forms of governance are complements or substitutes. Especially with respect to the fund-flow channel, existing empirical evidence, such as Edelen (1999), Alexander, Cici, and Gibson (2007) or Coval and Stafford (2007), is inconsistent with the beneficial impact of outflows on subsequent performance as proposed by Berk and Green (2004). The attempt is to better understand how these results can be reconciled.

In chapter 8, these equilibrium mechanisms are analyzed in more detail. First, in section 8.2, the question of whether and how the equilibrium mechanisms depend on the time dimension is raised. Different lengths of the formation and evaluation periods are compared in order to analyze over which horizon the performance response to fund flows and manager changes is strongest and to determine the "reaction time". Additional aspects related to the fund-flow mechanism are analyzed in sections 8.3 and 8.4. However, the manager-change mechanism cannot be further investigated due to data limitations.[424] In section 8.3 the functional form of capacity constraints is analyzed, i. e. do larger inflows or outflows also result in a larger performance response? To do so, more extreme split points are used between high-inflow and low-inflow funds and a sorting on fund size is performed. Previous literature has provided empirical evidence that the investment results of previously underperforming funds tend to stay poor (Carhart, 1997; Berk and Tonks, 2007). This may be because of a disposition effect of the fund manager who holds on to underperforming stocks due to a behavioral bias. Others have provided evidence that investors of poorly performing funds may also suffer from a disposition effect and are reluctant to take action (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lynch and Musto, 2003). Thus, looking at different mag-

[424] See footnote 435.

nitudes of outflows among loser funds allows a differentiation between these two potential explanations for continued underperformance of loser funds.[425] Moreover, combined with the results from section 8.2, the performance reversals for the same total amount of inflows or outflows occurring over different time periods can be compared, i. e. do lower flows over a longer period have the same effect on performance as the same amount of flows occurring only over a short period? This allows some conclusions on whether slow but constant inflows are easier to digest for winner-fund managers because they have more time to generate new investment ideas and whether loser-fund managers only respond to extreme fund-flow events as compared to small but steady outflows. Lastly, in section 8.4, the fund-flow mechanism and the fund-size mechanism are compared. Previous literature has focused on fund size as a measure of capacity constraints (Chen, Hong, Huang, and Kubik, 2004; Yan, 2008). However, fund size is a static measure and, therefore, is not the appropriate test of the Berk and Green (2004) hypothesis. Rather, fund flows, which represent the response of investors to past performance and the change in fund size that is attributable to this response, are the relevant variable. Thus, it is analyzed how both mechanisms interact and whether the fund-flow mechanism is still relevant after controlling for fund size. Moreover, this allows testing whether small and large funds are affected differently by fund flows.

In summary, this part offers new empirical evidence on the performance persistence debate along several dimensions related to the data set, to the methodology applied and to the economic questions and hypotheses that are investigated. This study directly tests the hypothesis of Berk and Green (2004) on performance reversals of previous winner and loser funds due to the investors' response to past performance in the form of fund flows. Manager changes are also investigated as an alternative explanation for performance reversals. More importantly, this study accounts for potential interaction effects between fund flows and manager changes as equilibrium mechanisms, which might otherwise bias the results. Moreover, it is investigated whether both mechanisms are complements or substitutes.

[425] On the one hand, if total outflows are still small even for the, for example, 20 percent of loser funds with the highest outflows, then a disposition effect of fund investors might be responsible for persistent underperformance because the mechanism suggested by Berk and Green (2004) relies on significant outflows for a proper functioning. On the other hand, if outflows for this group of funds is large but loser-fund performance still does not improve, then the reluctance of fund managers to respond to outflows by altering the portfolio composition might explain the persistent underperformance.

5.2 Data

The data on mutual funds and the benchmarks are obtained from the Center for Research in Security Prices (CRSP) of the University of Chicago. This is one of the most comprehensive databases on mutual funds and covers with a total of 30,361 (11,232 dead and 19,129 live) funds (as of April 2010) all U. S. funds in existence between 1962 and today. It was initially developed by Mark M. Carhart as the first "survivorship-bias-free" mutual fund database.[426] However, even the CRSP database is not completely free of data problems (Elton, Gruber, and Blake, 2001).[427] Consequently, the database suffers from an omission bias and performance is overstated when measured monthly similar to when a survivorship bias is present in the data. However, the Morningstar database, which presumably is the only relevant alternative to CRSP data, is also not without its own problems. First of all, it is not free of survivorship bias which causes performance to be overstated by 40 basis points to one percent per year (Elton, Gruber, and Blake, 1996b). Considerable differences between the two mutual fund databases emerge from a comparison of returns and alphas from a Carhart (1997) four-factor model (Elton, Gruber, and Blake, 2001) even after correcting for the known biases in both databases. These are most prominent among small funds and for earlier evaluation periods.[428]

However, it seems reasonable to believe that choosing the Morningstar database would not alter the conclusions and that the results are not affected by these issues. First, the performance of different funds in the cross section and changes in performance over time are compared rather than analyzing absolute levels of performance. Second, according to CRSP, several measures have been taken in recent

[426] See Carhart (1997) and http://www.crsp.com/products/mutual_funds.htm for more information.

[427] According to Elton, Gruber, and Blake (2001), monthly returns are not recorded for all funds in the database over their full lifetime. Some funds have only annual data and for others no returns are recorded at all. The liquidation and merger rates of the funds with missing returns are much higher than for the remainder of funds. As these problems only occur with funds that have less than 15 million USD in total net assets a simple strategy to avoid this bias is to use only funds larger than 15 million USD. Furthermore, returns of funds with multiple distributions at one day are overstated and merger dates are sometimes wrong.

[428] Specifically, differences in annualized alphas between CRSP and Morningstar are on average 5 basis points for large funds and 19 basis point for small funds over the whole period from 1979 to 1998. Average absolute differences in returns are 63 basis points for large funds and 134 basis points for small funds annually. Four percent of the differences in large funds and even nine percent in small funds are larger than 1 percentage point per month. These differences are economically meaningful and might influence inferences taking into account that alpha estimates of funds are seldom larger than one percent.

years to mitigate potential biases and to improve data quality. Third, the 2008 iteration of the database is used where Lipper is one of the major data providers while all studies cited above are based on earlier iterations of the database that were mainly sourced from Morningstar.

A minor concern is related to a potential incubation bias in the CRSP database. Funds might start as private funds and then be taken public, conditional on their track record during the private period (Evans, 2010). This induces a potential bias because the SEC allows investment management companies to backfill the full track record into public databases even though private funds that are never taken public, presumably due to bad performance results, do not appear in those databases. Evans (2010) documents that 39.4 percent of all funds are incubated, i. e. they started as private funds before being publicly available. Fama and French (2010), however, mention that for the period from 1999 to 2006 the performance results in their study based on all U. S. equity funds is not affected by a potential incubation bias. The measures taken to mitigate an incubation bias in the sample as far as possible are described below. Because young funds tend to be small but at the same time receive high net inflows, a potential incubation bias might affect the results when comparing funds with low and high inflows and should be kept in mind when interpreting the results.

The sample starts in 1992, the first year for which reliable information on manager changes became available, and ends in 2007. In constructing the sample, only actively managed domestic equity funds are selected, following the sample selection procedure of Pástor and Stambaugh (2002b). International funds, global funds, balanced funds, flexible funds, and funds of funds are excluded. Because CRSP does not provide an indicator for whether a fund is an active or passive fund, all funds containing terms in their name that commonly refer to passive vehicles are dropped.[429] The funds in the sample are classified into three groups: (1) large and mid-cap funds; (2) small-cap funds; (3) sector funds. Because ICDI classification codes are no longer available in the 2008 iteration of the CRSP mutual fund database, the selection criteria of Pástor and Stambaugh (2002b) are modified as follows. For the investment style classification, Lipper codes, Wiesenberger codes and Strategic Insight codes are used, with priority given in that order if different

[429] That is all funds that contain any of the following terms in their name (not case sensitive) are excluded from the sample: "index", "indx", "sp500", "sp 500", "s&p500", "s&p 500", "sp600", "sp 600", "s&p600", "s&p 600", "russell", "nasdaq", "msci", "dow jones", "djia", "etf", "exchange traded", "ishare".

codes are inconsistent. Details are given in Table A.2 in appendix A.2. A fund is assigned to one of the three groups for the total sample period if it belonged to this group for at least 50 percent of the observations in the sample period.[430] The sample is restricted to funds that have at least 12 months of available return data and information on the variable mgr_date in the CRSP database. All observations prior to the IPO date given by CRSP and funds without names are dropped in order to account for a potential incubation bias (Evans, 2010).

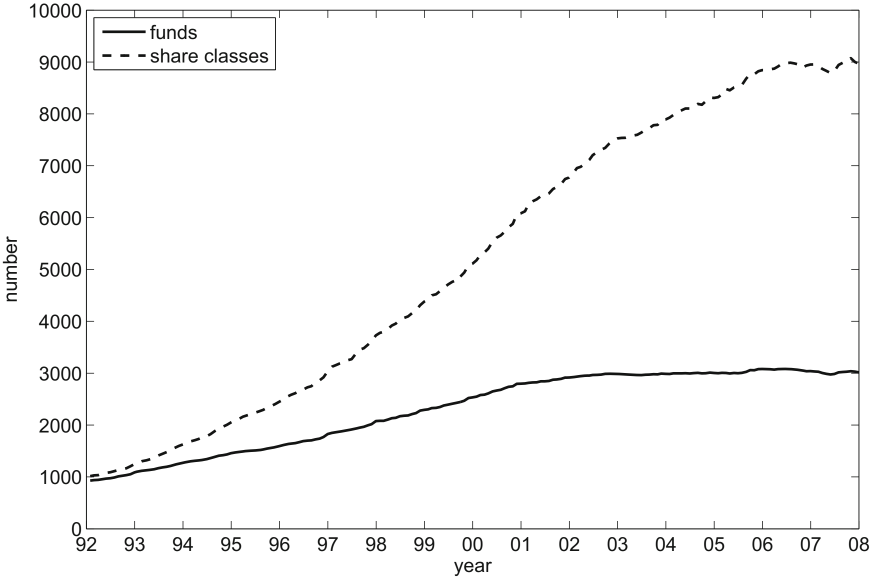
The CRSP mutual fund database treats each share class of a fund as a separate observation. Most previous studies on performance persistence have used this data as given without taking this issue into account (Carhart, 1997; Huij and Verbeek, 2007). However, different share classes of the same fund are identical in that they have the same manager and the same underlying portfolio of securities. They usually only differ with respect to their fee structure. Moreover, fund flows of individual share classes might cancel out at the portfolio level. Thus, not appropriately handling individual share classes might involve a potential bias due to double counting, which is especially relevant for recent periods during which many investment management companies initiated the offering of several share classes. Figure 5.1 presents the development of the total number of funds and the total number of share classes in the sample. At the beginning of the sample period in January 1992, 1,014 share classes exist which belong to 928 different funds. These numbers grow to 8,968 share classes belonging to 3,017 funds at the end of the sample period in December 2007. Thus, the number of share classes is almost three times the number of original funds. To avoid any biases, all share classes that belong to the same fund and have the same underlying portfolio are aggregated to one observation. A matching algorithm is used that combines information from the fund's name and the portfolio number variable given by CRSP.[431] Fund characteristics such as the investment objective or the first offer date are taken from the oldest share class, whereas quantitative information is either summed up, such as total net assets, or the weighted average over all share classes is taken, such as in the case of returns and fees. If two share classes of the same fund have different manager-change dates, the most recent date is used.

[430] For example, if a fund has 72 months of data and belongs to the small-cap group for 12 months, but eventually changes to the large and mid-cap group for the remaining 60 months, it is assigned to the large and mid-cap group for the total of 72 months.

[431] A matching solely based on the portfolio number variable is not possible, as this variable is available only from December 1998 onwards.

Figure 5.1: Number of funds and number of share classes

This figure presents for each month of the sample period the total number of funds in the sample (solid line) as well as the total number of share classes (dashed line) in the sample.



The final sample consists of 3,946 funds that existed at some point in time during the period from 1992 to 2007 for at least 12 consecutive months. These funds belong to 672 different fund families. Average raw returns (in excess of the return on the risk-free asset) over four-year subperiods vary between −0.29 and 1.36 percent per month indicating that the sample contains both bull markets and bear markets (Table 5.1). The portfolio turnover increased over time indicating more intense trading activity of fund managers, reaching its peak during the burst of the technology bubble from 2000 to 2003.[432] The funds in the sample have an average fund size of 899 million USD. Average fund size increased over the sample period, whereas average fees fell from 1.68 to 1.56 percent, most likely as a

[432] The portfolio turnover ratio is defined as the minimum of aggregated sales and aggregated purchases of securities, divided by the average 12-month total net assets of the fund. It measures the fraction of the portfolio traded over the previous 12 months. It should theoretically only measure discretionary trading but not liquidity-induced trading.

Table 5.1: Characteristics of sample funds

This table presents the characteristics of the sample of funds for 48-month subperiods and for the whole period from 1992 to 2007. Row (1) reports the number of months in the respective period; row (2) reports monthly (arithmetic) average raw returns in excess of the rate on the risk-free asset in percent; row (3) reports the average annual portfolio turnover; row (4) reports average fees in percent; row (5) reports the average age of the funds in years; row (6) reports the average fund size in million USD; row (7) reports average monthly absolute net inflows in million USD; row (8) reports the number of funds in existence; row (9) reports the number of manager changes that occurred during this period.

	Subperiods				Whole period
	1992–1995	1996–1999	2000–2003	2004–2007	
# months	48	48	48	48	192
Raw returns	0.72	1.36	-0.29	0.53	0.48
Portfolio turnover	0.83	1.10	1.40	1.02	1.13
Annual fees	1.68	1.64	1.67	1.56	1.63
Fund age	11.72	9.91	9.81	11.99	10.80
Fund size	461.42	853.36	849.27	1,178.46	899.26
Abs. net inflows	4.99	4.56	2.36	0.71	2.70
# funds	1,622	2,628	3,286	3,312	3,946
# manager changes	1,218	1,868	2,073	1,333	6,492

result of economies of scale in direct expenses involved in asset management and the increased competition from passive investment products.[433] Many new funds have been initiated over the sample period. The number of funds in existence increased from 1,622 in the first four-year subperiod (1992 to 1995) to 3,312 in the last four-year subperiod (2004 to 2007) in the sample, implying that many of new funds haven been initiated, especially during the rise of the market at the end of the 1990s. This development is also reflected in the change of the average fund age over time. Many new funds in the years 2000 to 2003 reduce the average age to 9.81 years in that period compared to 11.72 years for the subperiod from 1992 to 1995 and 11.99 years during the last subperiod from 2004 to 2007.

Monthly fund flows are constructed from the change in total net assets adjusted for internal growth due to investment returns according to equation (4.1) as introduced in section 4.2:

[433] Fees are calculated as the sum of the annual expense ratio and 1/7$^{\text{th}}$ of the sum of the front end and back end loads. See also French (2008) for an analysis of changes in the fee structure over time.

$$\text{flow}_{it} = \text{TNA}_{it} - \text{TNA}_{it-1}(1 + r_{it})$$

where TNA_{it} refers to the total net assets of fund i at the end of period t and r_{it} is the return of fund i between $t-1$ and t assuming that all distributions are reinvested and net of fund expenses.[434] Following the argument of Berk and Tonks (2007) absolute flows are scaled by $\text{TNA}_{it-1}(1 + r_{it})$ instead of TNA_{it-1} in order to obtain relative flows according to equation (4.2):

$$\text{rel\_flow}_{it} = \frac{\text{TNA}_{it} - \text{TNA}_{it-1}(1 + r_{it})}{\text{TNA}_{it-1}(1 + r_{it})} \ .$$

On average, each fund received 2.70 million USD net inflows per month. Fund flows significantly decreased after the burst of the bubble and have not yet reverted back to the same level as before. Furthermore, fund flows become more volatile over the sample period, especially following the burst of the technology bubble (Figure 5.2). This might be interpreted as a result of more sophisticated and performance-sensitive investors in mutual funds in recent years.

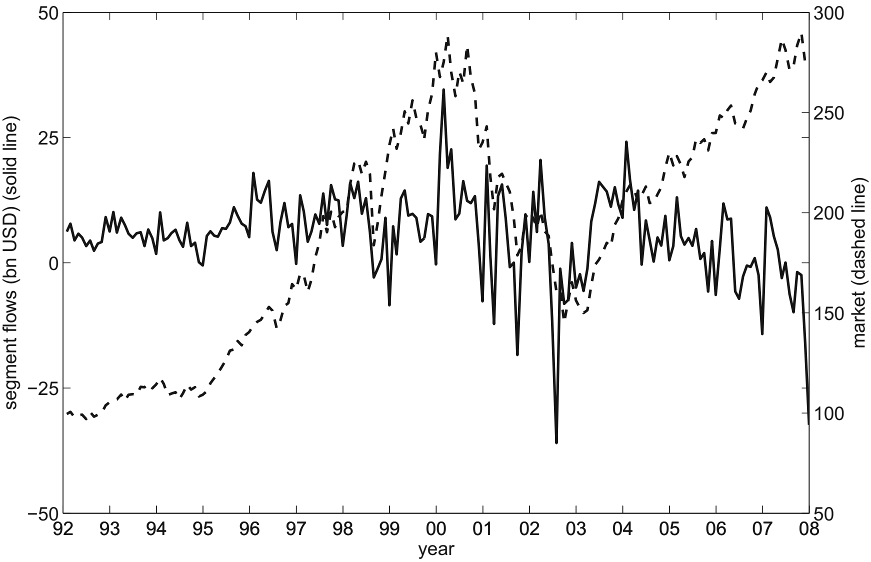
To obtain information on manager changes, the variable mgr_date in the CRSP database is employed instead of using the specific names of the managers.[435] This variable provides the date of the last manager change as reported by the investment management company. By using the mgr_date variable, any problems associated with different spellings of manager names are avoided. Furthermore, as the number of team-managed funds increased during recent years, the manager

[434] If a fund merges with another one, the incoming assets are not counted as fund flows, because there is no additional cash to invest. Thus, the fund manager does not face the immediate problem of investing the inflows, but can adjust the portfolio weights gradually over time to minimize the performance impact.

[435] This variable has also been used by Lynch and Musto (2003) and Cooper, Gulen, and Rau (2005). In theory, it shows the date that the manager leaves. However, for around 80 percent of observations, this is always the first of January. For the years 1992 and 1993, the variable is evenly distributed over different months. According to this observation, the variable can only be used as an indicator of the year in which there was a manager change but not for the month. One implication of this is that the data set is not sufficiently granular to investigate the impact of timing differences between fund flows and manager changes on subsequent fund performance. In other words, it is not possible to test whether fund flows pre-date and, hence, possibly cause a manager change or vice versa. It is only possible to observe fund flows as well as a manager change during the same year and then assess what effect these had on a fund's subsequent performance. Manager data seems to be more reliable in the Morningstar database compared to the CRSP database (Massa, Reuter, and Zitzewitz, 2010). This data was used e. g. by Jin and Scherbina (2010) but is not available for this study.

Figure 5.2: Fund flows

This figure presents the total absolute net inflows of all sample funds in each month of the sample period (solid line; left axis) as well as the rebased market index (dashed line; right axis).



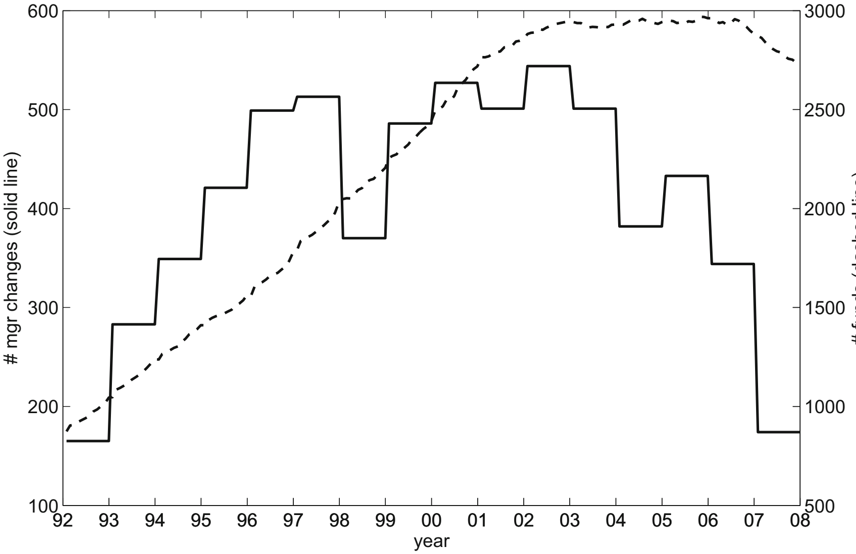
date variable has the advantage that investment management companies only report significant changes in management teams that might have an impact on performance (Massa, Reuter, and Zitzewitz, 2010). A total of 6,492 manager changes occurred during the sample period.[436] On average, 19 percent of the fund managers are replaced each year which is consistent with other studies.[437] The number of manager changes closely follows the development of the number of funds over time, with a slight drop in the year 1998 (Figure 5.3). The decrease at the end of the sample period results from a reporting lag but does not impact the results because only lagged manager changes are used in the analysis.

436 Note that the sample of Khorana (2001), who also analyzes the impact of managerial turnover on performance, contains only 393 funds.

437 Chevalier and Ellison (1999a) report 18 percent and Ding and Wermers (2006) report 14 to 18 percent using a more detailed database on fund managers constructed from various sources.

Figure 5.3: Number of manager changes

This figure presents the number of manager changes in each year of the sample period (solid line; left axis) as well as the corresponding number of funds (dashed line; right axis).



5.3 Methodology

Both ranked portfolio tests (Carhart, 1997; Carpenter and Lynch, 1999; Tonks, 2005) and a regression approach are applied to investigate the hypotheses. The ranked portfolio test has the advantage that it mirrors a real-time investment strategy that can be easily followed in reality.[438] Transaction costs for such a strategy should be relatively low for institutional investors who usually do not pay the full front-end load, if at all. Thus, this methodology provides direct estimates of the economic significance of the results. Moreover, Carpenter and Lynch (1999) conclude that ranked portfolio tests are the most powerful methodology for testing performance persistence.

[438] This is true for long-only positions in funds. Replicating spread portfolios in reality might not be possible in all cases and, if possible, might involve significant transaction costs.

5.3.1 Ranked Portfolio Test

5.3.1.1 Formation

Funds are first ranked into decile portfolios based on their previous year performance. Then, a second sorting of the top-decile-10 and the bottom-decile-1 funds is carried out.[439] In chapter 7, funds are sorted in the second step based on whether they experience a manger change and based on different fund-flow measures while in sections 8.3 and 8.4 funds are also sorted based on fund size.[440] The first sorting based on past performance separates good from bad managers since the focus is on whether the same mechanisms that prevent persistent outperformance of skilled managers can also explain why badly performing managers regress toward the mean. The aim is to separate the effects of a skilled manager leaving the fund or investors allocating large amounts of money to good managers from the effects of firing an unskilled manager (internal governance) or investors withdrawing money from a poorly performing manager (external governance). Then, the performance of these subgroups of top and bottom deciles is analyzed as well as the performance of spread portfolios to compare alternative investment strategies.

The formation of decile portfolios is created by the first sorting and, to do this, the investment performance of each fund in the previous year needs to be measured. However, raw returns, which have been used by Carhart (1997) for portfolio formation, not only depend on managerial skill but are also affected by the investment style such as growth or value, the risk level of the portfolio as well as luck. Thus, risk-adjusted returns that control for these factors are used in order to obtain a cleaner ranking measure that is a better representation of investment skills as compared to raw returns. Specifically, funds are ranked based on risk-adjusted returns from a Carhart (1997) four-factor model according to equation (3.23), estimated over the previous 12 months (formation period). This model incorporates the Fama and French (1993) size (SMB) and value (HML) factors and the Carhart (1997) momentum factor (MOM) in addition to the market excess return (r_{mt}) to explain fund excess returns and account for different fund styles.

[439] This methodology is similar to the one used for seasoned and unseasoned funds by Berk and Tonks (2007). However, their second sorting is based on the performance of the funds in the penultimate year.

[440] Details on the portfolio formation are given at the beginning of each section.

In order to efficiently estimate a four-factor model over such a short horizon, the Bayesian adjustment according to Huij and Verbeek (2007) is applied. This procedure involves the estimation of the four-factor model for each fund separately using OLS. Then the averages of the parameters of all other funds during the same period are used as priors. The final alpha and beta parameters for each individual fund are obtained as (matrix-) weighted averages of the OLS parameters and the prior, where the weights depend on the estimation efficiency of the OLS parameters.[441] Funds' alphas and factor loadings are assumed to follow a normal distribution in the cross-section:

$$\boldsymbol{\theta}_i \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \ , \tag{5.1}$$

where $\boldsymbol{\theta}_i = (\alpha_{4i}, \beta_{mi}, \beta_{\text{smb},i}, \beta_{\text{hml},i}, \beta_{\text{mom},i})'$ is a vector containing the alpha and factor loadings of fund i, $\boldsymbol{\mu}$ is a vector of the cross-sectional means and $\boldsymbol{\Sigma}$ the corresponding covariance matrix of alphas and factor loadings. Assuming that the error terms in the four-factor model of equation (3.23) are identically and independently distributed following a normal distribution $N(0, \sigma_i^2)$, the posterior distribution of $\boldsymbol{\theta}_i$ is also normal with expectation:

$$E(\boldsymbol{\theta}_i) = \left(\frac{1}{\sigma_i^2} \boldsymbol{X}_i' \boldsymbol{X}_i + \boldsymbol{\Sigma}^{-1} \right)^{-1} \left(\frac{1}{\sigma_i^2} \boldsymbol{X}_i' \boldsymbol{X}_i \hat{\boldsymbol{\theta}}_i + \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu} \right) \ , \tag{5.2}$$

where $\hat{\boldsymbol{\theta}}_i$ denotes the OLS estimate of the coefficients of fund i and σ_i^2 is the variance of ϵ_{it} in equation (3.23). The corresponding covariance matrix of the posterior distribution of $\boldsymbol{\theta}_i$ is:

$$V(\boldsymbol{\theta}_i) = \left(\frac{1}{\sigma_i^2} \boldsymbol{X}_i' \boldsymbol{X}_i + \boldsymbol{\Sigma}^{-1} \right)^{-1} \ . \tag{5.3}$$

Thus, the Bayesian adjustment "shrinks" any extreme parameters toward a grand mean, taking into account the cross-sectional distribution of the parameters. The intuition behind this Bayesian adjustment is that it is less likely that a fund will genuinely generate high alphas if all other funds generate relatively

[441] Further technical details are given in Huij and Verbeek (2007).

low alphas during the same period.[442] Using a similar argument, Cohen, Coval, and Pástor (2005) attribute a higher skill level to fund managers who produce their outperformance with a similar strategy to other skilled fund managers in comparison with managers who used a completely different strategy. The latter are classified as lucky rather than skilled. The degree of shrinkage depends on the precision of the fund-specific OLS estimate and the cross-sectional dispersion of alphas and factor loadings. Coefficients of funds with higher levels of unsystematic risk and shorter time series are shrunk relatively more toward the grand mean because their OLS estimates are usually less precise.[443]

5.3.1.2 Evaluation

In the evaluation period, the investment performance of the deciles and decile subgroups is investigated. A time series of decile and decile-subgroup returns is constructed by taking the equally-weighted average return across all funds in the specific portfolio for each month of the sample period. This results in one concatenated time-series of raw returns for each decile or decile subgroup of funds (concatenated approach). Funds that drop out of the portfolios due to mergers or closures remain in the decile until their last month of operation and then the portfolio weights are readjusted accordingly to avoid any look-ahead bias, which is defined by Carhart (1997) as the bias that results from eliminating funds from the sample that fail to survive a minimum period of time after the ranking period.[444] Four different factor models are used in addition to raw returns to evaluate performance.[445] Alphas and factor loadings are derived by estimating the model once per decile or decile subgroup over the full concatenated time series constructed as explained above.

The first model used is the three-factor model of Fama and French (1993) according to equation (3.22) which accounts for a potential size and value tilt of

[442] Moreover, as the betas of the underlying stocks change randomly over time, funds with similar holdings should be affected by these fluctuations to a similar degree.

[443] This also reduces a potential market-climate bias of the alpha due to omitted risk factors. I thank Hendrik Scholz for pointing this out. See also Scholz and Schnusenberg (2008).

[444] Assuming that in the case of a merger, which is the dominant reason for funds to disappear from the database, all investors of the acquired funds subsequently hold the acquiring funds by “following the money” according to Elton, Gruber, and Blake (1996b) does not alter the conclusions (the evidence for this is not reported but available on request).

[445] Note that raw returns can serve as an additional robustness test in case a risk factor is potentially omitted in the models used for formation and evaluation which would bias the results. Apart from this, raw returns have the advantage that they are observable and avoid any estimation error.

the portfolio. The second model is the four-factor model of Carhart (1997) as specified in equation (3.23) which is also used for portfolio formation. The third model is a five-factor model that adds a mean-reversion factor to the Carhart (1997) model: if winner funds hold on to winner stocks for another one or two years, these winner stocks might eventually experience mean reversion in returns (De Bondt and Thaler, 1985, 1987).[446] Because the focus of interest is on mean reversion in fund manager's skills, i. e. their alpha, it is important to control for mean reversion in the underlying stock returns. The mean-reversion factor is based on six value-weighted portfolios formed on the size and prior returns of all NYSE, AMEX and NASDAQ stocks. A stock is classified as large (small) if its market capitalization is higher (lower) than the median of all NYSE firms. Past returns are measured over the previous four years lagged by one year, where "high returns" means higher than the 70th percentile and "low returns" means lower than the 30th percentile. The mean-reversion factor is then the average of the low-prior-return portfolios minus the high-prior-return portfolios in both size groups. The resulting five-factor mean-reversion model is specified as follows:

$$\begin{aligned} r_{it} = \alpha_{5i}^{\mathrm{mr}} &+ \beta_{mi} r_{mt} + \beta_{\mathrm{smb},i}\mathrm{SMB}_t + \beta_{\mathrm{hml},i}\mathrm{HML}_t \\ &+ \beta_{\mathrm{mom},i}\mathrm{MOM}_t + \beta_{\mathrm{mr},i}\mathrm{MREV}_t + \epsilon_{it} \ , \end{aligned} \tag{5.4}$$

The fourth model is a five-factor model that adds a liquidity factor to the Carhart model on the grounds that fund flows might also affect portfolio liquidity.[447] Specifically, recent evidence points toward an illiquidity-premium in stock markets.[448] Managers of funds with excessive and extremely volatile fund flows usually tilt their portfolio toward more liquid securities (Huang, 2008; Chan, Faff, Gallagher, and Looi, 2009). This prevents them from earning an illiquidity-premium relative to their peers with less volatile fund flows. In fact, Sadka (2010) documents in a hedge-fund context that funds with high loadings on a market-wide liquidity factor earn on average 6 percentage points higher returns compared to their peers with low liquidity-loadings.[449] In order to distinguish between the

[446] I thank Kenneth French for providing these data on his website. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[447] I thank Ľuboš Pástor for providing these data on his website. See http://faculty.chicagobooth.edu/lubos.pastor/research.

[448] Amihud (2002), Amihud, Mendelson, and Pedersen (2005), Pástor and Stambaugh (2003) Liu (2006), Keene and Peterson (2007), Sadka (2006), and section 3.4.1.4.

[449] Note that this result cannot be explained by redemption restrictions of hedge funds with

different effects of fund flows on fund performance, it is important to control for the funds' loading on the liquidity factor. The liquidity factor is constructed as the value-weighted return on a spread portfolio long in the decile of stocks with the highest historical loading on a market-wide liquidity variable and short in the decile of stocks with the lowest historical loading on the market-wide liquidity variable.[450]

$$r_{it} = \alpha^{l}_{5i} + \beta_{mi} r_{mt} + \beta_{\mathrm{smb},i}\mathrm{SMB}_t + \beta_{\mathrm{hml},i}\mathrm{HML}_t + \beta_{\mathrm{mom},i}\mathrm{MOM}_t + \beta_{\mathrm{l},i}\mathrm{LIQ}_t + \epsilon_{it} \ , \tag{5.5}$$

Figure 5.4 and Table 5.2 provide a summary of the return series used as benchmarks. It becomes evident that the momentum factor generated the highest returns over the sample period of 0.87 percent per month, which came at the cost of the highest return variation of 4.87 percent per month and a steep decline after the burst of the technology bubble. Consistently high returns of 0.85 percent per month with low variation of only 3.45 percent per month have been provided by the liquidity factor, especially over the second half of the sample period. Somewhat surprising is the low performance of the size factor with monthly returns of only 0.15 percent per month. The size effect is almost negligible during the sample period and investing in small-cap stocks did not provide economically significant abnormal returns. The value and mean-reversion factors both provided mediocre returns of 0.40 and 0.41 percent per month, respectively, with a low variation of 3.46 percent per month for the value factor and only 2.29 percent per month for the mean-reversion factor. Inspecting the correlations reveals that the value-weighted market proxy is negatively correlated (−0.50) with the value factor, consistent with the market return being dominated by large-cap stocks. Also the size and value factors are negatively correlated with each other (−0.48), indicating that small-cap stocks tend to be growth stocks.[451] The size factor is also positively correlated with the mean-reversion factor implying that recent winner stocks suffering from mean reversion are rather small while recent loser funds benefiting from mean reversion are rather large. All remaining cross-correlations between the benchmark factors are below levels of 0.30. In particular, the liquidity

a higher loading on the liquidity factor in the sense of Aragon (2007).

[450] For details on the construction of the liquidity variables see Pástor and Stambaugh (2003).

[451] However, in theory this should not affect the correlations due the use of independent sorts when constructing the Fama and French (1993) factors. See section 3.3.2.3 for details.

factor is largely uncorrelated with the other factors, with all cross-correlations being at or below an absolute level of 0.20, which implies that liquidity risk is a new independent risk factor which is important to consider in performance evaluation analyses.

Table 5.2: Return characteristics of benchmark factors

This table presents the return characteristics of the factors used as a benchmark for 1993 to 2007 (because 1992 is only used as formation period). Columns (1) and (2) report the mean and the standard deviation, respectively, of monthly raw returns in excess of the rate on the risk-free asset in percent; columns (3) to (8) report the cross-correlations between the benchmark factors.

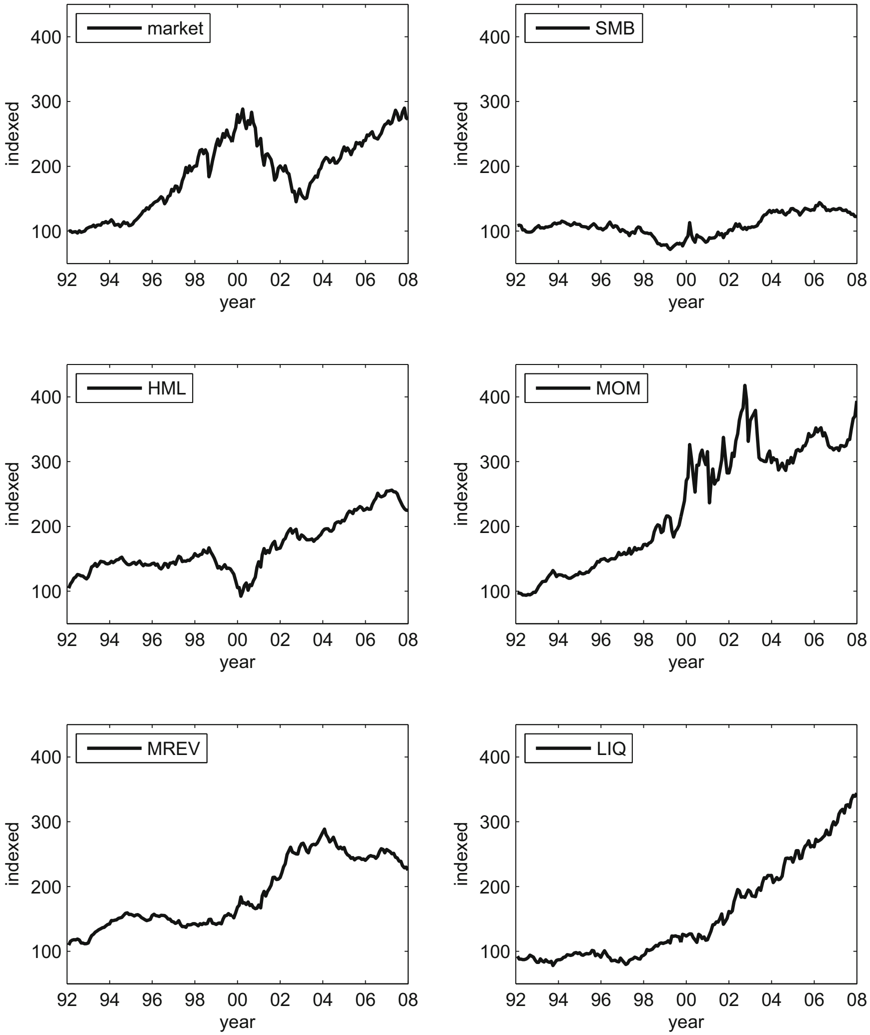
	Mean	SD	Cross-correlations					
			Market	SMB	HML	MOM	MREV	LIQ
Market	0.61	4.05	1.00	0.21	−0.50	−0.19	−0.19	0.20
SMB	0.15	3.76		1.00	−0.48	0.17	0.38	0.04
HML	0.40	3.46			1.00	−0.05	0.17	0.05
MOM	0.87	4.87				1.00	0.29	−0.14
MREV	0.41	2.29					1.00	0.03
LIQ	0.85	3.45						1.00

5.3.2 Regression Approach

In addition to the ranked portfolio test, a pooled regression is performed with the difference in annualized performance between the evaluation year and the formation year as the dependent variable. These performance changes over time are then regressed on a set of control variables, including net inflows and a manager-change dummy. This regression offers insights into the impact of fund flows and manager changes on fund performance over time. Furthermore, it provides the opportunity of not only separating the effects of fund flows and manager changes, but also of measuring their marginal impact and their interaction with other fund characteristics. Most importantly, it serves as a robustness test for whether the results based on the ranked portfolio test are driven by other variables known to affect fund performance. Specifically, despite its advantages the ranked portfolio test is only a univariate, or bivariate in the case of double sorting, methodology while the regression approach controls for several variables simultaneously.

Figure 5.4: Performance of benchmark factors

This figure presents the cumulative returns of the benchmark series. A market factor (market), a size factor (SMB), a value factor (HML), a momentum factor (MOM), a mean-reversion factor (MREV) and a liquidity factor (LIQ) are used as benchmarks.



6 Performance Persistence

6.1 Research Questions and Hypotheses

In this chapter, new empirical evidence on the performance persistence of active U. S. equity funds is provided for the period from 1992 to 2007, which immediately follows the sample period from 1962 to 1993 used in the seminal study of Carhart (1997).[452] Existing studies on performance persistence are extended in several dimensions. First, all share classes that belong to the same fund are aggregated to one observation. This avoids potential biases due to double counting of funds with several share classes. Nanda, Wang, and Zheng (2009) report that the number of single-class funds in their sample decreased from 313 in 1993 to 125 in 2002. The number of multiple-class funds increased, instead, from 40 to 838 in the same period.[453] In 2005, a total of 18,444 share classes existed in the U. S. which belonged to only 6,791 different funds (Table 1.5). However, Carhart (1997) and Huij and Verbeek (2007), for example, treat each share class of a fund as a separate entity.[454] This might be misleading as the underlying portfolio and the portfolio manager are identical across all share classes.[455]

Second, the performance evaluation methodology controls for mean-reversion in stock returns and a potential illiquidity-premium in addition to the conventional risk factors used in earlier studies by applying augmented factor models for performance evaluation.[456] Based on the discussion in section 3.4 these seem to be natural candidates to include and have been overlooked in existing studies so far.[457] The inclusion of all relevant risk factors is especially important when evaluating mutual fund performance. The omission of some risk factors might bias the alphas of funds in either direction. Thus, some funds producing true pos-

[452] Note that in both studies the first year is only used for portfolio formation.
[453] See also Figure 1 in Nanda, Wang, and Zheng (2009).
[454] Note that this should be less of a concern for the study of Carhart (1997) due to the earlier sample period and the lower number of multiple-class funds in earlier years.
[455] Usually, share classes only differ in their fee structure.
[456] Section 5.3.
[457] Higher-moment risk also seems to be important to control for (Kostakis, 2009). However, data limitations do not allow such an analysis based on the current data set.

P. Lückoff, *Mutual Fund Performance and Performance Persistence,*
DOI 10.1007/ 978-3-8349-6527-1_7,

itive alphas might be assigned negative alphas while other funds might be able to charge performance fees for positive alphas which in effect are only compensation for omitted beta risk. Thus, a more comprehensive specification of the model used as a benchmark seems important.

Third, and maybe most important, it is investigated how different methodologies used for ranking and evaluating fund performance affect the conclusions on performance persistence. Previous studies, for example Hendricks, Patel, and Zeckhauser (1993) and Carhart (1997), conclude that fund performance does not persist in the long run, i. e. over periods of one year or more. In contrast, the results of recent studies such as Bollen and Busse (2005) and Huij and Verbeek (2007) indicate that performance persists over short investment horizons of less than one quarter. The interpretation of this result is usually that short-term persistence exists but long-term persistence does not. However, the methodologies used in short-term and long-term studies differ and this might also be a potential explanation for the different results. Specifically, these studies differ with respect to the time horizons analyzed (short-term versus long-term) but also with respect to the ranking measure (raw returns versus risk-adjusted returns) and the evaluation measure (assuming fixed factor loadings or variable factor loadings). Therefore, a special focus of this chapter is on whether methodological aspects can explain the contradicting conclusions between short-term and long-term persistence studies. Bollen and Busse (2005), who provide evidence for short-term persistence based on daily data, note that the persistent outperformance of winner funds vanishes when they alter their methodology toward the approach used by Carhart (1997). Thus, performance persistence results are compared based on different methodologies over identical horizons in sections 6.2 and 6.3 and performance persistence is investigated over different horizons with identical methodologies in section 6.4. This analysis has important implications for the following chapter 7 in which economic reasons, specifically equilibrium mechanisms, are analyzed as a potential explanation for the decay of performance persistence over time.

A byproduct of this analysis is that it provides evidence on whether improved ranking methodologies as introduced in short-term persistence studies can also be used over longer holding periods to identify skilled fund managers ex ante. Bollen and Busse (2005, p. 571) conclude in their short-term persistence study that "the economic significance of the post-ranking abnormal returns is questionable, however, given the transaction costs and taxes levied on a strategy of capturing the persistent abnormal returns of the top decile." Specifically, the ranking methodology developed by Huij and Verbeek (2007) is used but, different to their approach of using 1-month holding periods, the decile portfolios are kept constant for periods from 1 to 36 months. For retail investors to be able to capture the persistence, it should last for a minimum of 12 months.

To summarize the research questions:

- How is performance persistence affected by using a recent fund sample from 1992 to 2007 which aggregates all share classes of the same fund (section 6.2)?

- How is performance persistence affected by using augmented factor models that control for stock-return mean reversion and liquidity risk in addition to the conventional factors (section 6.2)?

- Can methodological issues explain the finding that performance persists in the short-run but does not persist in the long-run? Specifically, can different ranking measures explain this finding (section 6.2.3)? Can different evaluation measures explain this finding (section 6.3)? Can different lengths of the formation and evaluation periods explain this finding (section 6.4)?

- Can investors benefit from more advanced ranking methodologies over holding periods of realistic and implementable length (section 6.4)?

6.2 Performance and Characteristics of Decile Portfolios

6.2.1 Characteristics

The presentation of the results begins with a discussion of the characteristics and performance of the fund deciles. Table 6.1 shows that decile-10 funds are among the second smallest size groups during the formation period, with an average size of only 757.58 million USD. This is consistent with the results of Chen, Hong, Huang, and Kubik (2004) that only small funds are able to beat the benchmark.[458] However, as a result of inflows and capital appreciation, winner funds grow to an average size of 1,059.93 million USD in the evaluation period which is larger than the average of the funds in any of the bottom five performing deciles (Table 6.2).

[458] The fact that decile-1-loser funds are also the smallest funds indicates that merely being a small fund is not sufficient to beat the benchmark.

The outperforming deciles, in particular the winner-decile-10 funds, have high net inflows, consistent with investors chasing past performance. Winner funds have on average absolute net inflows of 10.71 million USD per month in the formation period and they still experience even higher inflows in the evaluation period, with mean absolute inflows of 14.52 million USD per month. This suggests that some investors, i. e. the more sophisticated ones, have faster reaction times than others. An analysis of median fund size and median inflows reveals a similar picture. However, it also indicates that both variables are highly positively skewed. Indeed, the sample contains only few extremely large funds, the largest of which is the Growth Fund of America managed by American Funds, which grew in size from 3.5 billion USD at the beginning of 1992 to a sheer size of 193.5 billion USD at the end of 2007.[459]

Loser funds, in contrast, experience only modest average outflows of 1.23 million USD in the formation period and only slightly larger outflows of 4.05 million USD in the evaluation period, indicating some form of investor inertia. The average size of loser funds remains virtually unchanged between the formation period (684.31 million USD) and the evaluation period (673.59 million USD). Comparing average net inflows of winner and loser funds reveals an asymmetric response of investors to past performance with inflows into winner funds being much larger in size than outflows out of loser funds, even taking differences in fund size into account. This is consistent with the convex performance-flow relationship reported by earlier studies.[460] However, comparing the fund flows of median winner and loser funds, instead of average flows, reveals that fund flow levels are roughly equal in absolute size among winner and loser funds, especially in the evaluation period. The median winner fund receives 0.50 million USD inflows per month during the evaluation period while the median loser fund loses 0.53 million USD per month over the same interval. This suggests that the asymmetric flow response to positive and negative performance documented in the previous literature might be driven by extreme inflows into a small number of winner funds.[461]

Fund age follows an inverted U-shape which is increasing toward loser-ranked funds, implying that young funds outperform older funds, consistent with previous

[459] Note that all figures are combined for all share classes.
[460] Chevalier and Ellison (1997), Sirri and Tufano (1998), Lynch and Musto (2003), and section 4.2.
[461] Indeed, recent studies document that investors are now more likely to respond to bad performance by withdrawing money. See O'Neal (2004), Ivković and Weisbenner (2009) and section 4.2.6.

Table 6.1: Characteristics of decile portfolios in the formation period

This table presents the characteristics for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds for the formation period. Columns (1) and (2) report the average and median fund size in million USD, respectively; column (3) reports the average fund age in years; column (4) reports average fees in percent; column (5) reports the average annual portfolio turnover; column (6) reports the average manager tenure in years; column (7) reports the average family size in number of funds; column (8) reports the fraction of assets managed by a management team; column (9) reports the fraction of assets in retail fund share classes; columns (10) and (11) report average and median monthly absolute net inflows in million USD, respectively; column (12) reports the number of manager changes (MC) per fund. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Fund size		Fund-	Fees	Turn-	Man.	Family	Fract.	Fract.	Net inflows		MC /
	Mean	Median	age		over	tenure	size	team	retail	Mean	Median	fund
10 (winner)	757.58	109.70	9.58	1.69	1.24	3.56	20.51	0.42	0.90	10.71	0.42	0.21
9	891.03	136.00	11.10	1.61	1.10	3.84	20.61	0.44	0.88	6.24	0.16	0.20
8	1,127.44	149.40	11.39	1.56	1.01	3.89	19.54	0.44	0.88	5.41	0.10	0.21
7	1,015.31	151.80	11.26	1.55	0.94	4.01	20.20	0.46	0.87	4.23	0.06	0.19
6	1,032.41	145.69	11.72	1.55	0.96	3.91	20.60	0.44	0.86	3.12	0.02	0.21
5	863.43	143.70	11.55	1.60	1.00	3.80	21.73	0.44	0.88	2.68	0.03	0.21
4	951.42	143.09	11.34	1.62	1.03	3.86	24.49	0.44	0.87	1.22	−0.01	0.21
3	1,009.47	144.05	11.64	1.64	1.12	3.77	24.72	0.44	0.88	−0.30	−0.05	0.23
2	820.64	136.90	11.41	1.69	1.21	3.75	23.12	0.43	0.89	−0.47	−0.10	0.23
1 (loser)	684.31	104.60	10.45	1.88	1.63	3.77	26.32	0.43	0.91	−1.23	−0.26	0.23
10 − 1	73.27**	5.10***	−0.86***	−0.19***	−0.40***	−0.21***	−5.80***	−0.01***	−0.01***	11.94***	0.68***	–

Table 6.2: Characteristics of decile portfolios in the evaluation period

This table presents the characteristics for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds for the evaluation period. See the note to Table 6.1 for more explanation.

	Fund size		Fund-	Fees	Turn-	Man.	Family	Fract.	Fract.	Net inflows		MC /
	Mean	Median	age		over	tenure	size	team	retail	Mean	Median	fund
10 (winner)	1,059.93	180.06	10.58	1.67	1.16	4.06	21.43	0.46	0.89	14.52	0.50	0.20
9	1,118.03	184.13	12.10	1.59	1.04	4.33	21.41	0.48	0.88	8.41	0.12	0.21
8	1,329.14	192.50	12.39	1.55	0.95	4.34	20.18	0.49	0.88	6.35	0.06	0.18
7	1,181.07	182.70	12.26	1.55	0.89	4.51	20.90	0.50	0.86	4.43	−0.01	0.19
6	1,177.34	169.60	12.72	1.54	0.94	4.35	21.47	0.48	0.85	1.90	−0.03	0.18
5	968.96	170.40	12.55	1.60	0.97	4.25	22.53	0.47	0.88	1.45	−0.05	0.20
4	1,022.96	163.50	12.34	1.63	0.97	4.26	25.33	0.47	0.87	−1.13	−0.13	0.21
3	1,041.18	154.60	12.64	1.62	1.12	4.22	25.51	0.49	0.87	−4.21	−0.26	0.21
2	838.86	144.20	12.41	1.70	1.18	4.18	23.95	0.48	0.89	−3.77	−0.35	0.21
1 (loser)	673.59	100.30	11.45	1.88	1.57	4.22	27.22	0.48	0.90	−4.05	−0.53	0.21
10 − 1	386.33***	79.76***	−0.86***	−0.21***	−0.41***	−0.16***	−5.79***	−0.02***	−0.01***	18.58***	1.02***	–

results.[462] However, loser funds also tend to be younger on average which might be explained by managers of young funds assuming high risks and ending up either at the top or the bottom, depending on whether or not they are lucky. Consistent with Carhart (1997), loser funds have the highest fee levels of 1.88 percent annually, which can partly explain why they end up at the bottom of the performance ranking based on net returns. However, an annual spread in fees of 0.21 percentage points cannot explain the spread in performance between winner and loser funds in the evaluation period, as becomes clear below.[463] Fees also follow a U-shape and winner funds prove that higher fees might also signal higher skills. Indeed, decile-6 and decile-7 funds charge the lowest annual fees of on average 1.55 percent while winner funds charge 1.69 percent. Comparing fee levels between the formation and evaluation periods does not provide evidence for strategic fee setting by either winner or loser funds. Winner funds even seem to slightly reduce fees by 2 basis points to 1.67 percent, eventually in an attempt to attract more inflows based on their superior performance track record, while those of loser funds remain constant at 1.88 percent.

Similar to fees, portfolio turnover follows a U-shape and is highest for loser funds which trade 163 percent of their assets per year, compared to 94 percent for decile-7 funds and 124 percent for decile-10 funds. Turnover seems to improve performance when combined with true investment skills but reduces performance when the additional return is not sufficient to compensate for the resulting transaction costs.[464] Differences in manager tenure are statistically but not economically significant. Thus, winner funds do not seem to be managed by more or less experienced fund managers compared to loser funds.[465]

In contrast to the results of Chen, Hong, Huang, and Kubik (2004), winner funds in the sample tend to be associated with smaller fund families. The investment

[462] Blake and Timmermann (1998), Otten and Bams (2002), Huij and Verbeek (2007), Karoui and Meier (2009), and section 3.8.3.

[463] The spread in raw returns between winner and loser funds in the evaluation period is 0.32 percentage points per month or 3.84 percentage points per year (Table 6.3).

[464] This might explain why previous studies found inconclusive results on the relationship between portfolio turnover and fund performance. Elton, Gruber, Sanjiv, and Hvlaka (1993) and Carhart (1997) find a negative relationship, Wermers (2000) documents that turnover is not associated with fund performance and Dahlquist, Engström, and Söderlind (2000) and Chen, Jegadeesh, and Wermers (2000) find a positive relationship. See also section 3.8.1.1.

[465] Note that manager tenure measures the investment experience of the manager at a particular fund. Information on the manager age or the total investment experience throughout the whole career is not available.

management companies to which they belong have a smaller fund range of on average only 20.51 funds in the same segment on offer, precisely 5.8 funds less than the 26.32 funds offered by fund families with which loser funds are associated. The fraction of assets that is team-managed (as compared to single-managed) and the fraction of assets that belongs to a retail share class (as compared to an institutional share class) is almost evenly distributed over the performance deciles. Around 42 to 46 percent of assets are team-managed and the majority of assets, 86 to 91 percent, belong to a retail share class. The last column of Tables 6.1 and 6.2 reveals that loser-fund managers face a slightly higher risk of being replaced at 23 percent compared to average fund managers at between 19 and 21 percent. Also, the managers of winner funds seem to be inclined to leave slightly more often with a likelihood of 21 percent than their peers. This is consistent with the expectation and the arguments in chapter 7.

6.2.2 Performance

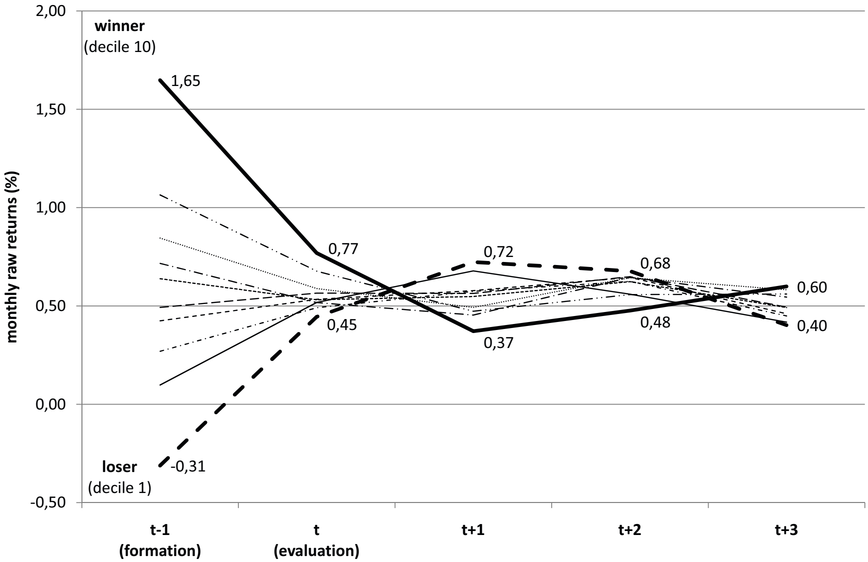
Next, the focus is on an analysis of investment performance. A first inspection of Figure 6.1 provides interesting insights. First, the spread in raw returns between winner and loser funds in the formation period is an impressive 1.96 percentage points per month (1.65 versus −0.31 percent), which is highly statistically significant (Table 6.3). In the evaluation period, performance almost monotonically decreases from winner to loser funds and winner funds continue to outperform loser funds, but on a much smaller scale. The raw-return spread between decile-10 and decile-1 funds in the evaluation period is 0.32 percent per month (0.77 versus 0.45 percent) and no longer significant. Thus, a strong tendency of mean reversion can be observed in fund performance. Figure 6.1 provides evidence that this tendency continues in the second year after portfolio formation, when loser funds outperform winner funds by 0.35 percentage points. This might indicate that the mechanisms which potentially lead to mean reversion are persistent over time.[466]

A similar pattern of mean reversion emerges for four-factor alphas, which are a better measure of managerial skill. The three top-ranked fund deciles have significantly positive alphas in the formation year, while the bottom five deciles significantly underperform the four-factor benchmark (Table 6.3). The spread be-

[466] This question is analyzed in more detail in section 6.4 below.

Figure 6.1: Mean reversion of fund returns

This figure presents average monthly raw returns for the decile portfolios 10 (winner) to 1 (loser) relative to the evaluation year (t).



tween the top and bottom decile is a significant 1.86 percentage points per month in the formation year. Also some evidence of mean reversion in risk-adjusted returns can be found in both winner and loser funds, particularly in the former. In the evaluation period, the alphas of the three highest deciles are insignificantly different from zero, while the bottom three deciles continue to significantly underperform, although their performance levels improve considerably in comparison with the formation period.

The monthly performance of winner funds decreases by significant 0.81 percentage points on average between the formation and evaluation periods to 0.07 percent in the evaluation period. Loser-fund performance improves from −0.97 to −0.24 percent per month between the formation and evaluation periods, a significant change of 0.73 percentage points.[467] The spread between winner and loser

[467] Note that the average mean reversion in raw returns, though comparable in magnitude to the average mean reversion in four-factor alphas, is not statistically significant due to

Table 6.3: Performance reversals of decile portfolios

This table presents the performance and mean reversion in performance for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. Columns (1) and (2) report monthly raw returns in the formation period and the evaluation period, respectively; column (3) reports the difference in raw returns between the formation and evaluation periods; columns (4) and (5) report monthly risk-adjusted returns based on the four-factor model of Carhart (1997) according to equation (3.23) in the formation period and the evaluation period, respectively; column (6) reports the difference in four-factor alphas between the formation and evaluation periods. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

	Raw returns			4-factor α		
	r_{t-1}	r_t	$\Delta r_{t-1,t}$	α_{t-1}	α_t	$\Delta\alpha_{t-1,1}$
10 (winner)	1.65	0.77	−0.88	0.88***	0.07	−0.81***
9	1.07	0.68	−0.39	0.43***	0.01	−0.43***
8	0.85	0.59	−0.26	0.25***	−0.05	−0.29***
7	0.72	0.52	−0.20	0.11	−0.11**	−0.22***
6	0.64	0.53	−0.11	−0.01	−0.10**	−0.10***
5	0.50	0.57	0.07	−0.12*	−0.09*	0.03
4	0.42	0.53	0.11	−0.24***	−0.11	0.13***
3	0.27	0.49	0.22	−0.38***	−0.14**	0.24***
2	0.10	0.52	0.42	−0.56***	−0.16*	0.40***
1 (loser)	−0.31	0.45	0.76	−0.97***	−0.24**	0.73***
10 − 1	1.96***	0.32	–	1.86***	0.32*	–

funds is reduced to 0.32 percentage points in the evaluation period. Since this spread is just weakly statistically significant, it seems fair to conclude that there is still some degree of performance persistence after one year. This residual spread of 0.32 percentage points per month can be partly attributed to higher fees and to potentially higher transaction costs arising from the higher turnover of decile-1 funds compared to decile-10 funds (Tables 6.1 and 6.2).[468]

Turning to a comparison of different multifactor models allows an attribution of the performance differentials to specific investment strategies or risk exposures.

the large cross-sectional variation within the decile portfolios. For example, the central 80 percent of the individual fund alphas of decile-10 (decile-1) funds vary between −2.28 and 2.74 (−2.68 and 2.14) percent per month (Table 6.13) while raw returns for the same group vary between −6.15 and 7.07 (−6.08 and 6.55) percent per month (Table 6.11).

468 Indeed, gross of management fees, the spread in four-factor alphas between winner and loser funds shrinks to an insignificant 0.28 percentage points (Table 7.18).

Judged by the three-factor model, which controls for a size and value tilt of the portfolio, winner funds continue to (weakly) significantly beat their benchmark with an alpha of 0.23 percent per month. However, controlling for momentum reduces the winner-fund alpha by 0.16 percentage points to 0.07 percent and further to 0.05 percent when additionally controlling for stock-return mean reversion or 0.06 percent when additionally controlling for illiquidity risk, respectively. As expected, controlling for funds accidentally holding the previous year's winner stocks and the longer-term loser stocks and loading on liquidity risk, and thus benefiting from these stock return patterns, results in a stricter benchmark.

Table 6.4: Performance of decile portfolios

This table presents different performance measures for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. Column (1) reports monthly raw returns; columns (2) to (5) report monthly risk-adjusted returns based on the three-factor model of Fama and French (1993) according to equation (3.22), the four-factor model of Carhart (1997) according to equation (3.23), a five-factor model that incorporates a mean-reversion factor according to equation (5.4) and a five-factor model that incorporates a liquidity factor according to equation (5.5). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
10 (winner)	0.77	0.23^{*}	0.07	0.05	0.06
9	0.68	0.05	0.01	0.01	0.01
8	0.59	−0.05	−0.05	−0.04	−0.03
7	0.52	-0.14^{***}	-0.11^{**}	-0.10^{*}	-0.09^{*}
6	0.53	-0.11^{***}	-0.10^{**}	-0.10^{**}	-0.09^{**}
5	0.57	-0.11^{**}	-0.09^{*}	−0.08	−0.07
4	0.53	-0.14^{**}	−0.11	−0.09	−0.08
3	0.49	-0.18^{***}	-0.14^{**}	-0.12^{*}	−0.11
2	0.52	-0.18^{**}	-0.16^{*}	-0.15^{*}	−0.13
1 (loser)	0.45	-0.28^{***}	-0.24^{**}	-0.21^{**}	-0.21^{**}
10 − 1	0.32	0.51^{**}	0.32^{*}	0.26	0.27

Loser funds, in contrast, benefit from adding more factors to the performance model because part of their significant underperformance of −0.28 percent per month judged by the three-factor model is due to unfavorable loadings on the momentum, mean-reversion and liquidity factors. Based on either of the five-factor models, loser-fund underperformance is reduced to −0.21 percent per month. The negative performance of loser funds is partly explained by these funds holding on to the last year's loser stocks and the longer-term winner stocks, suffering from negative momentum and mean reversion. A potential explanation is a disposition effect resulting in inertia among loser-fund managers. Apart from this, loser funds suffer from their tilt toward more liquid stocks, preventing them from earning an illiquidity premium. However, even based on the five-factor model the lowest decile (lowest three deciles for the mean-reversion-augmented five-factor model) continues to significantly underperform. Also, the spread between winner and loser funds can be explained to a large degree by the differences in the exposures to the momentum and mean-reversion factors. The spread between winner and loser funds is significant at 0.51 percentage points per month based on the three-factor model. After controlling for momentum and mean reversion the spread is reduced to an insignificant 0.26 percent while controlling for momentum and a liquidity tilt of the portfolio reduces it to 0.27 percent. These results reveal that winner and loser funds significantly differ in their risk exposures. Next, these effects are analyzed in more detail.

Table 6.5 presents the factor loadings, corresponding expected returns and the R^2 for the decile-fund portfolios based on the four-factor model, which serves as a base case, while Table 6.6 presents the same results for the three- and five-factor versions. The average market exposure is U-shaped across the different deciles with winner and loser funds having almost identical loadings on the market factor of 1.00 and 1.01, respectively. The loading on the size factor, also being U-shaped across all deciles, is 0.21 higher for winner funds as compared to loser funds (0.40 versus 0.20). The value exposure increases from winner to loser funds from −0.24 to 0.18 while the momentum exposure decreases from winners (0.14) to losers (−0.04), confirming the previous conclusions. Winner funds tend to be small-cap growth funds that benefit to a certain extent from stock-return momentum while loser funds are small-cap value funds suffering from negative stock-return momentum.

The expected returns presented in Tables 6.5 and 6.6 aggregate the effects of the loadings on the individual risk factors. Expected returns are computed by multiplying the average factor loadings of each decile by the average risk premium of the corresponding risk factor according to Table 5.2 and summing up. Both winner and loser funds face the strictest benchmarks because they have the highest risk

Table 6.5: Factor loadings of decile portfolios (4-factor)

This table presents the factor loadings for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. Columns (1) to (4) report the factor loadings based on the four-factor model of Carhart (1997) according to equation (3.23); column (5) reports expected monthly returns based on these factor loadings and the average factor returns as reported in Table 5.2; column (6) reports the average adjusted coefficient of determination (R^2). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

	Factor loadings				$E(r)$	R^2
	β_m	β_{smb}	β_{hml}	β_{mom}		
10 (winner)	1.00***	0.40***	−0.24***	0.14***	0.70	0.93
9	0.99***	0.27***	−0.03	0.04*	0.67	0.96
8	0.95***	0.19***	0.06**	−0.00	0.63	0.97
7	0.95***	0.13***	0.11***	−0.02	0.63	0.97
6	0.95***	0.10***	0.10***	−0.01	0.63	0.98
5	0.98***	0.13***	0.14***	−0.02	0.66	0.96
4	0.97***	0.10***	0.13***	−0.03	0.64	0.96
3	0.97***	0.10***	0.12***	−0.03*	0.63	0.96
2	1.01***	0.12***	0.15***	−0.02	0.68	0.93
1 (loser)	1.01***	0.20***	0.18***	−0.04	0.69	0.91
10 − 1	−0.01	0.21***	−0.43***	0.18***	0.01	0.48

exposures on aggregate.[469] Specifically, expected returns of winner funds are 0.70 percent per month compared to 0.69 percent for loser funds. In contrast, average funds (deciles 3 to 8) have lower risk loadings and face less strict benchmarks with expected returns between 0.63 and 0.66 percent per month. If true investment skill is represented by a parallel upward shift of the regression slope, i. e. a positive alpha, without affecting the other coefficients, then there should be no relationship between alphas and R^2. However, the inversely U-shaped R^2 across the deciles indicate that winner and loser funds follow investment strategies that are less precisely captured by the benchmark models. Consequently, it cannot be ruled out that the documented alphas of decile-10 and decile-1 funds are a result of omitted risk factors rather than true investment skill or the lack of skill.

[469] Note that the expected returns for winner funds may be slightly biased downwards due to the surprisingly low small-cap premium during the sample period. As a result, the benchmark of winner funds is not getting stricter even though they have a relatively high loading on the size factor.

These conclusions are confirmed by the alternative multifactor models (Table 6.6). Based on the three-factor model, winner funds face a less severe benchmark because their momentum exposure is ignored. However, especially adding the mean-reversion factor, with loadings steeply decreasing from winners (0.13) to losers (−0.16), makes the winner-fund benchmark stricter. In contrast, loser funds benefit from an addition of further risk factors to the benchmark. Expected returns decrease from 0.69 percent per month for the four-factor model to 0.66 percent per month for the mean-reversion-augmented and to 0.65 percent per month for the liquidity-augmented five-factor model. The spread in expected returns between winner and loser funds is 0.06 percentage points for both specifications of the five-factor models. Winner funds not only benefit from short-term stock-return momentum but also from long-term mean reversion in stock returns and, too a smaller degree, from a risk premium on their more illiquid holdings while loser funds seem to suffer from all of these exposures. From the raw-return spread between winner and loser funds of 0.32 percentage points, 0.06 percentage points can be explained by differences in risk exposures while 0.26 and 0.27 percentage points remain unexplained and can be interpreted as true alpha based on the mean-reversion-augmented and the liquidity-augmented five-factor models, respectively. Compared to the four-factor model, adding a mean-reversion or liquidity factor cannot, however, improve the explanatory power of the models significantly with R^2 being constant at 0.93 for winner funds and at 0.91 for loser funds based on either of the four- and five-factor models. Thus, there might still be additional factors missing and even based on the five-factor models and the alphas need to be interpreted with care.

Summarizing the previous section, it seems fair to conclude that mutual fund performance strongly reverts to average levels already one year after portfolio formation. The initial spread in four-factor alphas of 1.86 percentage points in the formation period is reduced to 0.32 percentage points in the evaluation period. Adding more factors to the benchmark model further reduces the performance of recent winner funds, because part of their investment returns can be attributed to positive loadings on the momentum, stock-return mean-reversion and liquidity factors. Conversely, the performance of recent loser funds is improved once more factors are included in the benchmark model, implying that part of the underperformance of recent losers is due to their unfavorable risk loadings rather than to poor stock selection skills.

Table 6.6: Factor loadings of decile portfolios (3- and 5-factor)

This table presents the factor loadings for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. Columns (1) and (2) report for the three-factor model of Fama and French (1993) according to equation (3.22) the expected monthly returns based on average factor loadings and the average factor returns as reported in Table 5.2, and the average adjusted coefficient of determination (R^2); columns (3) to (5) report for a five-factor model that incorporates a mean-reversion factor according to equation (5.4) the loading on the mean-reversion factor, the expected monthly returns and the average adjusted coefficient of determination (R^2); Columns (6) to (8) report for a five-factor model that incorporates a liquidity factor according to equation (5.5) the loading on the liquidity factor, the expected monthly returns and the average adjusted coefficient of determination (R^2). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

	3-factor		5-factor MREV			5-factor LIQ		
	$E(r)$	R^2	β_{mr}	$E(r)$	R^2	β_{l}	$E(r)$	R^2
10 (winner)	0.54	0.92	0.13^{**}	0.72	0.93	0.02	0.71	0.93
9	0.62	0.96	−0.00	0.67	0.96	0.00	0.67	0.96
8	0.63	0.97	−0.04	0.63	0.97	−0.03	0.61	0.97
7	0.65	0.97	-0.07^{***}	0.61	0.97	-0.03^{*}	0.61	0.97
6	0.64	0.98	−0.03	0.63	0.98	−0.01	0.62	0.98
5	0.67	0.96	-0.08^{***}	0.64	0.96	-0.04^{**}	0.63	0.96
4	0.67	0.96	-0.07^{**}	0.62	0.96	-0.03^{*}	0.61	0.96
3	0.66	0.96	-0.09^{**}	0.61	0.96	-0.04^{**}	0.60	0.96
2	0.70	0.93	−0.07	0.66	0.93	-0.05^{**}	0.64	0.93
1 (loser)	0.73	0.90	-0.16^{***}	0.66	0.91	-0.06^{**}	0.65	0.91
10 − 1	−0.18	0.40	0.28^{***}	0.06	0.49	0.07	0.06	0.47

6.2.3 Alternative Ranking Measures

So far, the ranking was based on the Bayesian version of the four-factor model as described in section 5.3. In this section, the sensitivity of the conclusions with respect to the use of different ranking measures is analyzed. Note that the advantages of the four-factor-alpha ranking, providing a cleaner measure of investment skill because it controls for investment style and risk, comes at the cost of a potential estimation error. Carhart (1997) used raw returns for ranking because these are easily observable.[470] The following ranking variables are compared: (1) raw returns; (2) the Sharpe ratio as defined in equation (3.3); (3) the one-factor alpha of Jensen (1968) according to equation (3.19); (4) the t-value of the one-factor alpha; (5) the Bayesian version of the four-factor model as used before for comparison. The formation period is still the previous 12 months and portfolios are formed at the beginning of each year. In addition to using decile portfolios The top and bottom deciles are also split into two equally-sized subgroups denoted by A and B. However, the following discussion will concentrate on the ranking on raw returns and on Bayesian four-factor alphas because the results based on the other alternative ranking measures (Sharpe ratio, α_1, t_{α_1}) are similar to the results on raw-return rankings.[471]

A comparison of monthly raw returns reveals that a return ranking produces the largest spread between winner and loser funds, irrespective of using the $10 - 1$ spread portfolio or the more extreme 10A $-$ 1B spread portfolio (Table 6.7). Based on the raw-return ranking, the spread between the top and bottom decile is 0.55 percentage points, though not significant. Recent winner funds generate raw returns of 0.83 percent per month in the evaluation period while recent loser funds only provide 0.28 percent. For the top and bottom five percent of funds, the corresponding spread is 0.69 percentage points per month, though again not significant. The highest performing five percent of funds over the previous year continue to provide high returns of 0.91 percent per month in the subsequent year compared to only 0.21 percent for the previously worst performing five percent. Moving toward risk-adjusted returns as the ranking measure reduces these spreads

[470] He also uses alpha-rankings based on the past three-years. However, because performance persistence seems to be relatively short-lived the focus is on 12 months ranking periods.

[471] Note that the differences between the results based on the Bayesian four-factor alphas and the other alternative ranking measures are slightly weaker because these measures capture at least part of the risk that explains the performance of the individual fund managers in the formation period which raw returns completely fail to account for.

between winner and loser funds to between 0.29 and 0.32 percentage points per month for the top-minus-bottom decile and between 0.31 and 0.41 percentage points for the top-minus-bottom five percent of funds. This implies that past raw returns have the strongest predictive power for future raw returns. However, in the case of some fund managers persistently following riskier investment strategies, i. e. have higher average loadings on the benchmark factors, this is exactly the expected outcome. Thus, it appears important and more appropriate to analyze risk-adjusted returns of the alternative portfolio-formation approaches in order to control for persistent differences in risk levels.

The picture which emerges from performance evaluation using risk-adjusted returns is clearly different (Table 6.8). For example, using the raw-return ranking, portfolio 10A yields raw returns of 0.91 percent per month while the same portfolio yields only raw returns of 0.84 percent per month when using the four-factor alpha ranking, a spread of 0.07 and pointing toward the superiority of the raw-return ranking. However, when controlling for investment risk the ranking is reversed: returns of portfolio 10A based on the raw-return ranking are reduced to −0.08 percent per month when adjusting for risk by the four-factor model but risk-adjusted four-factor alphas of portfolio 10A based on the four-factor-alpha ranking are 0.11 percent per month, a negative spread of −0.19 percent per month. In effect, none of the alternative ranking procedures is able to distinguish between fund managers who produce abnormal returns and those who do not after controlling for their size, value and momentum exposures, as evidenced by winner-minus-loser spreads of close to zero. Only for the ranking based on the Sharpe ratio the winner-minus-loser spread is positive at 0.07. However, none of the alternative ranking measures can identify winner funds with positive alphas while the Bayesian four-factor ranking does.

Using the Bayesian four-factor ranking, the winner-minus-loser spread is (weakly) significant at 0.32 percent and winner funds generate positive yet insignificant alphas of 0.07.[472] Moreover, the monthly spread for the more extreme spread portfolio between the top five percent of funds and the bottom five percent (10A − 1B) is 0.05 percentage points larger compared to the conventional winner-minus-loser portfolio at (weakly) significant 0.37 percent. Even within the top and bottom deciles, a higher ranking is associated with higher performance. But

[472] This improved ranking based on four-factor alphas compared to alternative ranking measures is consistent with the conclusions from Bollen and Busse (2001) using daily data.

Table 6.7: Returns based on alternative ranking measures

This table presents monthly raw returns for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. Decile-10 and decile-1 funds are further subdivided into halves and 10A − 10B is a spread portfolio long in the top five percent of funds and short in the bottom five percent of funds. Column (1) reports the results for a ranking based on the previous calendar year's raw returns; column (2) reports the results for a ranking based on the previous calendar year's Sharpe ratio according to equation (3.3); column (3) reports the results for a ranking based on the previous calendar year's alpha based on the one-factor model of Jensen (1968) according to equation (3.19); column (4) reports the results for a ranking based on the previous calendar year's t-value of the one-factor model; column (5) reports the results for a ranking based on the previous calendar year's Bayesian alpha based on the four-factor model of Carhart (1997) according to equation (3.23). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Ranking measure				
	Raw returns	Sharpe	α_1	t_{α_1}	α_4^{Bayes}
10A	0.91	0.82	0.79	0.67	0.84
10B	0.76	0.75	0.65	0.67	0.70
10 (winner)	0.83	0.79	0.72	0.67	0.77
9	0.77	0.67	0.65	0.68	0.68
8	0.70	0.66	0.57	0.64	0.59
7	0.65	0.64	0.59	0.65	0.52
6	0.56	0.54	0.55	0.58	0.53
5	0.50	0.55	0.54	0.55	0.57
4	0.45	0.48	0.56	0.53	0.53
3	0.47	0.52	0.51	0.47	0.49
2	0.42	0.43	0.52	0.48	0.52
1 (loser)	0.28	0.35	0.44	0.39	0.45
1A	0.36	0.41	0.46	0.42	0.46
1B	0.21	0.29	0.42	0.36	0.43
10 − 1	0.55	0.44	0.29	0.29	0.32
10A − 1B	0.69	0.53	0.38	0.31	0.41

Table 6.8: Performance based on alternative ranking measures

This table presents monthly risk-adjusted returns based on the four-factor model of Carhart (1997) according to equation (3.23) for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. Decile-10 and decile-1 funds are further subdivided into halves and 10A − 10B is a spread portfolio long in the top five percent of funds and short in the bottom five percent of funds. See the note to Table 6.7 for more explanation on the different ranking measures. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

	Ranking measure				
	Raw returns	Sharpe	α_1	t_{α_1}	α_4^{Bayes}
10A	−0.08	−0.04	−0.08	−0.13	0.11
10B	−0.13	−0.09	−0.15	−0.12	0.03
10 (winner)	−0.11	−0.07	−0.12	−0.12	0.07
9	−0.06	−0.12	−0.08	−0.09	0.01
8	−0.05	−0.07	-0.11^{*}	−0.09	−0.05
7	-0.08^{**}	-0.08^{*}	-0.09^{**}	−0.06	-0.11^{**}
6	-0.09^{**}	−0.09	−0.06	−0.05	-0.10^{**}
5	-0.10^{**}	−0.04	−0.07	−0.09	-0.09^{*}
4	-0.15^{*}	−0.10	−0.06	−0.08	−0.11
3	−0.08	−0.06	−0.10	−0.10	-0.14^{**}
2	−0.08	−0.14	−0.09	−0.09	-0.16^{*}
1 (loser)	−0.08	−0.14	−0.13	−0.13	-0.24^{**}
1A	−0.09	−0.15	−0.14	−0.14	-0.22^{**}
1B	−0.07	−0.13	−0.13	−0.12	-0.26^{**}
10 − 1	−0.02	0.07	0.02	0.01	0.32^{*}
10A − 1B	−0.01	0.09	0.05	−0.00	0.37^{*}

still, the top five percent of funds cannot significantly outperform the four-factor benchmark net of fees and transaction costs.

Part of the superiority of the four-factor ranking compared to alternative ranking measures might be due to a potential model bias when using the same factor model for portfolio formation and evaluation. However, the results in Table 6.9 indicate that this is not a problem. Rather, these results indicate that the four-factor alpha ranking does what it should do: it distinguishes between true selection skills in the formation period on the one hand and the impact of investment style, risk taking and luck on the other hand. Specifically, the alternative ranking measures select funds with extremely high risk loadings as winner funds. This is evident by a comparison of the factor loadings of winner funds sorted on raw returns and sorted on four-factor alphas: the difference in the loading on the market factor is 0.02 (1.02 versus 1.00), on the size factor 0.13 (0.53 versus 0.40), on the value factor 0.12 ($-0,12$ versus -0.24) and on the momentum factor 0.19 (0.33 versus 0.14). Thus, the raw-return ranking seems to select high-risk funds rather than skilled fund managers.

Table 6.9: Factor loadings based on alternative ranking measures

This table presents factor loadings for the decile-10 and decile-1 funds and a spread portfolio long in decile-10 funds and short in decile-1 funds. See the note to Table 6.7 for more explanation on the different ranking measures and the note to Table 6.5 for more explanation on the column specification.

Ranking measure	Factor loadings				$E(r)$	R^2
	β_m	β_{smb}	β_{hml}	β_{mom}		
Raw returns						
10	1.02^{***}	0.53^{***}	-0.12	0.33^{***}	0.94	0.91
1	1.02^{***}	0.15^{**}	0.05	-0.35^{***}	0.37	0.83
10 − 1	-0.00	0.38^{***}	-0.17	0.68^{***}	0.57	0.58
Sharpe ratio						
10	0.93^{***}	0.41^{***}	-0.01	0.26^{***}	0.85	0.88
1	0.93^{***}	0.12^{**}	0.14^{*}	-0.18^{***}	0.49	0.82
10 − 1	-0.01	0.30^{**}	-0.15	0.44^{***}	0.36	0.41
One-factor alpha (α_1)						
10	1.02^{***}	0.51^{***}	-0.12^{*}	0.21^{***}	0.84	0.89
1	1.03^{***}	0.15^{**}	0.11	-0.15^{***}	0.57	0.81
10 − 1	-0.01	0.36^{***}	-0.24^{*}	0.36^{***}	0.27	0.38
t-value of one-factor alpha (t_{α_1})						
10	0.95^{***}	0.40^{***}	-0.02	0.18^{***}	0.79	0.88
1	0.94^{***}	0.03	0.08	-0.10^{***}	0.52	0.89
10 − 1	0.01	0.36^{***}	-0.10	0.29^{***}	0.27	0.38
Bayesian four-factor alpha (α_4^{Bayes})						
10	1.00^{***}	0.40^{***}	-0.24^{***}	0.14^{***}	0.70	0.93
1	1.01^{***}	0.20^{***}	0.18^{***}	-0.04	0.69	0.91
10 − 1	-0.01	0.21^{***}	-0.43^{***}	0.18^{***}	0.01	0.48
Results of Carhart (1997) for comparison (sample from 1963 to 1993)						
Raw returns						
10	0.88^{***}	0.62^{***}	-0.05^{*}	0.29^{***}	0.80	0.93
1	0.93^{***}	0.32^{***}	-0.08^{**}	-0.09^{***}	0.41	0.89
10 − 1	-0.05	0.30^{***}	0.03	0.38^{***}	0.38	0.23

On aggregate, the winner funds selected by the return sorting have expected returns of 0.94 percent per month while the same group selected by the four-factor sorting has only expected returns of 0.70 percent per month, 0.24 percentage points lower (Table 6.9). The 0.06 percentage points higher (0.83 versus 0.77) raw returns of winner funds selected by a return sorting compared to a four-factor sorting are entirely due to their higher risk exposures (Table 6.7). Accounting for these risk differentials brings the spread to −0.18 percentage points (−0.11 versus 0.07), which is a clear indication of the superiority of the four-factor ranking in the identification of true selection skills (Table 6.8).

Loser funds provide a similar picture. The return ranking identifies loser funds with 0.17 percentage points lower (0.28 versus 0.45) raw returns in the evaluation period than the four-factor ranking (Table 6.7). In contrast, risk-adjusted returns of return-ranking loser funds are 0.16 percentage points higher (−0.08 versus −0.24) than those of the corresponding group based on a four-factor ranking (Table 6.8). Consequently, the impressive spread in raw returns between winner and loser funds based on the return sorting of 0.55 percentage points per month (Table 6.7) is entirely due to the return sorting picking up on differences in risk exposures but not in true selection skills. On aggregate, winner funds based on the return sorting are expected to yield 0.57 percentage points higher monthly returns because of their riskier portfolios as compared to loser funds. This is due to the return-sorting picking up funds that benefit or suffer from stock-return momentum as evidenced by a spread in the loading on the momentum factor of 0.68 between winner and loser funds (Table 6.9). Accounting for differences in risk loadings in the evaluation period yields a corresponding spread in risk-adjusted returns between winner and loser funds that is even below zero at −0.02 (Table 6.8). An alternative is to account for differences in risk levels already in the formation period: based on the four-factor sorting, the spread in expected raw returns between both subgroups is almost indistinguishable (0.70 versus 0.69).

Comparing these results with those of Carhart (1997) for his sample from 1963 to 1993 yields some interesting insights (bottom panel of Table 6.9).[473] First of all, both winner and loser funds seem to have higher market exposures nowadays. This is eventually explained by the more frequent use of derivatives by mutual fund managers in recent years due to relaxed regulation on this issue which allows them to maintain the desired market exposure even though the open-end

[473] Note that Carhart (1997) uses a return-sorting approach.

structure of mutual funds forces them to hold a significant fraction of assets in cash. Moreover, it was less clear in his study that winner funds tend to favor growth stocks. The most notable difference, however, is that winner funds in his study significantly outperform loser funds by 0.29 percentage points (-0.12 versus -0.40) per month based on four-factor alphas while in this study the same spread is negative at -0.02 (-0.11 versus -0.08) in the case of a return-sorting.[474] This is because the underperformance of loser funds in in the present study is, to a large extent, explained by their negative loading on the momentum factor, suffering from negative stock return momentum. Thus, while in the sample of Carhart (1997) loser-fund managers seem to have consistently picked the wrong stocks this rather seems to be a one-time mistake in the sample of this study and loser funds subsequently suffer from the continued underperformance of these stocks.[475]

It does not seem to be the case, however, even after the publication of the study of Carhart (1997) that fund managers tried to beat their benchmark by simply loading high on the risk factors, especially the momentum strategy, in the hope that their investors would use simpler performance measures to evaluate their skill which would not allow them to detect these tactics. The winner-fund loadings on size, value and momentum in this sample are comparable to those in the sample of Carhart (1997).

In summary, the empirical evidence indicates that, based on a recent sample period, the Bayesian version of risk-adjusted returns according to the four-factor model of Carhart (1997) strongly dominates all other potential ranking measures analyzed with respect to the predictive power for future performance if controlling for investment risk. Thus, part of the result that Huij and Verbeek (2007) document performance persistence in the short run over one month might be attributable to them using an improved ranking methodology. Moreover, the results of this section indicate that even within the top and bottom deciles, past performance is positively related to future performance.

[474] Compare Table 6.9 and Table 3 in Carhart (1997).

[475] Note that this is only true in the case of a return sorting. If the four-factor sorting is used fund managers who consistently pick the wrong stocks can be identified, as evidenced by their significantly negative risk-adjusted returns of -0.24 percent (Table 6.8).

6.3 Performance of Individual Decile Funds

6.3.1 Objective

The previous literature has provided evidence in favor of short-term performance persistence but has also documented a lack of long-term performance persistence.[476] However, these studies not only differ in the time horizon analyzed but also in the methodology applied. The aim of this section is to investigate whether long-term performance persistence can be found if the same (or a similar) methodology is applied as in the studies on short-term persistence. Thus, the question is whether differences in the methodology explain differences in results rather than differences in the time period considered.

In previous studies, the analysis of long-term performance persistence was based on static performance measures estimated for decile portfolios and assuming fixed coefficients across all funds in the same decile and over time. However, this potentially masks differences in alphas and factor loadings across funds in the same decile and time variability of performance and investment style. In this section, the empirical analysis, therefore, focuses on individual funds and explicitly allows for cross-sectional and time-series variation in factor loadings and alphas.[477]

By focusing on individual funds a potential bias in the alpha estimation can be mitigated. The composition of the decile portfolios changes significantly over time because every 12 months new decile portfolios are formed.[478] Additionally, the funds themselves change the composition of their portfolios in buying and selling stocks. Both effects contribute to a high portfolio turnover when broken down to the underlying stock level and give rise to a high degree of time-variability in the model parameters which cannot be accounted for by an unconditional model (Elton, Gruber, and Blake, 1996a). This time variability might bias the estimation results if not properly accounted for (Bollen and Busse, 2005).

Apart from time variability, individual funds that belong to the same decile might differ significantly in their investment strategies, which implies cross-sectional variability in parameters within each decile and might also bias the

[476] See Hendricks, Patel, and Zeckhauser (1993) and Carhart (1997) for long-term persistence and Bollen and Busse (2005) and Huij and Verbeek (2007) for short-term persistence. See also section 4.1.

[477] Details on the different estimation methodologies are given in Table 6.10.

[478] Indeed, Table 6.20 reveals that only 15.69 or 15.70 percent of winner and loser funds, respectively, survive a second year in the same decile. This implies that a strategy of buying decile-10 or decile-1 funds involves an annual turnover of about 84 percent.

inferences. For example, if there are only a few number of funds with genuine skills, which is what might be expect based on the literature, see e. g. Fama and French (2010), but the majority of the funds ending up in decile 10 hold the last year's winner stocks only by luck, then regressing the decile-10 portfolio on the four factors of the Carhart (1997) model might lead to biased conclusions. Specifically, due to the majority of decile-10 funds holding the last year's winner stocks, the benchmark used for all decile-10 stocks has a high loading on the momentum factor. Because the same benchmark is used for all funds that belong to a certain decile, the few winner funds with true investment skill but no loading on the momentum factor are also evaluated against this strict benchmark. Such an approach might not be correct because those funds with true skills consistently select the winning stocks and do not continue to hold on to the last year's winners which benefit from stock-return momentum. To avoid this bias, the four-factor model needs to be estimated separately for each fund.[479]

Focusing on individual funds further allows an investigation of the whole panel of individual funds. Loughran and Ritter (2000, p. 363) argue that "in general, tests that weight firms equally should have more power than tests that weight each time period equally". The concatenated approach introduced in section 5.3.1.2 weights all time periods equally, irrespective of how many funds exist at that time. Table 5.1 reveals that the number of funds in the last three-year subperiod of the sample (2004 to 2007) is more than twice as high as the number of funds in the first three-year subperiod (1992 to 1995). Thus, weighting all periods equally is not representative for the size of the industry. Moreover, if the cross-section of fund performance is skewed, it is important to analyze means and medians because both parameters might imply different inferences (Ferson and Kang, 2002). Moreover, households are usually unable to follow a trading strategy implied by a ranked portfolio test and to earn average decile returns because this involves holding a large number of funds. Consequently, the moments of the whole panel of returns and alphas for each decile are analyzed (panel approach).

[479] An alternative to the non-parametric approach of introducing variation in the cross-section within each decile by estimating the model for each fund separately would be a parametric approach that specifies a functional form of the cross-sectional variation in factor loadings. This would be similar to conditional performance evaluation models in the fashion of Ferson and Schadt (1996), who model the variability of factor loadings over time depending on certain information variables. However, no such approach exists so far in the literature for the cross section even though the generalized calendar-time approach of Höchle, Schmid, and Zimmermann (2008) would theoretically be capable of doing this.

6.3.2 Methodology

In section 6.2, the concatenated approach for portfolio evaluation as introduced in section 5.3.1.2 has been applied. This approach forms an equally-weighted portfolio return of all funds in a certain decile and a certain year, based on previous year performance. This yields 12 monthly return observations for each decile portfolio. Then, these (12×1)-return vectors are concatenated to one time-series vector for each decile portfolio. A factor-model regression is applied to each decile-portfolio time series over the whole sample period. In order to deal with the time-variability and cross-sectional variation of the parameters in the four-factor model a different methodology is applied in this section, namely a rolling window regression for each individual fund. Estimating performance for each fund individually is similar to the methodology applied by Busse, Goyal, and Wahal (2010). According to Bollen and Busse (2005), a rolling-window regression can be interpreted as a non-parametric approach of a conditional performance evaluation model which neither requires the specification of information sources nor of the response of factor loadings to information.[480] Specifically, the parameters are estimated from equation (3.23) in the Bayesian version of equations (5.1) to (5.3) using a window of 24 months. The alpha of fund i at time $t = 13$ of this window is the realized return at time $t = 13$ minus the expected return for that month:

$$\begin{aligned} \alpha^B_{i,t=13} &= r_{i,t=13} - E(r_{i,t=13} | \hat{\boldsymbol{\beta}}_{t-12;t+11}) \\ &= r_{i,t=13} - \hat{\beta}_{mi} r_{m,t=13} - \hat{\beta}_{\text{smb},i} SMB_{t=13} \\ &\quad - \hat{\beta}_{\text{hml},i} HML_{t=13} - \hat{\beta}_{\text{mom},i} MOM_{t=13} \ , \end{aligned} \tag{6.1}$$

where $\hat{\beta}$ denotes the coefficient estimate from the rolling-window regression. Then the estimation window moves on one month until the end of the fund's return time series is reached.[481] Because the performance measurement in the evaluation period is ex-post by nature this procedure does not suffer from a look-ahead bias.[482]

[480] Specifically, neither $\boldsymbol{z}_t$ nor $\boldsymbol{\gamma}'_i$ and $\boldsymbol{\delta}'_i$ in equation (3.29) have to be specified.

[481] Elton, Gruber, and Blake (1996a) use a similar approach but estimate the model parameters at once over the whole life of the fund instead of using a rolling window. Bollen and Busse (2005) use non-overlapping periods of one quarter and daily data to estimate the model for each individual fund. All three approaches are very similar in the underlying concepts and objectives, though they differ in the specific implementation.

[482] In addition to the centered window, a lagged rolling window is applied. In this case, the

Following this methodology, one alpha estimate is obtained for each fund and each month. Similar to the presentation of raw returns a time series of decile-portfolio alphas is constructed for each decile as the cross-sectional equally-weighted average of the alphas of all funds that belong to a specific decile (portfolio approach):

$$\alpha^B_{port,t} = \frac{1}{n}\sum_{i=1}^{n}\alpha^B_{it} \ . \tag{6.2}$$

In the tables, the time-series mean of these portfolio alphas over the sample period is presented.

$$\overline{\alpha}^B_{port} = \frac{1}{T}\sum_{t=1}^{T}\alpha^B_{port,t} \ . \tag{6.3}$$

This approach has the advantage that it accounts for differences in investment strategies across individual funds within one decile and for changes in the investment strategy over time. In addition to the portfolio approach, the moments of the whole panel of alphas for each decile are analyzed (panel approach):

$$\overline{\alpha}^B_{pan} = \frac{1}{T}\frac{1}{n}\sum_{t=1}^{T}\sum_{i=1}^{n}\alpha^B_{it} \ . \tag{6.4}$$

As described above, this accounts for the increasing number of funds in existence over time and puts more weight on more recent periods.[483] Moreover, it provides insights into the shape of the alpha distribution within the deciles. Panels (a) and (b) of Table 6.10 summarize the technical details of the estimation and aggregation of fund performance used in the following section for raw returns and risk-adjusted returns, respectively.

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factor loadings are estimated over the period $t-24$ to $t-1$ in order to compute the Bayesian alpha in $t+25$: $\alpha^B_{i,t=25} = r_{i,t=25} - E(r_{i,t=25}|\hat{\boldsymbol{\beta}}_{t-24;t-1})$ using the $\hat{\beta}$'s from a regression over $t-24$ to $t-1$.

[483] Specifically, the average return or alpha from the portfolio approach and from the panel approach differ in the weighting of the time periods. In the portfolio approach the cross-sectional mean is taken first and then the time-series mean. This assigns an equal weight to each month of the sample irrespective of the number of funds in existence. Instead, the mean from the panel approach assigns equal weights to each fund-month. This accounts for the increasing number of mutual funds in recent years.

Table 6.10: Approaches used to estimate and aggregate performance

This table presents the different approaches used in the empirical part to estimate fund performance and to aggregate performance measures for decile portfolios.

Approach	Description
(a) Raw returns	
Portfolio	First, the cross-sectional equally-weighted mean is taken across all funds that belong to the same decile which results in a concatenated time series of decile returns. Second, the mean (or standard deviation) of this time series is presented in the tables. This procedure weights all periods equally.
Panel	The equally-weighted mean (or other empirical moments) of all funds that belong to the same decile is taken in one step in the cross-section and over time. This procedure weights all observations (fund-months) equally.
(b) Risk-adjusted returns (alphas)	
Concatenated	Decile alphas are estimated by regressing the concatenated time series of decile returns from the portfolio approach in panel (a) on the benchmark factors. Funds are first aggregated into deciles and then alpha is estimated. One regression is estimated for each decile over the whole sample period. Coefficients are fixed across all funds in the same decile and over time. This approach corresponds to the methodology used by Carhart (1997).
Portfolio	First, individual fund alphas are estimated using a rolling-window regression as described in equation (6.1). This results in one alpha-estimate for each fund and each month. Second, the cross-sectional equally-weighted mean is taken across all funds that belong to the same decile which results in a concatenated time series of decile alphas according to equation (6.2). Third, the mean of this time series is presented in the tables. This procedure weights all periods equally. Alphas are estimated in the first step and then aggregated into deciles. One regression is estimated for each fund and each 24-month rolling window. Coefficients can vary across individual funds and over time. This approach is similar in fashion to the ones used by Elton, Gruber, and Blake (1996a) and Bollen and Busse (2005).
Panel	First, individual fund alphas are estimated using a rolling-window regression as described in equation (6.1). This results in one alpha-estimate for each fund and each month. Second, the equally-weighted mean (or other empirical moments) of all funds that belong to the same decile is taken in one step in the cross-section and over time. This procedure weights all observations (fund-months) equally.

Bollen and Busse (2005) compare two different approaches of estimating evaluation-period performance. The first approach corresponds to the concatenated approach of Carhart (1997) and the second is closely related to the portfolio approach of estimating alphas, though Bollen and Busse (2005) use daily data. Allowing for time variation and cross-sectional differences in alphas, which the portfolio approach does, yields on average abnormal returns of the winner-fund decile of significant 0.39 percent per quarter. In contrast, the alpha of the concatenated approach applied to the same data is insignificant at 0.09 percent per quarter. Bollen and Busse (2005) show that the difference between the concatenated alphas and alphas that are estimated for each fund separately allowing for time variation of factor loadings is approximately equal to the covariance between factor loadings and factor returns, which is a measure of factor-timing abilities.[484] Furthermore, they argue that this alpha differential between both approaches can be attributed to perverse factor timing by the changing composition of the top fund portfolio. Indeed, the correlation between factor loadings and factor returns for the concatenated time series of top funds turns out to be negative. This result highlights that risk changes might be significant and that it is important to control for this variability when estimating fund performance.

6.3.3 Bayesian Alphas

Table 6.11 presents the raw returns of the decile portfolios according to the portfolio approach and the panel approach.[485] According to the panel approach, average raw returns are in general slightly lower than according to the portfolio approach. The reason for this is that the former gives more weight to the more recent periods which have been characterized by lower market returns (Table 5.1). The spread between winner and loser funds is on average 0.32 or 0.30 percentage points per month based on the portfolio or panel approach, respectively, but significant only for the latter.[486]

Interestingly, median returns are consistently higher compared to mean returns indicating that average decile-fund performance might be biased downward due to some funds with extremely low returns. This is especially evident for loser funds

[484] See equation (11) in Bollen and Busse (2005).

[485] Note that the mean of the portfolio approach corresponds to column (2) in Table 6.3 and column (1) in Table 6.4.

[486] Note that the significance might also result from a much larger number of observations in the panel approach compared to the portfolio approach.

Table 6.11: Returns of individual decile funds

This table presents monthly raw returns for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. Columns (1) and (2) report the mean and the standard deviation, respectively, of a concatenated time series of decile-portfolio returns following the methodology of Carhart (1997) (portfolio approach), i. e. first taking the cross-sectional average of individual fund returns and then the time-series average; columns (3) to (6) report the mean, median, 10th percentile and 90th percentile, respectively, of the panel of monthly raw returns of all funds that belong to the decile portfolio (panel approach), i. e. taking the average over the whole panel of individual fund returns in one step. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns					
	Portfolio		Panel			
	Mean	SD	Mean	Median	$Perc_{10}$	$Perc_{90}$
10 (winner)	0.77	5.31	0.66	0.85	−6.15	7.07
9	0.68	4.44	0.58	0.79	−5.60	6.51
8	0.59	4.02	0.49	0.73	−5.31	6.10
7	0.52	3.87	0.42	0.70	−5.16	5.87
6	0.53	3.82	0.45	0.70	−5.04	5.77
5	0.57	3.95	0.48	0.73	−5.10	5.86
4	0.53	3.90	0.45	0.68	−5.14	5.93
3	0.49	3.96	0.40	0.67	−5.32	5.92
2	0.52	4.11	0.42	0.67	−5.63	6.19
1 (loser)	0.45	4.21	0.36	0.64	−6.08	6.55
10 − 1	0.32	3.18	0.30***	0.21***	–	–

implying that their persistent significant underperformance might stem from only a few funds.[487] As a result, the spread in medians between winner and loser funds is lower at 0.21 percent per month but still significant.

The standard deviation of raw returns (portfolio approach) confirms the previous impression that both, winner and loser funds, follow riskier strategies than average funds. Monthly raw returns of winner funds vary by 5.31 percent and those of loser funds by 4.21 percent while the standard deviation of monthly returns of average funds (deciles 3 to 7) is well below 4 percent. Thus, a certain fraction of fund managers in the top and bottom decile might end up there due to high portfolio risk combined with good luck (top decile) or bad luck (bottom

[487] This conjecture is supported by the results in Table 6.7: the lowest five percent of funds have average returns of 0.21 percent per month while the second-lowest decile of funds already generates average raw returns of 0.42 percent per month.

decile). This is also supported by the 10th and 90th percentile of panel returns. The former follows an inverted U-shape while the latter follows a U-shape. Thus, the cross-sectional variation in raw returns of funds within the winner or loser decile is much larger than the corresponding variation in average-fund deciles. Specifically, the raw returns of winner funds fall in a centered 80-percent interval from −6.15 to 7.07 percent per month and those of loser funds fall in a centered 80-percent interval from −6.08 to 6.55 percent per month. Raw returns of decile-6 funds, for example, fall in a much narrower interval of between −5.04 and 5.77 percent per month. Thus, some of the recent winner funds generate extremely low returns in the evaluation period while some of the recent losers also revert and provide extremely high returns. This result is especially important for retail investors, who usually hold only a few funds. The level of portfolio risk and randomness seem to be important determinants of fund performance over time.

After the analysis of individual fund returns, the analysis commences with a presentation of the results for the four-factor model estimated for each individual fund over a rolling window.[488] In order to motivate this approach, the characteristics of the factor loadings are discussed first before the performance results are investigated. Table 6.12 presents the statistical properties of the factor loadings for winner and loser funds. The R^2 for the individual-fund regressions over 24-month windows are, as expected, smaller than those for the decile portfolios estimated over the whole sample period. However, 75 percent of the R^2 are above 0.80 or 0.79 for winner and loser funds, respectively.[489] Based on these results, it seems that the estimation error, which is the cost from the individual fund regressions, is in an acceptable range. Already the average exposures in the first row of panel (a) for winner funds and panel (b) for loser funds differ from the corresponding factor loadings based on the concatenated approach as reported in Table 6.5. The average winner fund has a loading on the market factor of 0.99 based on the individual-fund regressions compared to 1.00 based on the concatenated approach, not a large difference. However, within the group of winner funds, this loading has a standard deviation of 0.27, implying that the market loading strongly varies over time and across funds in the winner decile.[490] Size value

[488] First, the results on the centered window are discussed while the results for the lagged window are presented below.
[489] Note that these R^2 are from the first-step OLS regression and do not take the Bayesian shrinkage into account.
[490] Note that all moments are taken in both dimensions, cross section and over time, in one step, i. e. the mean, for example, is the panel mean.

and momentum loadings of winner funds are 0.26, −0.08 and 0.06, respectively, based on the individual-fund regressions. Based on the concatenated approach the corresponding figures are more extreme with 0.40, −0.24, and 0.14, respectively. Again, the standard deviations of the loadings on the size, value and momentum factor for winner funds are 0.35, 0.43 and 0.19, respectively, consistent with large variation within the winner decile. For loser funds, individual-fund regressions yield on average a market loading of 0.99, a size loading of 0.29, a value loading of 0.01 and a momentum loading of 0.07, respectively. The corresponding loadings based on the concatenated approach are higher for the market factor at 1.01 and the value factor at 0.18 but lower for the size factor at 0.20 and the momentum factor at −0.04. More interestingly, however, the loadings also vary strongly among loser funds with standard deviations of the market, size, value and momentum loadings of 0.29, 0.37, 0.40 and 0.20, respectively. These results support the hypothesis that factor loadings vary across funds in the same decile and over time.[491] Moreover, the skewness and kurtosis parameters reveal that the distribution of the factor loadings is not symmetric and that in particular the distribution of the market exposure exhibits fat tails, i. e. some of the funds have extreme market exposures. For example, the 1st percent and 99th percentile of β_m are 0.25 and 1.90 for winner funds and even −0.10 and 1.64 for loser funds.

With respect to the portfolio characteristics, winner and loser funds seem to favor small stocks but do not show a clear preference for value or growth. Moreover, it also becomes clear that not all winner funds have a high loading on the momentum factor: 25 percent of all winner funds have momentum loadings of −0.07 or lower. Thus, benchmarking all winner funds against an identical parameterization of the factor model with high loadings on the momentum factor yields misleading results. In the case of loser funds, the centered 98 percent interval of momentum loadings varies between −0.42 and 0.64 with a median of 0.05. Thus, some loser funds might have high loadings on the last year's winner stocks, with 25 percent of loser funds having momentum loadings of more than 0.18.

Figures 6.2 and 6.3 show boxplots of the factor loadings of the winner and loser funds, respectively. The horizontal red line denotes the median and the horizontal blue lines the lower and upper quartile. The whiskers are lines extending 1.5 times the inter-quartile range, i. e. $1.5 \cdot (\mathrm{perc}_{75} - \mathrm{perc}_{25})$ from each end of the

[491] Hence, part of this variation is due to estimation error. However, as will be argued below, a large fraction of this tends to be true variation in risk loadings.

Table 6.12: Factor loadings of individual winner and loser funds

This table presents the statistical properties of the factor loadings based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23) for the decile portfolios 10 (winner) in panel (a) and 1 (loser) in panel (b). Individual fund alphas are computed as the difference between realized and expected returns in period t while expected returns are based on the factor loadings estimated over a centered rolling 24-month window from $t-12$ to $t+11$ and realized factor returns in t. See the note to Table 6.5 for more explanation on the column specification. Rows (1) to (4) report the mean, standard deviation, skewness and excess kurtosis; rows (5) to (11) report the 99th, 95th, 75th, 50th, 25th, 10th and first percentile. The mean, skewness and excess kurtosis are tested on significant differences from zero (from one for the mean of β_m). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

(a) Decile-10 funds

	Factor loadings				$E(r)$	R^2
	β_m	β_{smb}	β_{hml}	β_{mom}		
Mean	0.99^{***}	0.26^{***}	-0.08^{***}	0.06^{***}	0.67	0.84
SD	0.27	0.35	0.43	0.19	0.26	0.14
Skewness	0.55^{***}	0.30^{***}	-0.24^{***}	0.34^{***}	0.31^{***}	-1.73^{***}
Kurtosis	2.48^{***}	-0.63^{***}	-0.44^{***}	-0.03^{***}	-0.08^{***}	2.70^{***}
Perc_{99}	1.90	1.09	0.82	0.58	1.33	0.98
Perc_{90}	1.27	0.73	0.44	0.31	0.99	0.96
Perc_{75}	1.10	0.50	0.22	0.18	0.82	0.93
Median	0.98	0.23	−0.05	0.05	0.64	0.89
Perc_{25}	0.86	−0.02	−0.38	−0.07	0.50	0.80
Perc_{10}	0.73	−0.16	−0.65	−0.16	0.36	0.63
Perc_{1}	0.25	−0.41	−1.11	−0.35	0.12	0.33

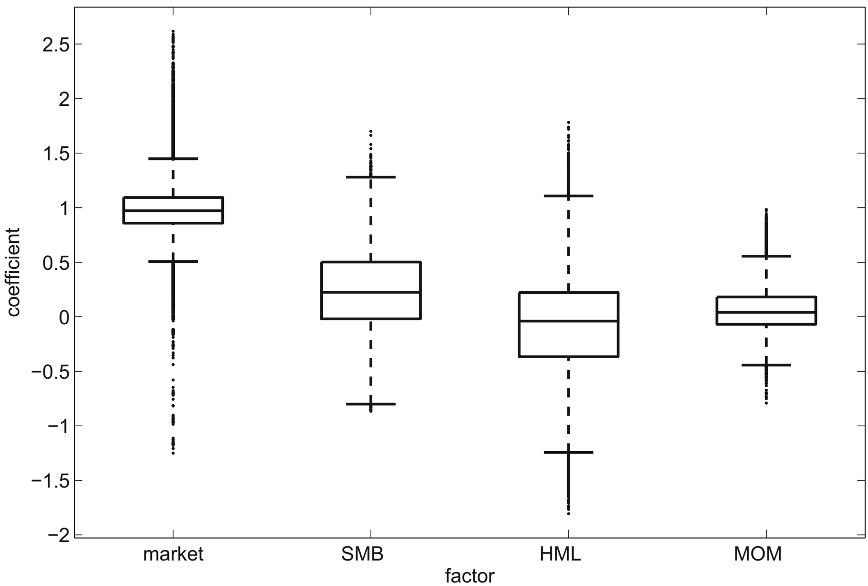
(b) Decile-1 funds

	Factor loadings				$E(r)$	R^2
	β_m	β_{smb}	β_{hml}	β_{mom}		
Mean	0.99^{***}	0.29^{***}	0.01^{***}	0.07^{***}	0.71	0.83
SD	0.29	0.37	0.40	0.20	0.27	0.14
Skewness	-1.01^{***}	0.20^{***}	-0.12^{***}	0.35^{***}	0.02^{***}	-1.70^{***}
Kurtosis	4.69^{***}	-0.75^{***}	0.11^{***}	0.55^{***}	0.71^{***}	2.94^{***}
Perc_{99}	1.64	1.16	0.96	0.64	1.44	0.98
Perc_{90}	1.24	0.78	0.50	0.31	1.02	0.95
Perc_{75}	1.11	0.57	0.27	0.18	0.86	0.93
Median	1.00	0.27	0.02	0.05	0.71	0.88
Perc_{25}	0.89	0.00	−0.23	−0.06	0.56	0.79
Perc_{10}	0.75	−0.17	−0.47	−0.16	0.41	0.64
Perc_{1}	−0.10	−0.41	−1.01	−0.42	−0.02	0.31

boxes. Black circles mark outliers. Boxplots neatly summarize the distributional characteristics of variables. Figures 6.2 and 6.3 strongly support the conclusions from above. Factor loadings vary strongly, even if outliers are ignored. Ignoring this variation and assuming that factor loadings are fixed within the deciles and over time might bias the results.

Figure 6.2: Boxplot of factor-loadings distribution of individual winner funds

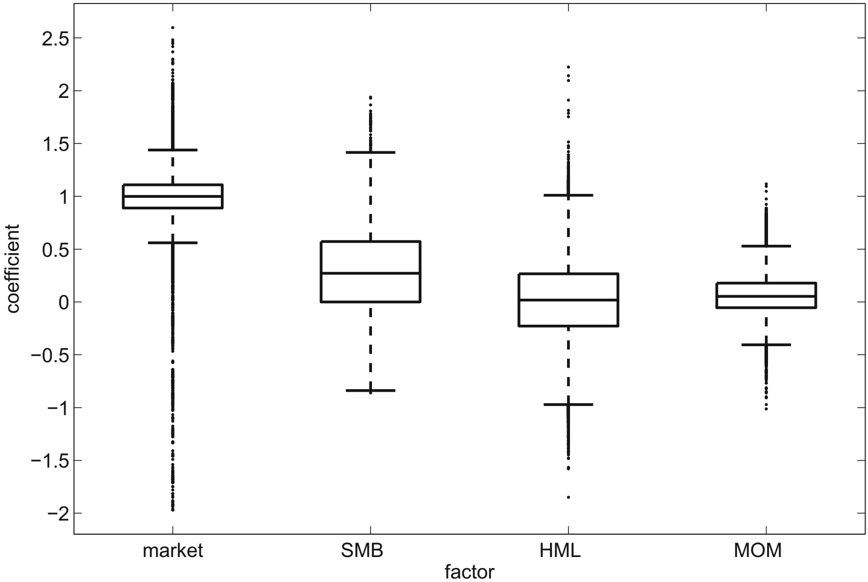
This figure presents boxplots of factor loadings based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23) for the winner decile 10. Factor loadings are estimated over a centered (from $t-12$ to $t+11$) rolling 24-month window. The horizontal red line denotes the median and the horizontal blue lines the lower and upper quartile. The whiskers are lines extending 1.5 times the inter-quartile range, i. e. $1.5 \cdot (\text{perc}_{75} - \text{perc}_{25})$ from each end of the boxes. Black circles mark outliers.



After having established the advantages of the Bayesian four-factor alphas, the following section turns to fund performance. Figure 6.4 presents the monthly Bayesian four-factor alphas for the decile portfolios. The picture is very similar to the one in Figure 6.1. The alpha spread between decile-10 and decile-1 funds in

Figure 6.3: Boxplot of factor-loadings distribution of individual loser funds

This figure presents boxplots of factor loadings based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23) for the loser decile 1. See the note to Figure 6.2 for more explanation.



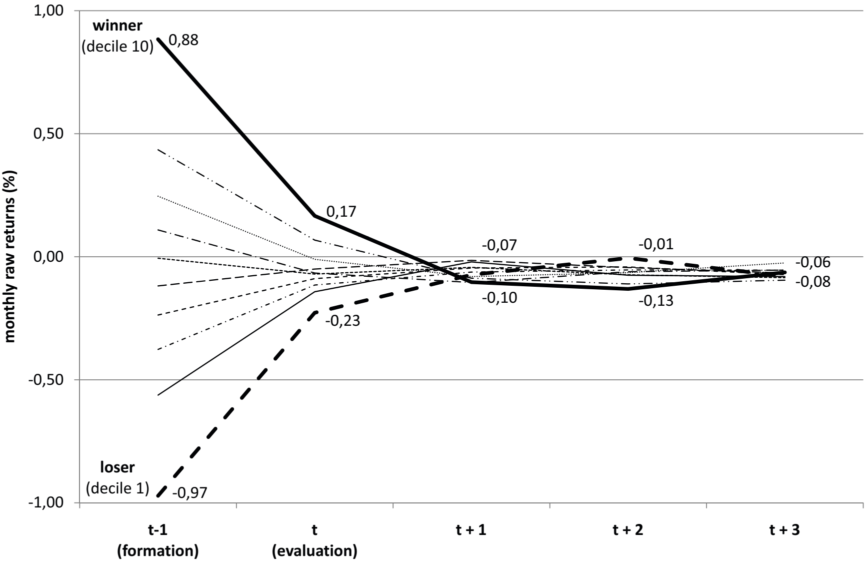
the formation period is large at 1.86 percentage points per month.[492] Winner-fund alphas decrease and loser-fund alphas improve afterwards in the evaluation period and a strong tendency of mean reversion in fund performance can be observed.

However, some interesting differences are notable. Compared to the pattern of raw returns in Figure 6.1 the overshooting of winner- and loser-fund performance in the second and third year after portfolio formation cannot be observed in Figure 6.4. Based on raw returns, loser funds outperformed winner funds by 0.35 and 0.20 percentage points in the second and third year after portfolio formation, respectively (Figure 6.1). Based on alphas and controlling for time-variation of factor loadings, this difference reduces to 0.03 and 0.12 percentage points, respec-

[492] Note that this result corresponds to column (4) of Table 6.3 where Bayesian four-factor alphas were also used for ranking.

Figure 6.4: Mean reversion of individual decile fund performance

This figure presents average monthly risk-adjusted returns based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23) for the decile portfolios 10 (winner) to 1 (loser) relative to the evaluation year (t).



tively (Figure 6.4). Thus, this outperformance can almost completely be explained by relatively higher risk exposures of loser funds. Indeed, winner-fund performance is almost flat for the years $t+1$ to $t+3$ in Figure 6.4. This result highlights that it is important to properly account for time variation in risk loadings.

Table 6.13 presents the Bayesian four-factor alphas of individual funds in the evaluation period for a regression over a centered 24-month window. Individual fund alphas are computed as the difference between realized and expected returns in period t while expected returns are based on the factor loadings estimated over a centered rolling 24-month window from $t-12$ to $t+11$ and realized factor returns in t. It is interesting to note that based on this approach using the centered rolling window decile-10 funds clearly outperform the four factor benchmark on average for both the portfolio and the panel approach. The alpha of winner funds is between 0.17 (portfolio approach) and 0.18 percent per month (panel approach) which is much higher than the alpha of 0.07 percent based on the concatenated approach (Table 6.3). This observation is in line with the results of Bollen and Busse (2005): Once the factor loadings are allowed to vary over time and across funds, the significant outperformance of winner funds persists even in the evaluation period.[493] Based on median alphas of the panel approach, the outperformance is lower but still significant, which implies that part of the superior abnormal returns stems from a few extremely well performing funds.

These results may be interpreted as evidence in favor of tournament behavior on an annual basis, which has been documented to affect the risk taking of portfolio managers within one calendar year.[494] Winner-fund managers of the previous year seem to significantly reduce the risk of their funds and this risk-reduction explains a large fraction of their underperformance judged on raw returns in the second year after ranking, as evidenced in Figure 6.1.

The same analysis from above is repeated but a lagged rolling 24-month window ($t-24$ to $t-1$) is used instead of the centered window to estimate the parameters (Table 6.14). The results for the lagged 24-month window are weaker which supports the conjecture that winner-fund managers reduce the risk of their portfolios over time. Because the lagged-window approach estimates risk loadings over the periods $t-24$ to $t-1$ it only captures part of the risk reduction. The centered-window approach is based on returns of a 24-month window exactly one year later in time ($t-12$ to $t+11$), when the fund manager has already reduced the risk.[495] Consequently, the benchmark is stricter compared to the centered-window approach. It is not clear, however, if this risk reduction is a result of discretionary decisions by the portfolio manager or a direct consequence of the equilibrium mechanisms which is analyzed in detail in chapter 7. If winner funds receive a lot of inflows and these inflows are held in cash, the portfolio risk is

[493] Note that determining statistical significance of a group of individual fund alphas is no trivial exercise due to various forms of potential correlations. Thus, the results on statistical significance should be judged with care. This is the cost of allowing for cross-sectional and time-series variation. The generalized calendar-time approach can mitigate this problem at the cost of assuming fixed coefficients as discussed below.

[494] See section 2.1.1.1 for a discussion of tournament behavior.

[495] For example, when the funds' alphas for the year 2000 (evaluation period) are estimated, the first 24-month window of the centered-window approach, which is used to estimate alphas in January 2000, ranges from January 1999 to December 2000. The last 24-month window of the centered-window approach, which is used to estimate alphas in December 2000, ranges from December 1999 to November 2000. The corresponding 24-month windows of the lagged-window approach range from January 1998 to December 1999 (for the alpha in January 2000) and from December 1998 to November 1999 (for the alpha in December 2000).

Table 6.13: Performance of individual decile funds (centered window)

This table presents monthly risk-adjusted returns based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23) for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. Individual fund alphas are computed as the difference between realized and expected returns in period t while expected returns are based on the factor loadings estimated over a centered rolling 24-month window from $t-12$ to $t+11$ and realized factor returns in t. Column (1) reports the mean of a concatenated time series of decile-portfolio four-factor alphas (portfolio approach), i. e. first taking the cross-sectional average of individual-fund four-factor alphas and then the time-series average; columns (2) to (5) report the mean, median, 10th percentile and 90th percentile, respectively, of the panel of monthly four-factor alphas of all funds that belong to the decile portfolio (panel approach), i. e. taking the average over the whole panel of individual-fund four-factor alphas in one step. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Bayesian four-factor alphas				
	Portfolio	Panel			
	Mean	Mean	Median	$Perc_{10}$	$Perc_{90}$
10 (winner)	0.17^{**}	0.18^{***}	0.07^{***}	-2.28	2.74
9	0.07	0.08^{**}	-0.03	-1.99	2.12
8	-0.01	-0.01	-0.06^{***}	-1.91	1.88
7	-0.07^{*}	-0.07^{***}	-0.09^{***}	-1.82	1.67
6	-0.07^{**}	-0.07^{***}	-0.09^{***}	-1.77	1.62
5	-0.05	-0.05	-0.10^{***}	-1.81	1.62
4	-0.09^{**}	-0.09^{***}	-0.12^{***}	-1.87	1.69
3	-0.12^{***}	-0.12^{***}	-0.13^{***}	-1.91	1.70
2	-0.14^{***}	-0.15^{***}	-0.16^{***}	-2.20	1.82
1 (loser)	-0.23^{***}	-0.24^{***}	-0.24^{***}	-2.68	2.14
10 − 1	0.39^{***}	0.42^{***}	0.31^{***}	–	–

reduced even though this is not an active decision by the portfolio manager.[496]

For loser funds, the results of the individual fund alphas are not largely different from the results based on the concatenated approach. For all measures, concatenated, portfolio mean, panel mean and panel median, the underperformance of loser funds is significant between −0.24 and −0.23 percent per month. A comparison of the centered-window approach and the lagged-window approach suggests that tournament behavior between years also exists in the case of loser

[496] However, the decision of the portfolio manager not to invest the inflows might also be interpreted as active tournament behavior, especially because futures and exchange-traded funds provide a cost-efficient mechanism to equitize fund flows.

Table 6.14: Performance of individual decile funds (lagged window)

This table presents monthly risk-adjusted returns based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23) for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. Individual fund alphas are computed as the difference between realized and expected returns in period t while expected returns are based on the factor loadings estimated over a lagged rolling 24-month window from $t-24$ to $t-1$ and realized factor returns in t. See the note to Table 6.13 for more explanation.

	Bayesian four-factor alphas				
	Portfolio	Panel			
	Mean	Mean	Median	$Perc_{10}$	$Perc_{90}$
10 (winner)	0.09	0.09^{***}	0.02^{***}	−2.76	3.07
9	0.03	0.03	-0.06^{***}	−2.45	2.46
8	−0.06	-0.06^{***}	-0.09^{***}	−2.32	2.20
7	-0.12^{***}	-0.12^{***}	-0.12^{***}	−2.26	1.97
6	-0.13^{***}	-0.12^{***}	-0.13^{***}	−2.17	1.92
5	-0.10^{*}	-0.10^{***}	-0.13^{***}	−2.23	1.97
4	-0.13^{***}	-0.13^{***}	-0.15^{***}	−2.26	2.01
3	-0.14^{***}	-0.14^{***}	-0.16^{***}	−2.33	2.03
2	-0.16^{***}	-0.17^{***}	-0.18^{***}	−2.57	2.21
1 (loser)	-0.21^{***}	-0.20^{***}	-0.22^{***}	−3.12	2.74
10 − 1	0.30^{***}	0.28^{***}	0.24^{***}	–	–

funds. Using the factor loadings estimated over a period which is more distant in the past results in slightly higher alphas of between −0.22 (panel median) and −0.20 (panel mean) due to a less strict benchmark. Thus, loser-fund managers increase the risk of their exposure in the following year which may contribute to their outperformance in raw returns in the second year after ranking compared to winner funds (Figure 6.1). It seems fair to conclude that both winner- and loser-fund managers engage in tournament behavior between years, i. e. the last year's winner funds reduce risk and the last year's loser funds increase risk, which explains part of the mean reversion and overshooting as presented in Figures 6.1 and 6.4.

Similar to the factor loadings, individual fund alphas also vary strongly within the deciles. Figures 6.5 and 6.6 present boxplots of individual-fund alphas for each decile. Figure 6.5 presents the whole range of monthly alphas including outliers while Figure 6.6 presents a restricted range of monthly alphas between

−1.5 and 1.5 percent, i. e. the body of the boxplot.[497] Note that in Figure 6.5 the level of alphas is increasing from decile 1 to decile 10 as indicated by the location parameters mean and median. Winner funds provide higher alphas than loser funds. Admittedly, the overlap of the performance range is quite high: many loser funds (those in the upper part of the boxplot's body) provide higher abnormal returns than many of the winner funds (those in the lower part of the boxplot's body). Consequently, selecting one or two out of the last year's winner funds, a strategy many retail investors might follow, still bears a high risk of generating risk-adjusted returns that are inferior compared to just picking any one or two funds out of the whole range of offered products.

Both the upper quartile and the upper whisker clearly follow a U-shape while the lower quartile and the lower whisker follow an inverted U-shape. Winner and loser funds have a larger dispersion in alphas within their deciles compared to funds in deciles 4 to 7, implying that performance in the top and bottom deciles is driven to a large degree by portfolio risk and luck. Again, part of this result might be attributed to estimation error, despite using the Bayesian algorithm. Thus, not all of the cross-sectional variation seen in Table 6.12 and Figures 6.2 and 6.3 is true variation. However, because the results in Table 6.11 are very similar it seems reasonable to conclude that a significant fraction of the variation in winner- and loser-fund alphas depicted in Figures 6.5 and 6.6 is true.

6.3.4 Alternative Estimation Methodologies

In order to further understand the impact of different estimation techniques used for portfolio evaluation, the results based on six different estimation techniques are compared. These methodologies mainly differ in the degree of variation allowed in factor loadings. The first approach is a static approach that estimates average factor loadings in one step using an equally-weighted portfolio of all mutual funds in the sample over the whole sample period. That is, only one regression is estimated and each fund inherits the factor loadings of this regression. This has the advantage that the static exposures should usually be estimated with the lowest estimation error. Alphas are then calculated as the difference between realized returns and expected returns based on the factor loadings similar to equation 6.1. This approach serves as an extreme case without any variation of factor loadings.

[497] Also see the last two columns in Table 6.13.

Figure 6.5: Boxplot of alpha distribution of individual decile funds

This figure presents a boxplot of monthly risk-adjusted returns based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23) for the decile portfolios 10 (winner) to 1 (loser). Individual fund alphas are computed as the difference between realized and expected returns in period t while expected returns are based on the factor loadings estimated over a centered (from $t-12$ to $t+11$) rolling 24-month window and realized factor returns in t. The horizontal red line denotes the median and the horizontal blue lines the lower and upper quartile. The whiskers are lines extending 1.5 times the inter-quartile range, i. e. $1.5 \cdot (\text{perc}_{75} - \text{perc}_{25})$ from each end of the boxes. Black circles mark outliers.

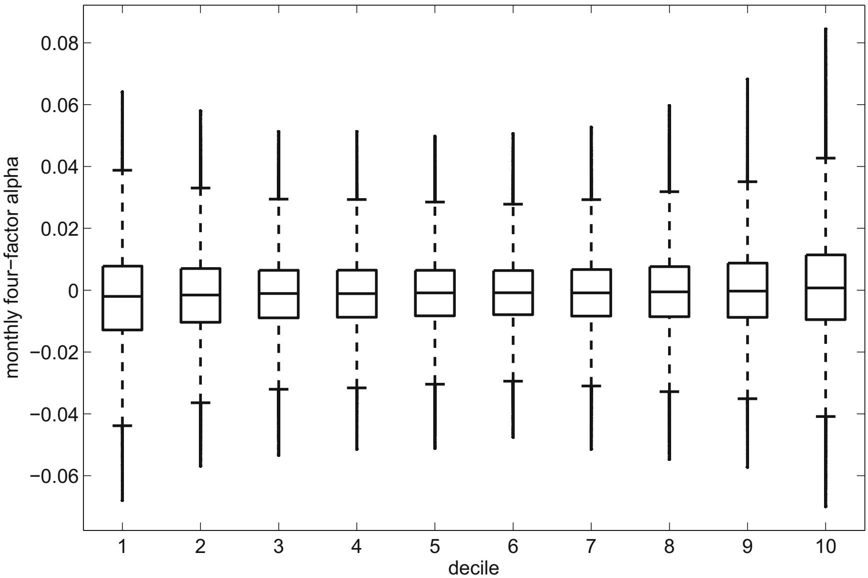
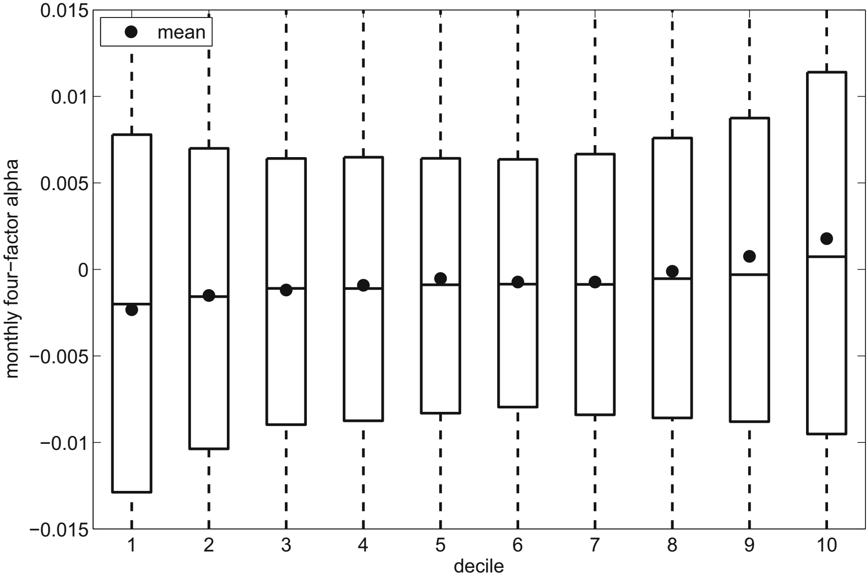


Figure 6.6: Restricted boxplot of alpha distribution of individual decile funds

This figure presents a boxplot of monthly risk-adjusted returns based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23), for a restricted range of monthly alphas between −1.5 and 1.5 percent, for the decile portfolios 10 (winner) to 1 (loser). See the note to Figure 6.5 for more explanation. Black dots indicate the mean.



The second approach is a time-varying approach that uses the same 24-month rolling window methodology outlined above to allow for time variation but keeps factor loadings fixed in the cross section. Specifically, a rolling-window regression is estimated for the portfolio of all sample funds and each fund inherits equal factor loadings in each month. Alphas are again calculated as the difference between realized returns and expected returns.

The following three approaches keep factor loadings constant over time but allow for cross-sectional variation in factor loadings. The first of these three, the third approach, is the concatenated approach presented above. Factor loadings are allowed to vary across the decile portfolios by estimating the model separately for each decile. This is a non-parametric approach which allows for cross-sectional variation.

The fourth approach is the generalized calendar-time (GCT) approach of Höchle, Schmid, and Zimmermann (2008). Factor loadings are allowed to vary across the decile portfolios by using dummy variables (parametric approach) while it assumes coefficients to be fixed over time. Specifically, this approach uses a panel estimator which estimates the factor loadings in one step for all deciles identified by a separate dummy variable. The number of dummy variables that can be used simultaneously in the model is restricted. The major advantage of this methodology is that it controls for quite general forms of autocorrelation and heteroscedasticity of the error term based on Driscol-Kraay standard errors when assessing the significance of parameters. Thus, inferences are "robust to very general forms of cross-sectional and temporal dependence" in fund returns (Höchle, Schmid, and Zimmermann, 2008). Only one dummy variable is used to identify the funds in the decile of interest and the model is estimated ten times, i. e. for each decile. Table 6.15 reports the alpha for the average funds (those not identified by the dummy, i. e. the dummy equals zero) and the decile of interest (dummy equals one).[498]

The fifth approach goes one step further and allows for cross-sectional variation in factor loadings across individual funds but still keeps factor loadings constant over time. Specifically, one regression is estimated for each fund using its entire time series. Then, each fund inherits the factor loadings of this regression in each month and alphas are calculated as the difference between realized returns and expected returns. The last approach is the Bayesian approach using rolling-window alphas as outlined above (portfolio approach). This is the most flexible of all methodologies, allowing factor loadings to vary across individual funds and over time.

Table 6.15 presents the alphas for each of the estimation methodologies.[499] Focusing on winner funds, it can be documented that the alphas are quite different, with the GCT approach providing the lowest estimate of 0.06 percent per month and the approach that only allows for time variability providing the highest alpha of 0.19 percent per month. Only the alpha of the Bayesian approach is significantly positive at 0.17 percent per month, as already documented above. In general, the alphas of the three approaches only allowing for cross-sectional varia-

[498] Hence, the results for the average or remaining funds differ slightly when different deciles are separated by the dummy. This can be seen when moving down column (4) in Table 6.15.

[499] Table A.3 in appendix A.3 presents the corresponding factor loadings.

tion (concatenated, GCT and the cross-sectional approach) are lowest while those of the methodologies accounting for time variability (the time varying and the Bayesian approach) are highest. This again supports the conclusion that factor loadings of funds vary over time. However, as the time-varying approach does not differentiate between different deciles, part of the variation in factor loadings over time might also be associated with market states in addition to winner-fund managers actively altering the portfolio risk.

With respect to loser funds, all estimation methodologies provide a similar picture. The highest alpha is -0.22 when allowing only for time variation and the lowest is -0.28 when allowing only for cross-sectional variation across individual funds. All of these alphas are significantly negative implying that the conclusion of persistent underperformance of loser funds is robust to a variety of estimation methodologies.[500]

Based on the findings in this section it seems reasonable to conclude that the results on performance persistence are affected by three methodological determinants. First, the methodology used to evaluate fund performance has an impact on the conclusions as already suggested by Bollen and Busse (2005). Allowing factor exposures to vary over time and across funds within deciles leads to stronger results in favor of persistent outperformance of winner funds. Thus, these funds seem to reduce risk over time which is not captured by the conventional concatenated approach used by Carhart (1997). Going from Bayesian alphas estimated separately for individual funds over rolling windows to OLS regressions for decile portfolios that are constant over time, the results on performance persistence change toward less support of the persistence hypothesis, consistent with Bollen and Busse (2005). Second, irrespective of the methodology applied, performance persistence decays over the length of the evaluation period. Thus, the conclusions of short-term persistence studies are still valid and are not a result of these studies using different methodologies compared to long-term persistence studies. Third, the results on the superiority of ranking on risk-adjusted returns compared to ranking on raw returns remain mixed. Judged based on the conventional concatenated approach, ranking on risk-adjusted returns seems to have more predictive

[500] Note that for the GCT approach ***, ** and * indicate significant differences from the coefficients of average funds at the 1%, 5%, and 10% levels, respectively. Thus the -0.24 percent alpha per month is not statistically significant from the -0.07 percent alpha of decile-10 to decile-2 funds. However the GCT approach does not test whether this alpha is significantly different from zero.

Table 6.15: Performance of individual winner and loser funds based on alternative estimation methodologies

This table presents the monthly risk-adjusted returns based on the four-factor model of Carhart (1997) according to equation (3.23) for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds for alternative estimation methodologies. Column (1) reports the results for the static approach where each fund inherits the factor loadings from the equal-weighted portfolio of all funds; column (2) reports the results for the time-varying approach where in addition to the static approach factor loadings are allowed to vary over time based on a centered rolling 24-month window; column (3) reports the results for the concatenated approach where factor loadings are allowed to vary across the decile portfolios by estimating the model separately for each decile (non-parametric approach); column (4) reports the results for the generalized calendar-time (GCT) approach where factor loadings are allowed to vary across the decile portfolios by using a dummy variable (parametric approach); column (5) reports the results for the cross-sectional approach where factor loadings are allowed to vary across individual funds by estimating the model separately for each fund (non-parametric approach); column (6) reports the results for the Bayesian approach where factor loadings are allowed to vary across individual funds and over time by estimating the model separately for each fund based on a centered rolling 24-month window (non-parametric approach). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. In the case of the GCT approach, ***, ** and * indicate significant differences from the coefficients of average funds at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

	Static	Time	Concate-	GCT		Cross-	Bayesian
		varying	nated	Av. fund	Decile	section	alphas
10 (winner)	0.14	0.19	0.07	-0.10^{*}	0.06	0.12	0.17^{**}
9	0.04	0.09	0.01	-0.09	-0.02	0.02	0.07
8	-0.05	-0.00	-0.05	-0.09	-0.06	-0.07	-0.01
7	-0.13^{**}	-0.08	-0.11^{**}	-0.08	-0.13	-0.12^{***}	-0.07^{*}
6	-0.13^{**}	-0.08	-0.10^{**}	-0.09	-0.11	-0.13^{***}	-0.07^{**}
5	-0.10	-0.05	-0.09^{*}	-0.09	-0.09	-0.12^{**}	-0.05
4	-0.13^{*}	-0.08	-0.11	-0.09	-0.11	-0.14^{***}	-0.09^{**}
3	-0.19^{**}	-0.14^{**}	-0.14^{**}	-0.08	-0.13	-0.16^{***}	-0.12^{***}
2	-0.16^{*}	-0.11	-0.16^{*}	-0.08	-0.16	-0.19^{***}	-0.14^{***}
1 (loser)	-0.27^{**}	-0.22^{**}	-0.24^{**}	-0.07	-0.24	-0.28^{***}	-0.23^{***}
10 − 1	0.41	0.41	0.32^{*}	–	0.29	0.40^{***}	0.39^{***}

power for future fund performance and results in superior abnormal performance in the evaluation period compared to a raw-return ranking. However, this advantage vanishes when funds are evaluated based on the portfolio approach using Bayesian four-factor alphas that allow for variation in factor loadings.

Having established that investment performance is mean reverting amongst both winner funds and loser funds, chapter 7 investigates how fund flows and manager changes influence this relationship. Before that, the following section 6.4 focuses on the question of whether persistence decays more over longer periods compared to short periods while section 6.5 analyzes the migration of funds between the different deciles and the survival of funds in the winner and loser deciles.

6.4 Alternative Formation and Evaluation Periods

Previous literature suggests that performance persistence is a short-term phenomenon which decays over longer horizons (Bollen and Busse, 2005; Busse and Irvine, 2006; Huij and Verbeek, 2007). Section 6.3 has provided empirical evidence that methodological aspects contribute to the findings of these earlier studies. Specifically, the methodologies used in short-term studies are more in favor of performance persistence also among winner funds as compared to the methodologies used in long-term studies. However, so far the empirical analysis in section 6.3 was restricted to 12-month formation and evaluation periods. In this section, this assumption is relaxed and the performance persistence of the winner and loser funds is investigated using different lengths of the formation and evaluation periods. Specifically, for the formation period the past 3, 12 and 24 months are used and the portfolio is held constant for the following 1, 3, 6, 12, 24 and 36 months. Raw returns and Bayesian four-factor alphas are used as ranking measures to form portfolios which results in 30 different combinations ($3 \cdot 6 + 2 \cdot 6$) because the four-factor ranking is not available for 3-month formation periods. This allows testing whether performance persistence still decays over time even if identical methodologies are used over different time horizons. For performance evaluation, three different performance measures are used: (1) raw returns; (2) four-factor alphas based on the concatenated approach, which dominate in long-term studies; (3) Bayesian four-factor alphas (portfolio approach) for individual funds, which are closely related to the methodologies used in short-term studies.

Raw Returns

The findings of this section confirm the results previously documented in the literature: performance persistence is strongest over shorter horizons and decays over longer horizons. Table 6.16 presents the results using raw returns as performance measure in the evaluation period and for formation periods of 3, 12 and 24 months and evaluation periods ranging from 1 to 36 months. The highest monthly returns by investing in recent winner funds can be earned when the portfolio is rebalanced frequently, i. e. over short evaluation periods. For example, the raw returns earned by 1-month evaluation periods range between 0.82 and 1.15 percent per month according to the first row in panel (a) and decrease over longer holding periods to 0.33 to 0.92 percent per month for 36-month evaluation in the last row. This strongly indicates that winner-fund performance tends to revert to the mean over longer horizons. Moreover, past returns are more useful than past alphas for predicting future raw returns as the investment results based on a raw-return ranking are consistently higher compared to the alpha ranking.[501] Lastly, the past 12 months of performance seem to be a better predictor of future performance than the past 3 or 24 months. Consequently, combining these conclusions, a maximum raw return of 1.21 percent per month can be earned when winner funds are selected based on their past 12-month raw returns and the portfolio is rebalanced every month, a strategy most likely suffering from high transaction costs in reality.

In the case of loser funds the picture is similar. Negative performance persistence as measured by raw returns is strongest when funds are selected based on their past 12-month raw returns and the portfolio is held for one month. Raw returns in this case are only 0.10 percent per month. Increasing the length of the evaluation period results in higher returns. For example, based on the same portfolio formation as above but holding the portfolio for 36 months results in raw returns of 0.37 percent per month. Thus, also in the case of loser funds investment performance reverts to average levels over longer evaluation periods. Moreover, poor past returns are again more predictive for future underperformance as compared to past poor alphas.[502] Raw returns measured over the previous year also have a stronger predictive power for future returns as compared to shorter (3 months) or longer (24 months) formation periods.

[501] With one exception for 12-month formation and 36-month evaluation periods.
[502] With one exception for 24-month formation and 36-month evaluation periods.

Table 6.16: Raw returns of decile portfolios based on alternative formation and evaluation periods

This table presents raw returns for decile-10 funds in panel (a), for decile-1 funds in panel (b) and for a spread portfolio long in decile-10 funds and short in decile-1 funds in panel (c) using alternative lengths of the formation and evaluation periods. Columns (1), (3) and (5) refer to rankings based on the previous 3, 12 and 24 months raw returns, respectively; columns (2), (4) and (6) refer to rankings based on the previous 3, 12 and 24 months Bayesian four-factor alphas, respectively. Rows (1) to (6) refer to evaluation periods of 1, 3, 6, 12, 24 and 36 months, respectively. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

(a) Decile-10 funds

Evaluation period	Formation period and ranking measure					
	3 months[a]		12 months		24 months	
	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}
1 month	1.15	–	1.21	1.04	0.93	0.82
3 months	1.06	–	1.06	0.91	0.85	0.76
6 months	0.98	–	1.05	0.91	0.84	0.72
12 months	0.90	–	0.83	0.77	0.65	0.60
24 months	0.77	–	0.77	0.65	0.44	0.41
36 months	0.92	–	0.76	0.77	0.36	0.33

(b) Decile-1 funds

Evaluation period	Formation period and ranking measure					
	3 months[a]		12 months		24 months	
	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}
1 month	0.14	–	0.10	0.25	0.30	0.32
3 months	0.22	–	0.19	0.29	0.34	0.36
6 months	0.26	–	0.16	0.31	0.32	0.41
12 months	0.44	–	0.28	0.45	0.45	0.54
24 months	0.45	–	0.30	0.52	0.64	0.63
36 months	0.29	–	0.37	0.45	0.70	0.67

(c) Spread portfolio 10 − 1

Evaluation period	Formation period and ranking measure					
	3 months[a]		12 months		24 months	
	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}
1 month	1.01**	–	1.11**	0.79***	0.63*	0.50*
3 months	0.84**	–	0.88**	0.62**	0.51	0.40
6 months	0.72*	–	0.89**	0.60***	0.52	0.30
12 months	0.46	–	0.55	0.32	0.20	0.06
24 months	0.32	–	0.47*	0.13	−0.19	−0.22
36 months	0.62**	–	0.40	0.32	−0.35	−0.34

[a] Note that Bayesian four-factor alphas cannot be computed based on three months of data.

The raw-return spread between winners and loser is also decreasing going down the columns in panel (c) of Table 6.16.[503] The highest winner-minus-loser return spread of significant 1.11 percentage points per month can be earned when choosing funds based on their previous 12-month returns and holding them for only one month. This confirms that the past year seems to contain more information on managerial skills than the past quarter and that investment skills are relatively short lived. Extending the holding period to 36 months reduces the winner-minus-loser spread to insignificant 0.40 percentage points per month. Using longer or shorter formation periods also reduces the return spread. Similarly, when alphas are used as the ranking measure, the winner-minus-loser spread decreases. For 24-month formation and 24- or 36-month evaluation periods, loser funds even outperform winner funds which is indicative of mean reversion in mutual fund performance and even an overshooting as already evidenced in Figure 6.1.

Risk-Adjusted Returns of Decile Portfolios

It seems more important, however, to analyze risk-adjusted return when judging managerial skill as compared to using raw returns for performance evaluation. The results in Table 6.17 confirm the conclusions from Table 6.16, especially that performance persistence decays over longer holding periods. Past raw returns do not seem to contain much information about future risk-adjusted returns. Most of the winner funds do not significantly outperform the four-factor benchmark when these winner funds are selected based on past raw returns. Similarly, all loser funds with poor past raw returns do not significantly underperform the four-factor benchmark. However, two exceptions exist among winner funds. First, in the very short run, based on 3-month formation and 1-month evaluation periods, winner funds significantly outperform the four-factor benchmark by 0.36 percentage points per month. However, this positive alpha is most likely due to a short-term momentum effect of stock returns that is not captured by the benchmark momentum factor, which is based on medium-term momentum over the previous 11 months. Second, based on 3-month formation and 36-month evaluation periods winner funds also slightly significantly outperform their benchmark. While it is hard to come up with an explanation for this observation one might suspect that it is driven by some outliers.

[503] Only over 36 months holding periods the spread increases for some of the ranking measures. However, these results should be interpreted carefully because the sample only contains five three-year evaluation periods.

Table 6.17: Performance of decile portfolios based on alternative formation and evaluation periods

This table presents monthly risk-adjusted returns based on the four-factor model of Carhart (1997) according to equation (3.23) for decile-10 funds in panel (a), for decile-1 funds in panel (b) and for a spread portfolio long in decile-10 funds and short in decile-1 funds in panel (c) using alternative lengths of the formation and evaluation periods. See the note to Table 6.16 for more explanation on the column and row specification. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

(a) Decile-10 funds

Evaluation period	Formation period and ranking measure					
	3 months[a]		12 months		24 months	
	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}
1 month	0.36^{**}	–	0.17	0.29^{**}	0.06	0.18
3 months	0.17	–	0.03	0.18^{*}	0.01	0.12
6 months	0.03	–	0.06	0.19^{*}	0.05	0.12
12 months	0.05	–	−0.11	0.07	−0.11	0.03
24 months	−0.01	–	−0.03	−0.03	−0.24	−0.14
36 months	0.15^{*}	–	0.03	0.08	-0.26^{*}	-0.23^{*}

(b) Decile-1 funds

Evaluation period	Formation period and ranking measure					
	3 months[a]		12 months		24 months	
	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}
1 month	−0.29	–	−0.16	-0.40^{***}	−0.13	-0.37^{***}
3 months	−0.08	–	−0.08	-0.37^{***}	−0.10	-0.33^{***}
6 months	−0.05	–	−0.16	-0.37^{***}	−0.20	-0.30^{**}
12 months	−0.06	–	−0.08	-0.24^{**}	−0.12	-0.21^{*}
24 months	−0.12	–	−0.18	-0.15^{*}	−0.00	−0.11
36 months	−0.21	–	−0.25	-0.21^{**}	−0.01	−0.07

(c) Spread portfolio 10 − 1

Evaluation period	Formation period and ranking measure					
	3 months[a]		12 months		24 months	
	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}
1 month	0.65^{*}	–	0.33	0.69^{***}	0.19	0.55^{**}
3 months	0.24	–	0.11	0.55^{***}	0.11	0.45^{**}
6 months	0.08	–	0.22	0.56^{***}	0.25	0.42^{*}
12 months	0.11	–	−0.02	0.32^{*}	0.01	0.23
24 months	0.11	–	0.14	0.12	−0.24	−0.03
36 months	0.36	–	0.27	0.28^{**}	−0.25	−0.16

[a] Note that Bayesian four-factor alphas cannot be computed based on three months of data.

Based on a ranking on past four-factor alphas, significantly positive alphas of between 0.19 and 0.29 percent per month can be earned by investing in winner funds of the previous year and holding the portfolio constant for one, three or even six months. For evaluation periods of 12 or more months the alphas are no longer significantly different from zero. Thus, also based on risk-adjusted returns, performance persistence of winner funds strongly decays over longer periods. A similar result holds for loser funds. Negative performance persistence is strongest for short holdings periods and alphas of recent loser funds increase when the holding period is extended, also indicating a strong tendency of mean reversion. Specifically, based on 12-month formation periods the loser-fund alpha is significant -0.40 percent per month for a 1-month evaluation period but increases to only weakly significant -0.15 percent per month based on a 24-month evaluation period, before decreasing slightly to significant -0.21 percent per month for a 36-month evaluation period.

Again, the highest spread in risk-adjusted returns between winner and loser funds can be realized by a 12-month formation period and a 1-month evaluation period. Specifically, winner funds outperform loser funds by highly significant 0.69 percentage points per month based on this combination. This number exactly resembles the spread between winner and loser funds documented by Huij and Verbeek (2007) using the same ranking methodology but a slightly different sample.[504] In contrast to the present study, Huij and Verbeek (2007) do not aggregate individual share classes to one observation but treat them as distinct funds, which gives them a sample of 6,429 equity funds for the period from 1984 to 2003. This spread tends to decrease when the holding period is extended, with a minimum of insignificant 0.12 percentage points per month for a 24-month evaluation period. However, in the case of a risk-adjusted-return evaluation, the four-factor ranking clearly dominates the raw-return ranking, especially over shorter evaluation periods. It seems reasonable to conclude from this that the four-factor alphas measured over the previous 12 months contain the most valuable information regarding true investment skills of the fund manager. These skills significantly persist for up to 12 months, though a significant drop in evaluation-period performance is already evident after the 6-month holding period.[505]

[504] See panel (c) of Table 5 in Huij and Verbeek (2007).
[505] Again, the 36-month result should be interpreted carefully.

Risk-Adjusted Returns of Individual Decile Funds

Next, the performance persistence over alternative formation and evaluation periods is analyzed based on individual fund performance as introduced in section 6.3. This methodology is similar to the approach used in short-term persistence studies in the literature. Specifically, Table 6.18 corresponds to Table 6.17, though the former is based on the portfolio approach of Bayesian alphas allowing for variation in factor loadings while the latter is based on the concatenated approach that assumes fixed factor loadings across funds within each decile and over time and was mainly used by long-term persistence studies. This allows one to test whether the finding in section 6.3, that winner-fund performance significantly persists once controlled for variation in the factor loadings, depends on the time horizon studied. If performance persistence still decays over longer horizons, then both the different methodologies and the different time horizons can explain why short-term persistence studies have documented a significant outperformance of winner funds while long-term persistence studies lacked to do so.

Indeed, winner-fund performance is significantly positive between 0.17 and 0.33 percent per month for up to an evaluation period of 12 months when using Bayesian four-factor alphas over the previous year as the ranking measure. However, outperformance decays the longer the evaluation period even if factor exposures are allowed to vary over time and across funds. With respect to the ranking period, a length of 12 months again seems to have the most predictive power for future performance. Interestingly, the four-factor ranking is not superior compared to the raw-return ranking when judged based on Bayesian four-factor alphas. This result is in contrast to the conclusions based on concatenated alphas in Table 6.17.

Loser-fund performance is significantly negative for all combinations of formation- and evaluation-period lengths and both ranking measures.[506] However, the conclusions from winner funds are also valid for losers: persistence decays over longer horizons of the evaluation period and 12 months formation has the most predictive power for future performance, with no notable difference between a raw-return and four-factor ranking.

A comparison of the spread-portfolio alphas long in decile-10 funds and short in decile-1 funds from the concatenated approach in Table 6.17 and from the portfolio approach using Bayesian alphas in Table 6.18 reveals that performance persistence

[506] With one exception for 24-month formation and evaluation based on a raw-return ranking.

Table 6.18: Performance of individual decile funds based on alternative formation and evaluation periods

This table presents monthly risk-adjusted returns based on a Bayesian version (portfolio approach) of the four-factor model of Carhart (1997) according to equation (3.23) for decile-10 funds in panel (a), for decile-1 funds in panel (b) and for a spread portfolio long in decile-10 funds and short in decile-1 funds in panel (c) using alternative lengths of the formation and evaluation periods. See the note to Table 6.16 for more explanation on the column and row specification.

(a) Decile-10 funds

Evaluation period	Formation period and ranking measure					
	3 months[a]		12 months		24 months	
	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}
1 month	0.29***	–	0.34***	0.33***	0.20**	0.23***
3 months	0.22**	–	0.26***	0.25***	0.17*	0.18**
6 months	0.23**	–	0.23**	0.24***	0.13	0.13
12 months	0.22***	–	0.16*	0.17**	0.05	0.07
24 months	0.13	–	0.09	0.05	−0.05	−0.02
36 months	0.16***	–	0.06	0.10	−0.04	−0.03

(b) Decile-1 funds

Evaluation period	Formation period and ranking measure					
	3 months[a]		12 months		24 months	
	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}
1 month	−0.23***	–	−0.32***	−0.37***	−0.25***	−0.29***
3 months	−0.20**	–	−0.30***	−0.32***	−0.24***	−0.26***
6 months	−0.20**	–	−0.29***	−0.31***	−0.24***	−0.25***
12 months	−0.25***	–	−0.25***	−0.23***	−0.18**	−0.20***
24 months	−0.20***	–	−0.25***	−0.18***	−0.11	−0.14**
36 months	−0.23***	–	−0.18**	−0.16***	−0.12*	−0.13***

(c) Spread portfolio 10 − 1

Evaluation period	Formation period and ranking measure					
	3 months[a]		12 months		24 months	
	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}	Returns	α_4^{Bayes}
1 month	0.52***	–	0.66***	0.69***	0.46***	0.53***
3 months	0.42***	–	0.56***	0.57***	0.41***	0.45***
6 months	0.42***	–	0.51***	0.55***	0.37***	0.38***
12 months	0.47***	–	0.41***	0.39***	0.22**	0.27***
24 months	0.34***	–	0.34***	0.22***	0.06	0.12
36 months	0.39***	–	0.24**	0.26***	0.08	0.10

[a] Note that Bayesian four-factor alphas cannot be computed based on three months of data.

decays faster when evaluated based on the former approach. In particular, for 12- and 24-month periods the Bayesian alphas of the portfolio approach are larger at 0.39 and 0.22, respectively, and still highly significant while the corresponding numbers of the concatenated approach are 0.32 and 0.12 with only the former being weakly significant.

Discussion

In summary, performance persistence decays over the length of the evaluation period irrespective of the methodology used. The conclusions of studies analyzing short-term persistence are still valid and are not entirely explained by different methodologies used in these studies compared to papers that focus on long-term persistence. Specifically, performance of winner funds is negatively related to the length of the evaluation period for all three methodologies, raw returns, concatenated alphas as applied in long-term studies and Bayesian alphas allowing for cross-sectional and time-series variation in the regression parameters and as applied in short-term studies. However, at least part of the different results also seem to be attributable to the differences in methodology. This section confirms the conclusions from section 6.2.3 that improved ranking measures lead to a stronger performance persistence. Moreover, past 12-month alphas seem to have the highest predictive power for future performance of funds as compared to longer or shorter formation periods. However, part of this result might be explained by manager changes weakening the relationship between past and future performance over longer formation periods. Additionally, certain managers might follow certain investment strategies that generate abnormal returns in one market environment but not in another. Thus, a change in the management structure or the market climate might also explain why past 12-month performance is more predictive than past 24-month performance.

Significantly positive risk-adjusted returns can be earned by investors following a buying-winner strategy that involves only long positions in mutual funds based on a ranking on the last year's Bayesian four-factor alphas. These alphas are between 0.19 and 0.29 percent per month and significant for holding periods of up to six months based on the concatenated approach (Table 6.17) and between 0.17 and 0.33 percent per month and significant for holding periods of up to 12 months based on the Bayesian portfolio approach (Table 6.18). Bollen and Busse (2005) provide evidence that performance persists over quarterly formation and evaluation periods but rely on daily data, which is usually not available for many mutual funds. Huij and Verbeek (2007) show that in combination with the Bayesian approach, a similar result can be obtained using monthly data but they only focus on 1-month holding periods which might induce significant transaction costs in reality. The results of this section provide evidence that the Bayesian ranking methodology can also be applied to monthly data and more realistic holdings periods to earn significant abnormal returns. In chapters 7 and 8, the focus is on the 12-month formation and evaluation periods because this seems to be the time frame when persistence clearly decays in order to identify potential explanations for this effect.

6.5 Migration

As an additional test of performance persistence this section investigates the tendency of funds to migrate between different deciles over their lifetime and their survival probability in the top and bottom deciles. Figure 6.7 and Table 6.19 present the transition probabilities for each decile. Based on the assumption that fund performance is independently identically distributed (*iid*) over time and across funds and that no funds enter or leave the sample, funds have a 10 percent probability of entering each of the ten deciles in the following year.[507] Thus, in the case a higher fraction of funds stay in their decile as compared to funds migrating to a different decile, performance persistence exists. A visual inspection of Figure 6.7 reveals that face of the boxes on the main diagonal is slightly lighter, which indicates that a higher fraction of funds stay in their respective deciles, as compared to the off-diagonal elements. In particular, in the case of decile-10 funds the chances are relatively high at 16 percent that these funds stay in the same decile in the following year (Table 6.19). The combined probability of staying in one of the top two deciles is almost one third at 29 percent. However, there is still a considerable risk of 8 percent to migrate to the lowest decile in the following year and a combined risk of almost one quarter (23 percent) to migrate to one of the lowest three deciles. However, the probability of ending up in one of the deciles almost monotonically increases for the previous

[507] Note that this probability is reduced slightly to around 9 percent considering that the fraction of newly issued funds to existing funds is on average 10 percent according to Table 1.4 and that a somewhat smaller fraction of funds is closed every year, due to the fact that on average the number of funds in existence is increasing over time.

year's winner funds with the decile rank, i. e. the lower the decile the less likely a recent winner fund ends up in this decile. Moreover, being a recent winner funds reduces the probability of being closed to 2 percent which is quite intuitive. There is no incentive for the investment management company to close a winner fund due to the convex performance-flow relationship. Rather, the main objective of the investment management company in the short run is to generate winner funds that attract the majority of net inflows.

Figure 6.7: Transition matrix

This figure presents the transition probabilities of funds from one year ($t-1$) to the following year (t) based on 12-month formation and evaluation periods (12/12).

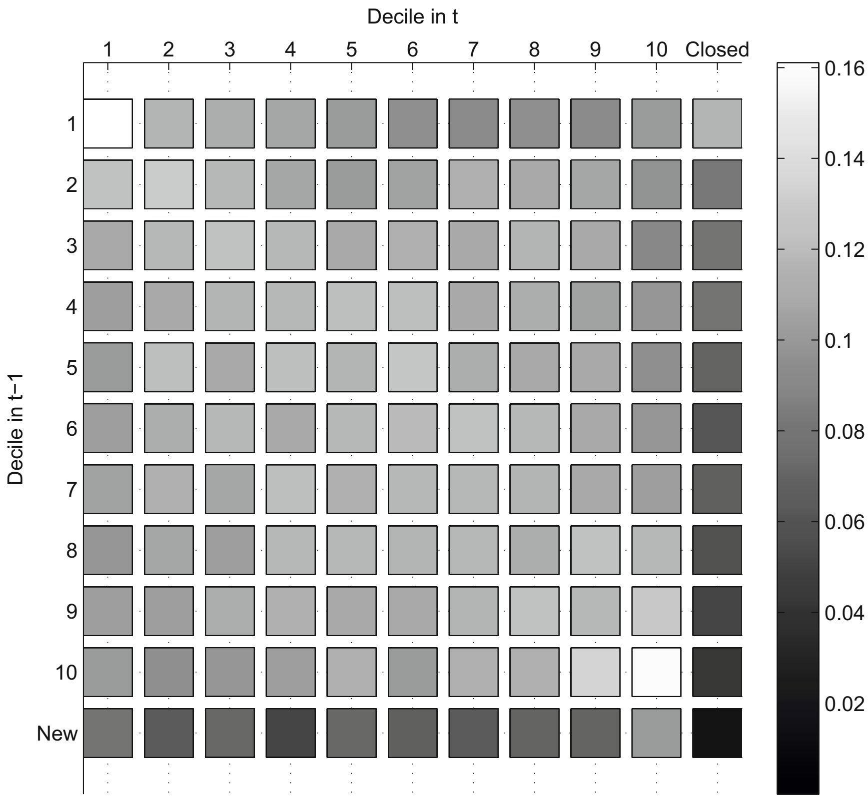


Table 6.19: Transition matrix

This table presents the transition probabilities of funds from one year ($t-1$) to the following year (t) based on 12-month formation and evaluation periods (12/12).

decile	Decile in t										
in $t-1$	1	2	3	4	5	6	7	8	9	10	Closed
1	0.16	0.10	0.09	0.09	0.08	0.07	0.07	0.07	0.07	0.08	0.10
2	0.11	0.12	0.10	0.09	0.08	0.09	0.10	0.09	0.09	0.08	0.06
3	0.09	0.10	0.11	0.10	0.09	0.10	0.09	0.10	0.09	0.07	0.06
4	0.08	0.09	0.10	0.10	0.11	0.11	0.09	0.09	0.09	0.08	0.06
5	0.08	0.11	0.09	0.11	0.10	0.11	0.10	0.09	0.09	0.07	0.05
6	0.08	0.10	0.10	0.09	0.10	0.10	0.11	0.10	0.09	0.08	0.04
7	0.09	0.10	0.09	0.11	0.10	0.10	0.10	0.10	0.09	0.09	0.04
8	0.08	0.09	0.08	0.10	0.10	0.10	0.10	0.09	0.11	0.10	0.04
9	0.08	0.09	0.10	0.10	0.09	0.09	0.10	0.11	0.10	0.11	0.03
10	0.08	0.07	0.08	0.08	0.10	0.08	0.10	0.10	0.13	0.16	0.02
New	0.06	0.04	0.05	0.03	0.05	0.04	0.04	0.05	0.05	0.08	–

In the case of recent loser funds, chances are high at 16 percent that these losers will continue to be among the lowest-performing funds in the subsequent year. The combined probability of being among the three lowest deciles is slightly larger than one third at 35 percent. However, from the last year's loser funds still 8 percent manage to become a winner fund in the next year and 22 percent end up among the top three deciles. Similar to winner funds, but in the opposite direction, the probability of a recent loser fund to end up in a certain decile almost monotonically decreases with the decile rank, the highest probability is clustered at the lowest ranks. In addition, loser funds face a high risk of 10 percent of being closed. This is an alternative strategy for the investment management company as compared to changing the investment strategy or bringing in a new manager: close a fund with a poor track record and start a new fund with a clean record.

Newly established funds have a high probability of being ranked in one of the extreme deciles in their second year of existence with even higher chances of becoming a winner fund. This is consistent with previous results that fund starts follow riskier strategies in order to profit from the convex incentive structure that they face (Karoui and Meier, 2009). Moreover, only the successful funds become public after a private incubation period (Evans, 2010). Based on these strategies, new funds have a higher probability of generating extreme performance with a bias toward successful strategies while they are less likely to end up at some mediocre performance rank. With respect to fund closures, the probability of an existing fund to discontinue activities is clearly negatively related to past performance and decreases monotonically from winner to loser funds.

In general, the minimum probability in the transition matrix of 7 percent[508] and the maximum probability of 16 percent[509] indicate that probabilities are still relatively evenly distributed across all deciles, an observation which also becomes evident from an inspection of Figure 6.7 where only a few cells stand out with very light or very dark color. Even funds that generated only average performance results during the previous year have a relatively decent chance of becoming the next year's winner fund approximately equal to that of becoming the next year's loser fund. Consequently, with the exception of decile-10 and decile-1 funds, performance persistence does not seem to be very pronounced in the data.

Next, the migration of winner and loser funds is analyzed in more detail. The general conclusion regarding weak signs of performance persistence is also supported by an analysis of the survival rates of funds in the top and bottom decile (Figure 6.8 and Table 6.20). The fraction of funds that survive in the top decile (panel (a)) and bottom decile (panel (b)) for a second year, a third year, a fourth year or a fifth year in series are reported separately for each year in which the funds entered the decile.[510] Similar to the argument above, if fund performance is independently identically distributed (*iid*) over time and across funds and no funds enter or leave the sample, ten percent of winner or loser funds would be expected to stay in the same decile in the following year.

Overall, 1,615 out of the 3,946 funds in the sample enter decile 10 at least once during the sample period, which corresponds to a probability of 41 percent $(1,615/3,946)$ of becoming a winner fund at least once. Thus, the majority of funds still do not manage to enter the winner decile at some point in time. Out of these 1,615 funds, 341 funds stay in decile 10 for at least two consecutive periods, corresponding to 21 percent $(341/1,615)$ of all funds that ever enter decile 10. Focussing on individual years, the fraction of winner funds that stay in the winner-fund decile for a second year is higher than the expected 10 percent

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508 For the following cases: decile 1 → decile 6, 7, 8 or 9; decile 3 → decile 10; decile 5 → decile 10; decile 10 → decile 2.

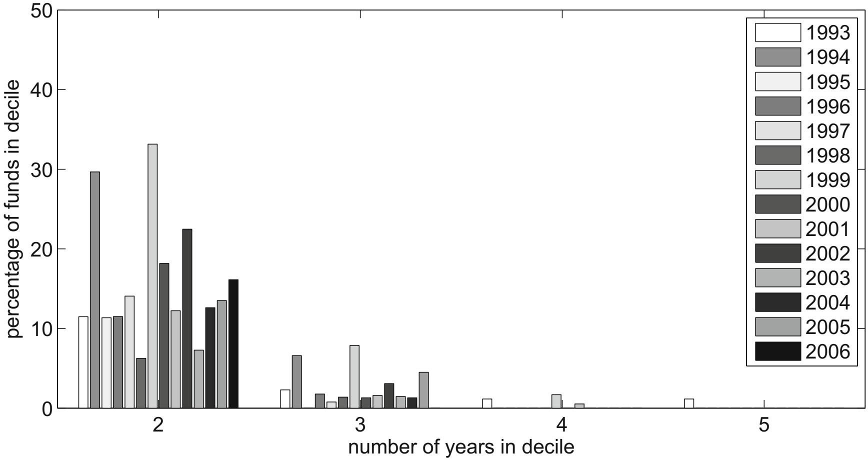
509 For the following cases: decile 1 → decile 1; decile 10 → decile 10.

510 Rankings are based on Bayesian four-factor alphas but the results based on a return-sorting are very similar.

Figure 6.8: Survival function in top and bottom decile

This figure presents in panel (a) the share of funds in percent that survive more than one year in decile 10 and in panel (b) the share of funds that survive more than one year in decile 1. The bars represent the percentage of funds still in the respective decile two, three, four and five years after entering the decile and the colors represent the year of entering the respective decile.

(a) Winner funds



(b) Loser funds

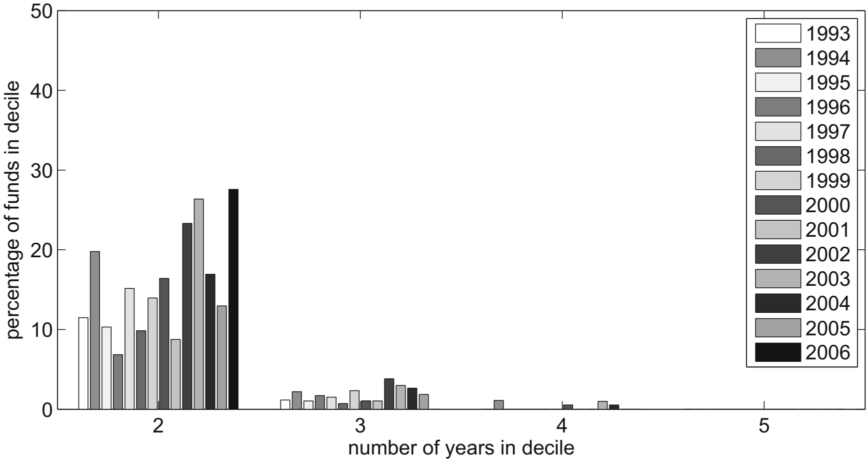


Table 6.20: Share of surviving funds

This table presents in the left panel the share of funds in percent that survive more than one year in decile 10 and in the right panel the share of funds that survive more than one year in decile 1. The columns report the percentage of funds still in the respective decile two, three, four and five years after entering the decile and the rows report the year of entering the respective decile. The last three rows present column averages and expected column averages based on the assumption that fund performance is identically independently distributed (*iid*) over time and across funds and that no funds enter or leave the sample as well as the p-value of a t-test on differences between the column average and the expected column average.

	Decile 10				Decile 1			
	2nd	3rd	4th	5th	2nd	3rd	4th	5th
1993	11.49	2.30	1.15	1.15	11.49	1.15	0.00	0.00
1994	29.67	6.59	0.00	0.00	20.00	2.22	1.11	0.00
1995	11.36	0.00	0.00	0.00	10.31	1.03	0.00	0.00
1996	11.50	1.77	0.00	0.00	5.98	1.71	0.00	0.00
1997	14.06	0.78	0.00	0.00	15.04	1.50	0.00	0.00
1998	6.25	1.39	0.00	0.00	9.93	0.71	0.00	0.00
1999	32.96	7.82	1.68	0.00	13.95	2.33	0.00	0.00
2000	18.18	1.30	0.00	0.00	16.40	1.06	0.53	0.00
2001	12.23	1.60	0.53	0.00	8.76	1.03	0.00	0.00
2002	22.47	3.08	0.00	0.00	23.31	3.81	0.00	0.00
2003	7.28	1.46	0.00	0.00	26.50	3.00	1.00	0.00
2004	12.55	1.30	0.00	–	17.02	2.66	0.53	–
2005	13.51	4.50	–	–	13.43	1.85	–	–
2006	16.13	–	–	–	27.70	–	–	–
Mean	15.69	2.61	0.28	0.10	15.70	1.85	0.26	0.00
E(mean)	10.00	1.00	0.10	0.01	10.00	1.00	0.10	0.01
p-value	0.02	0.03	0.29	0.39	0.01	0.01	0.20	0.00

in all but two years, indicating a positive relationship between past and future performance for winner funds. The average share of top funds that survive a second year and third year in decile 10 across all entering years is 15.69 percent[511] and 2.61 percent, respectively, both significantly higher than the expected values based on *iid* performance. However, after three years persistence fades away as survival rates are no longer significantly higher than expected. Only 1.15 percent of funds that enter decile 10 in 1993 are able to stay in this decile for 5 years in a row. In no other case can such successful performance be observed.

[511] Note that this number is slightly lower than the 21 percent reported above due to different weighting. More funds survive in decile 10 for at least another year during more recent years when a higher number of funds exists.

An analysis of individual years in which funds entered the winner or loser decile also allows testing whether the market environment explains performance persistence. If persistence is not a result of persistent manager skills but rather certain strategies providing superior abnormal returns in certain market environments, as argued by Brown and Goetzmann (1995), then a changing market environment should result in a lower fraction of funds surviving in the decile. Based on the returns of the U. S. stock market, as measured by annual returns of the S & P 500 Index, the years 1993 and 1994 were characterized by a sideways movement of the market while 1995 to 1999 was a clear bull market. A bear market followed in the years 2000 to 2002 while the subsequent period beginning in early 2003 until the end of the sample period in 2007 was dominated by a strong reversal in the form of a bull market. Consequently, funds that entered the winner or loser decile in the first year of a new market phase should have a lower likelihood of surviving a second year in this decile if performance persistence depends on the market environment.[512]

In particular, winner funds that entered the top decile in the years 1994 and 1999, and to a lesser extent those that entered decile 10 in 2002, were in large numbers able to survive for a second year and also for a third year. In all three cases the market environment was relatively stable over the relevant years: in 1993 and 1994 U. S. stock market returns were modest at 7.1 and −1.5 percent with relatively low volatilities, in 1998 and 1999 returns were exceptionally high at 26.7 and 19.5 percent per year, and 2001 and 2002 were two consecutive years of exceptionally low returns of −13.0 and −23.4 percent per year.[513] In contrast, funds entering decile 10 in the years 1998 or 2003 performed very poorly in their attempt to survive among the top-performing funds. This is somewhat surprising for the year 1998 because these funds also faced a similar market environment in both relevant periods as the S & P 500 Index rose by 31.0 percent in 1997 and by 26.7 percent in 1998. However, the year 2002 was marked by exceptionally low returns of −23.4 percent while the S & P 500 Index strongly rebounded at 26.4 percent over the following year. In the case of stable market environments over

[512] This is because funds belong to a certain decile in the current year based on their performance during the previous year. Thus, being in a certain decile in the first year of a new market phase is based on the performance during the last year of the old market phase while a second consecutive year in the same decile would be based on the performance during the first year of the new market phase.

[513] Note that, for example, funds that entered decile 10 in 1994 and stayed in decile 10 for two consecutive years did so because of their exceptional performance in the years 1993 and 1994. Thus, these years are relevant in explaining their persistent outperformance.

time, be it a bull or a bear market, winner funds tend to survive in the top decile while they do not succeed in doing so when the market environment changes. Thus, a large part of the performance of winner-fund strategies seems to be time varying and to depend on the specific period. Skill is only persistent as long as the market environment does not change or, put differently, different markets have different winning strategies. Slightly in contrast to this conjecture, the fraction of winner funds that continue to be among the top ten percent is relatively low during the second half of the nineties, with the exception of funds entering decile 10 in 1999, even though the whole period can be characterized as a bull market.

Compared to winner funds, a slightly higher number of the 3,946 funds in the sample enter the loser decile at least once during the sample period. In total, 1,684 funds or 43 percent $(1,684/3,946)$ are ranked among the lowest ten percent of funds at some point in time. Out of these funds, 363 or 22 percent (363/1684) stay in the loser decile for at least two consecutive years. Analyzing individual years reveals that in 11 out of the 14 years considered, more than the expected 10 percent of loser funds according to the *iid* assumption, remain in the loser decile for a second year, which is evidence in favor of persistence among loser funds. On average, significantly more funds survive in year two with 15.70 percent[514] and year three with 1.85 percent than expected under *iid* performance before persistence again vanishes for horizons longer than three years.[515] There is no case where a loser fund remains in the bottom decile for five years in a row, which is significantly lower than the expected probability for this to happen. This is consistent with the investment management company taking action after several periods of underperformance by either changing the investment strategy, replacing the manager or even closing or merging the fund.

The years 1994, 2002, 2003 and 2006 stand out because in these years exceptionally high numbers of loser funds remain loser funds for a second year in a row. In the case of 1994 and 2006, a potential explanation for this observation is similar to the explanation in the case of winner funds. U. S. stock market returns were modest at 7.1 and -1.5 percent in 1993 and 1994, respectively, and also relatively

[514] Note that this number is slightly lower than the 22 percent reported above due to different weighting. More funds survive in decile 1 for at least another year during more recent years when a higher number of funds exists.

[515] Recall that 19 percent of all fund managers are replaced every year or, put differently, that one manager-fund combination on average lasts for about 5 years which might explain why persistence starts to fade away around this period. In the case of loser funds, manager replacements are likely to occur more often, which further reduces this period.

low at 3.0 and 13.6 percent in 2005 and 2006, respectively, with relatively low volatilities. Thus, the market environment was quite stable and losing investment strategies remained losing strategies. A similar argument holds for funds entering the loser decile in the year 2002. Both 2001 and 2002 are dominated by a bear market with negative annual returns of −13.0 and −23.4 percent. Funds with presumably risky strategies, that were poorly performing in 2001, continued to do so in the similar market environment of 2002. However, this argument does not hold for the higher survival of loser funds that entered the bottom decile in 2003 and stayed there for two consecutive years. Market returns were largely negative in 2002 at −23.4 percent but dominated by a strong reversal of 26.4 percent positive returns in 2003. Thus, funds that fared relatively badly in the downturn continued to do so in the following upturn. Also, the year 1996 does not support the conjecture that persistent poor performance is stronger when the market environment remains stable. Both 1995 and 1996 are characterized by a bull market with annual market returns of 34.1 and 20.3 percent, though only 5.98 percent of loser funds that entered the bottom decile in 1996, based on 1995 performance, continued to do badly in 1996. Consequently, it seems less convincing to explain persistent mutual fund underperformance by the market environment. Rather, other reasons seem to play a role in explaining when losers remain losers and when losers strongly revert to the mean.

Summarizing these findings, performance persistence does not seem to be very pronounced among most performance deciles. However, the probability of winner and loser funds remaining in their respective decile is higher than expected under the *iid* assumption. For winner funds, persistence seems to be partly explained by the market environment with only a few funds being able to remain in the top decile over periods when the market switches from a bull to a bear market or vice versa. In contrast, the continued underperformance of loser funds does not seem to be largely affected by changes in the market environment.

7 Fund Flows and Manager Changes as Equilibrium Mechanisms

7.1 Research Questions and Hypotheses

In the previous chapter, the question of whether the existence of short-term persistence but the lack of long-term persistence documented in the literature can be explained by different methodologies applied in these studies has been analyzed. It seems that, even though methodological issues contribute to this observation, persistence indeed decays over longer horizons, even if analyzed with identical methodologies. Consequently, this chapter goes on to further investigate potential reasons for this pattern of performance persistence over time by concentrating on economic explanations for the observed mean reversion in fund performance among both recent winner and recent loser funds. The theoretical grounds have been laid down in chapter 4.

The main argument is that fund flows and manager changes are both sensitive to past performance and, at the same time, affect future performance.[516] Investors tend to chase recent winner funds which results in large net inflows into the top-performing funds of the previous calendar year.[517] Moreover, fund managers of these funds might not be able to negotiate an adequate compensation package and decide to leave to a better paid job.[518] Alternatively, they might be lured away by competing fund companies. The performance of recent winner funds suffers from both large inflows and the leaving of the skilled fund manager. Also for loser funds, investors might decide to withdraw their money and the investment management company might replace the fund manager in order to avoid money flowing out of the fund. Subsequent fund performance eventually benefits from a smaller fund size and a new manager.

Both effects, fund flows and manager changes, seem to be triggered by past performance. Thus, it is important to analyze both effects simultaneously and

[516] Hence, this poses the threat of endogeneity in the relationship between fund flows and fund performance. However, the ranked portfolio test is believed to avoid potential biases as far as possible.

[517] Section 4.2.

[518] Section 4.4.

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DOI 10.1007/ 978-3-8349-6527-1_8,

to explicitly allow for potential interaction. Moreover, some of these mechanisms might be more effective in combination or alone in removing performance persistence. So far, studies have usually concentrated on only one of these effects individually but have not taken potential interaction effects into account. The aim is to fill this gap in the present chapter and the following chapter 8, which takes a more detailed look at the underlying determinants explaining the impact of fund flows on fund performance.

7.1.1 Winner Funds

Berk and Green (2004) argue convincingly in their theoretical paper that, if there are decreasing returns to scale in active management and investors react to past performance, the asset base managed by a portfolio manager adjusts to his individual skill level, driving away previous out- or underperformance.[519] Their model implies that fund flows is one key mechanism that prevents persistent outperformance, but also removes persistent underperformance, i. e. mutual fund market equilibrium is attained through fund flows.[520] Several studies show that investors do indeed respond to recent superior performance and ratings by investing additional funds and thus increasing the asset size of winner funds.[521]

Large money inflows into recent winner funds usually reduce future performance through transaction costs and distorted trading decisions. Chen, Hong, Huang, and Kubik (2004) and Yan (2008) provide evidence that average transaction costs are positively correlated with fund size and the degree of illiquidity of the investment strategy. New investments of large funds are typically restricted to a limited range of liquid stocks and good investment opportunities eventually vanish as funds hit the capacity constraints on their investment strategies. Pollet and Wilson (2008) show that, rather than generating more best ideas, fund managers instead tend to scale up existing holdings as a response to inflows. Edelen (1999) and Alexander, Cici, and Gibson (2007) argue that excessive fund flows encourage liquidity-motivated, rather than valuation-motivated, investments and induce

[519] Section 4.3.

[520] The literature on the smart-money effect also analyzes the predictive content of fund flows for fund performance (e. g. Gruber, 1996; Zheng, 1999; Sapp and Tiwari, 2004; Keswani and Stolin, 2008c). In contrast to this literature, funds are conditioned in this study first on past performance as a proxy for skills and then the predictive power of conditioning on fund flows is investigated in the second step. On the smart-money effect see also section 3.7.3.

[521] Sirri and Tufano (1998), Lynch and Musto (2003), Del Guercio and Tkac (2008), Goriaev, Nijman, and Werker (2008), and section 4.2.

immediate transaction costs, both of which are detrimental to fund performance in the short run.

Consistent with the Berk and Green (2004) hypothesis of decreasing returns to scale, Chen, Hong, Huang, and Kubik (2004) document that small funds significantly outperform large funds. However, differences in fund sizes are the result of both differences in the inflows cumulated throughout a fund's entire history since inception (external growth) and differential performance (internal growth) and so will only be of indirect relevance for testing the hypothesis of Berk and Green (2004). In contrast, the analysis in this chapter directly investigates the role of investors' responses to past performance and the importance of fund flows as an equilibrium mechanism. The study of Chen, Hong, Huang, and Kubik (2004) is extended, first, by asking whether the response of fund flows to past performance is large enough to explain the mean reversion in performance of both winner and loser funds, second, by considering differences in capacity constraints between winner funds and loser funds and, third, by allowing for capacity constraints relative to initial fund size, but at different levels of absolute fund size. This accounts for the possibility that capacity constraints differ across funds depending on their investment strategy.

Fund growth is a relevant objective for fee-maximizing investment management companies because management fees are usually a percentage of assets under management. However, large net inflows do not benefit existing investors. To minimize the negative impact of inflows, while simultaneously increasing the compensation to successful managers, some funds might close to new investors in an attempt to preserve their superior performance and then increase fees. Empirical evidence, however, suggests that this does not tend to prevent a subsequent significant deterioration in alpha (Bris, Gulen, Kadiyala, and Rau, 2007). Star fund managers can extract a larger share of the higher fee income by either moving to a larger fund within the same organization or to another investment management company altogether if they are unable to negotiate an acceptable compensation package related to the higher fee income received by the investment management company.[522] Moreover, a successful manager anticipating that he will not be able to repeat his outstanding performance in the future may decide to use his current

[522] Anecdotal evidence suggests that some mutual fund managers have increased their personal wealth by quitting their job as an employee in the mutual fund industry and setting up a hedge fund, such as Jeffrey N. Vinik, the former manager of Fidelity's Magellan fund, in 1996.

favorable track record to find a higher paid job with a new investment management company. In this case, the decision to stay or to leave will be the result of the manager's own assessment of his investment skill.

Alternative to this argument, a manager change among winner funds does not necessarily lead to a performance deterioration in the subsequent year (Dangl, Wu, and Zechner, 2008). If a winner-fund manager consistently ranks among the top 20 percent of funds but not among the top 10 percent over several years, the investment management company might have an incentive to replace this manager due to the convex incentive structure. Specifically, it is usually only the top decile that receives the majority of inflows. The longer the tenure of the manager, the more the uncertainty about his investment skills is reduced. Thus, in the case of a top-20 but not top-10 manager, the likelihood is relatively high that this manager will not attract the inflows directed toward recent top-decile funds and the investment management company might rationally decide to replace this manager with one who is presumably better skilled. In this case, if the investment management company is able to identify and attract this highly skilled manager, performance would not be expected to decrease but rather to increase in the following year. The subsequent change in performance depends on the reason for the manager change, voluntary versus forced, and the cohort from which the new manager is drawn. However, both are unobservable and thus it is not possible to distinguish between both reasons for manager changes. But it seems reasonable to expect that voluntary turnover dominates among winner funds, resulting in a subsequent decrease in performance rather than an increase.

Empirical evidence indicates that promotions, with a successful fund manager subsequently managing a larger fund, are positively linked to past performance (Hu, Hall, and Harvey, 2000; Baks, 2003). In any case, a winner fund that loses its star manager will need to hire a new manager, presumably with lower skills. Therefore, fund performance is expected to deteriorate after the hiring of a new manager. It appears to be the case that manager changes can act as an additional curb on performance persistence to that arising from fund flows.

Building on these arguments, the data set allows an investigation into the following hypotheses and questions regarding the joint effects of fund flows and manager changes on performance persistence in outperforming equity mutual funds:[523]

[523] Further, different underlying determinants of how fund flows and manager changes translate into performance are distinguished by studying various specifications of multifactor

- Fund flows: Does the future performance of recent winner funds suffer from high inflows, due to investors chasing past performance, leading to a stronger mean reversion for winner funds with higher net inflows (section 7.3.1)?[524]

- Manager changes: Does the future performance of recent winner funds suffer from a manager replacement leading to a stronger mean reversion for winner funds with a manager change (section 7.3.1)?

- Which effect has the bigger impact on eliminating performance persistence? Are both effects in combination additive, magnifying or offsetting (section 7.3.2)?

- Are the results on fund flows and manager changes as equilibrium mechanism robust to differences in fee levels (section 7.6) and the influence of other performance determinants in a regression framework (section 7.7)?

In terms of Berk and Green (2004), for those winner funds that need to replace a departing fund manager, the fund size is now too large relative to the skill level of this new manager. These funds should subsequently underperform compared to winner funds without a manager change. Thus, an increase in fund size relative to managerial skill is the underlying determinant causing both equilibrium mechanisms to lower performance.

In addition to the long-term effect through an increased fund size, the fund-flow mechanism also captures the negative short-term effect of liquidity-induced transactions on performance, which is absent in the case of a fund-size adjustment through a manager change. Therefore, the fund-flow mechanism is expected to act as a stronger curb on performance. On the other hand, the departure of a star fund manager might have a more negative impact on performance than the transaction costs associated with increased fund flows. Thus, which effect has the larger impact will be an empirical issue. The combination of high inflows and manager changes is expected to result in even further pronounced mean reversion. But it will also be an empirical issue whether the combined negative impact of inflows and manager changes on performance is simply the sum of the individual effects or whether the two effects are reinforcing or offsetting.

models. Details are given in section 7.2.2 and Table 7.2.

524 Additionally, differences between absolute and relative capacity constraints are analyzed.

7.1.2 Loser Funds

In the case of underperforming funds, Dangl, Wu, and Zechner (2008) consider alternative strategies for investors and the investment management company. Once a fund has been identified as poorly performing, investors could choose to move their assets to a fund with greater potential: in other words, investors could exercise external governance and vote-by-feet. Yet, empirical evidence indicates that many investors in poorly performing funds fail to withdraw their investments (Sirri and Tufano, 1998; Lynch and Musto, 2003).[525] This could be because they anticipate a strategy change by the incumbent manager, or the firing of a poorly performing manager, or because of a disposition effect.[526] Transaction costs and the costs involved in gathering information about alternative funds will further reduce the mobility of capital. The consequence is that the fund-flow equilibrium mechanism might be weaker in underperforming funds and poor performance may persist, at least in the short term (Berk and Tonks, 2007).

Large outflows, in particular, result in liquidity-motivated transactions which distort fund performance in the short term and impose an even stronger cost on loser funds than they do on winner funds. Coval and Stafford (2007) find that the performance of loser funds in distress and experiencing large outflows, hence making their trades predictable by others, deteriorates even further. Edelen (1999) and Alexander, Cici, and Gibson (2007) also report that distorted trading decisions and transaction costs induced by outflows are as harmful for future performance as inflows, a finding that is incompatible with the claim of Berk and Green (2004) that underperforming funds benefit from withdrawals. These short-term liquidity-induced trading effects work in the opposite direction of the long-term effects on returns from decreasing returns to scale, thus making it more difficult for the performance of loser funds to return to the mean.[527] Consequently, the fund-flow mechanism will be weaker among loser funds compared to winner funds.

It is not only outside investors who react to past poor performance but the investment management company might also react: the investment management

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[525] See the discussion in section 4.2.

[526] Investors are reluctant to realize losses and so stay invested until the fund price returns to the original purchase price (Shefrin and Statman, 1985).

[527] Note that in the case of winner funds, the short-term effects of liquidity-induced trading and the long-term effects of decreasing returns to scale both operate in the same direction, magnifying the negative impact of inflows on winner-fund performance.

company can replace a poorly performing manager and an alternative mechanism to explain mean reversion in fund performance is manager changes (Khorana, 1996, 2001).[528] Indeed, several studies also document an inverse relationship between fund performance and manager changes (Khorana, 1996; Chevalier and Ellison, 1999b; Gallagher and Nadarajah, 2004). Hence, manager changes also appear to place a curb on (poor) performance persistence. Dangl, Wu, and Zechner (2008) develop a model in which poorly performing managers are subject to both external governance from investors withdrawing funds and internal governance associated with the termination of their contracts. It is important to analyze both mechanisms jointly because both depend on past performance.

The following hypotheses and questions regarding the effects of fund flows and manager changes on performance persistence in underperforming equity mutual funds will be investigated:[529]

- Fund flows: Does the future performance of recent loser funds benefit from a smaller asset base due to withdrawals, i. e. outflows, from investors, although this effect might be dampened by any investor inertia and by the costs of rearranging portfolios, leading to a stronger mean reversion for loser funds with lower net inflows (section 7.4.1)?[530]

- Manager changes: Does the future performance of recent loser funds benefit under a newly appointed manager after the investment management company fired the previously underperforming fund manager, leading to a stronger mean reversion for loser funds with a manager change (section 7.4.1)?

- Which effect has the bigger impact on eliminating performance persistence? Are both effects in combination additive, magnifying or offsetting (section 7.4.2)?

- Are the results on fund flows and manager changes as equilibrium mechanism robust to differences in fee levels (section 7.6) and the influence of other performance determinants in a regression framework (section 7.7)?

[528] See the discussion in section 4.4.

[529] Further, as in the case of winner funds, different underlying determinants of how fund flows and manager changes translate into performance are distinguished by studying various specifications of multifactor models. Details are given in section 7.2.2 and Table 7.2.

[530] Additionally, differences between absolute and relative capacity constraints are analyzed.

Loser funds which replace their underperforming manager with a presumably better manager should subsequently outperform loser funds without a manager change. Loser funds are expected to benefit more from a manager replacement than from outflows. This is because the fund-flow mechanism involves transaction costs arising from the forced sales of assets. While the new manager will almost certainly change the asset composition of the fund, this can be done gradually without a market impact. On the other hand, significant fund outflows will lead to a faster and more radical restructuring of the portfolio and consequently a faster return to normal performance. So again it is an empirical matter about which effect dominates and how both mechanisms interact. They are likely to be reinforcing when both mechanisms occur simultaneously, such as when an investment management company fires a poorly performing fund manager in an attempt to stem outflows.[531] But their effects would be neutralized in the case where investors fail to withdraw money from poorly performing funds in anticipation of a manager change, but the investment management company delays firing the poorly performing fund manager because outflows did not materialize.

7.2 Methodology

7.2.1 Portfolio Formation

The methodology used in this chapter is similar to the one in chapter 6. Specifically, after ranking funds into deciles based on the previous year performance subgroups of the winner and loser deciles are formed based on a single sorting on fund flows (high net inflows / low net inflows) or manager changes (with manager change / without manager change), respectively (panels (a) and (b) in Figure 7.1). Furthermore, as the interaction effects between both mechanisms are of special interest, subgroups of the winner and loser deciles are formed based on a double sorting on fund flows and manager changes simultaneously (high with / high without / low with / low without) (panel (c) in Figure 7.1).

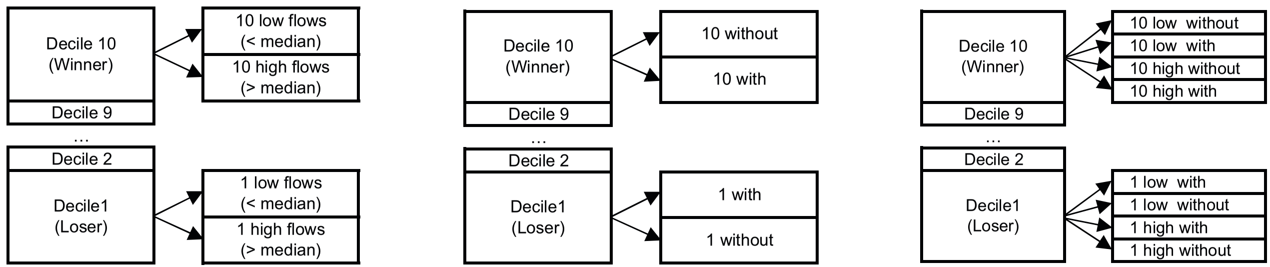
In Berk and Green (2004), active management suffers from decreasing returns to scale, but it is an empirical question whether these capacity constraints are absolute or relative. Absolute capacity constraints arise once a certain threshold of absolute fund size is exceeded and depend on absolute fund flows. Relative

[531] In the case of corporations, Parrino, Sias, and Starks (2003) provide empirical evidence that a reduction in institutional ownership increases the likelihood of forced CEO turnover.

Figure 7.1: Portfolio formation based on fund flows and manager changes

This figure presents the methodology applied to construct the subgroup portfolios based on fund flows and manager changes. Funds are first sorted into deciles based on their performance in the formation period. Then, the decile-10 (winner) and decile-1 (loser) funds are further divided into: (a) a low-net-inflow (low) or high-net-inflow (high) subgroup based on whether their net inflows during the formation period are lower or higher than the median net inflows of all other funds in the same decile (using either absolute net inflows or relative net inflows and presenting the results for both); (b) a no-manager-change (without) or manager-change (with) subgroup based on whether their fund manager changed during the formation period; (c) into four subgroups combining the criteria in (a) and (b) in a double sorting mechanism (using absolute fund flows).

(a) Absolute / relative flows (b) Manager change (c) Double sorting



capacity constraints differ across investment strategies and arise after the fund receives a certain level of inflows relative to the initial fund size. Both absolute and relative net inflows are analyzed but the presentation of the results concentrates on absolute flows and only discusses relative flows when there are additional insights.

The composition of the subgroups based on managerial turnover and fund flows shows distinct differences indicating that both mechanisms are relatively independent. Table 7.1 presents the fraction of fund-months in the subgroups of decile 10 and decile 1 with high and low fund flows and with and without managerial turnover.[532] The composition of funds within different subgroups is comparable to the composition of the whole sample. Specifically, decile-10 funds with a manager change are almost equally distributed across the groups with high and low net inflows. Almost exactly half (50.11 percent)[533] of the funds that suffer from the loss of their star manager suffer at the same time from high net inflows. Similarly, 20.09 percent of funds with high net inflows at the same time have a change in management which equals the corresponding number for all decile-10 funds at 20.09 percent. This is not surprising because the occurrence of both mechanisms should not be strongly interacted.[534] However, both mechanisms might well interact in their impact on fund performance, a question that will be analyzed below, even though their occurrence is relatively independent of each other.

The results for decile-1 funds are similar. The share of funds with a manager change within the low-net-inflow subgroup is 23.83 percent which is only slightly higher than the corresponding number of 21.78 percent for all decile-1 funds. Similarly, out of the group with a change in management 54.58 percent have low net inflows at the same time whereas 49.88 of all decile-1 funds have low net inflows. Thus, the occurrence of low net inflows (or outflows) and a change in management is slightly positively related indicating that internal and external governance mechanisms are complementary, i. e. tend to be applied in combination, rather than being substitutes. This is interesting because if internal governance is applied, future performance should be less predictable by past performance which at least

[532] Note that the fraction of fund-months with lower (higher) than median fund flows is not exactly 50 percent because outflows seem to be associated with a slightly higher number of fund closures or mergers.

[533] This number is computed as 10.07 divided by 20.09. The same principle is applied to the following numbers. Differences are due to rounding.

[534] On the one hand, one might conjecture that winner-fund managers receiving high inflows already anticipate their detrimental impact on future performance, which would increase their likelihood to leave. While, on the other hand, inflows might also allow them to negotiate a more favorable compensation package, which is a reason to stay.

Table 7.1: Composition of absolute-fund-flow and manager-change subgroups

This table presents in panel (a) the share of decile-10 funds and in panel (b) the share of decile-1 funds in the low-absolute-fund-flow (low) and high-absolute-fund-flow (high) subgroup and in the manager-change (with) and no-manager-change (without) subgroup, respectively, based on the total number of fund months on the sample. See the note to Figure 7.1 for more explanation on the portfolio formation.

(a) Decile-10 funds

Net inflows	Manager change: 10 with	10 without	Sum
10 low	10.02	39.85	49.87
10 high	10.07	40.06	50.13
Sum	20.09	79.91	100.00

(b) Decile-1 funds

Net inflows	Manager change: 10 with	10 without	Sum
1 low	11.89	37.99	49.88
1 high	9.89	40.23	50.12
Sum	21.78	78.22	100.00

reduces the incentive to withdraw money from the fund. However, when loser funds continue to underperform despite replacing the manager, it rather seems rational to withdraw money from loser funds, irrespective of whether the manager is replaced or not, and to direct this money to recent winner funds which continue to outperform recent losers based on the results in section 6.2. Moreover, the finding that internal and external governance seem to be complementary might also be explained by the delayed disclosure of manager replacements in (semi-) annual reports. Some investors might continue to withdraw money, i. e. apply external governance, despite the fact that the investment management company has already applied internal governance and replaced the manager because these investors are not yet aware of the manager replacement. In addition, the manager might have been replaced at the end of the year while money was flowing out of the fund in the same year but prior to the manager replacement. Both of these effects would show up as internal and external governance being complements in the data due to the annual frequency of the manager-change variable.

7.2.2 Specification of Multifactor Models

In order to gain a more detailed understanding of the underlying determinants which potentially drive the impact of the equilibrium mechanisms on fund performance, several specifications of multifactor models are applied. This allows a detailed analysis of the impact of fund flows on different determinants of fund performance depending on the specific response of the fund manager to inflows or outflows. The following Table 7.2 presents the expectations on how different performance measures are affected by fund flows, separately for inflows and outflows.[535]

The top panel (a) presents determinants that are detrimental to fund performance, irrespective of whether the fund receives inflows or experiences outflows. These include transaction costs involved with liquidity-induced trades, a cash drag due to a higher fraction of the portfolio held in the risk-free asset when flows are more volatile and the performance impact of distorted trading decisions.[536] Because all of these determinants have a negative impact on performance, at least in the short run, the fund-flow mechanism is expected to be weaker among loser funds as compared to winner funds. Specifically, the determinants in panel (a) reinforce the determinants in panel (b) for winner funds but compensate for part of the beneficial determinants of outflows on loser funds in panel (b).

The bottom panel (b) presents determinants that are capable of explaining mean reversion in fund performance due to investors' response to past performance. In the case of inflows, price pressure due to upscaling existing holdings has a positive short-term effect which reverts over the longer term. In contrast to this, in the case of outflows, downscaling reduces performance over the short run but again, this reverses over the longer term. Unintentional beta variation also affects raw returns but not risk-adjusted returns because even the most parsimonious model (the one-factor model) controls for the loading on the market factor and, therefore, should not, theoretically, be not affected by any variation in beta.[537] However, beta cannot be observed but needs to be estimated in empirical applications. Thus, it is likely that the estimation procedure does not capture the full variation of beta over time. As a result, even the empirical estimates of the different alpha

535 This table is based on Table 4.1. See section 4.3 for a more detailed discussion of the individual effects.

536 Note that transaction costs only affect performance measures net of transaction costs but not raw returns before transaction costs (r^g).

537 However, alpha measures might still be affected by a variation in beta indirectly. Recall that alpha cannot be used for rankings because it is sensitive to the leverage of the fund. Thus, an increase in beta also increases alpha even if the fund is still on the same line in the μ-σ diagram, which indicates the same level of investment skills. However, based on the simple CAPM equation (3.17) a doubling of beta doubles the expected excess returns. It also doubles realized excess returns. If alpha, which is the difference between realized and expected returns, is positive then it is strictly increasing in beta. Thus, a beta variation also effects alphas indirectly, even though this is not indicative of higher or lower investment skills.

Table 7.2: Expected response of fund performance to fund flows (multifactor models)

This table presents the potential response of different performance measures for funds that receive inflows (left panel) and funds that experience outflows (right panel) compared to funds without fund flows, respectively. A black triangle (▼) indicates a decrease and a white triangle (△) indicates an increase in performance. Panel (a) refers to potential explanations for average underperformance and panel (b) refers to potential explanations for mean reversion in performance. Columns (1) and (8) report raw returns gross of transaction costs (r^g); Columns (2) and (9)report raw returns net of transaction costs (r^n); Columns (3) and (10) report monthly risk-adjusted returns based on the one-factor model of Jensen (1968) according to equation (3.19); Columns (4) and (11) report monthly risk-adjusted returns based on the three-factor model of Fama and French (1993) according to equation (3.22); Columns (5) and (12) report monthly risk-adjusted returns based on the four-factor model of Carhart (1997) according to equation (3.23); Columns (6) and (13) report monthly risk-adjusted returns based on a five-factor model that incorporates a mean-reversion factor according to equation (5.4); Columns (7) and (14) report monthly risk-adjusted returns based on a five-factor model that incorporates a liquidity factor according to equation (5.5).

	Inflows							Outflows						
Description	r^g	r^n	α_1	α_3	α_4	α_5^{mr}	α_5^{l}	r^g	r^n	α_1	α_3	α_4	α_5^{mr}	α_5^{l}
(a) Explaining average underperformance														
cash drag	▼	▼	–[a]	–[a]	–[a]	–[a]	–[a]	▼	▼	–[a]	–[a]	–[a]	–[a]	–[a]
transaction costs	–	▼	▼	▼	▼	▼	▼	–	▼	▼	▼	▼	▼	▼
distorted security selection	▼	▼	▼	▼	▼	▼	▼	▼	▼	▼	▼	▼	▼	▼
(b) Explaining mean reversion														
price pressure (short term)	△	△	△	△	△	△	△	▼	▼	▼	▼	▼	▼	▼
beta variation	▼	▼	–[a]	–[a]	–[a]	–[a]	–[a]	△	△	–[a]	–[a]	–[a]	–[a]	–[a]
variation of average market cap	▼	▼	▼	–	–	–	–	△	△	△	–	–	–	–
variation of asset liquidity	▼	▼	▼	▼	▼	▼	–	△	△	△	△	△	△	–
variation of position liquidity	–	▼	▼	▼	▼	▼	▼	–	△	△	△	△	△	△
information advantage	▼	▼	▼	▼	▼	▼	▼	△	△	△	△	△	△	△
best ideas	▼	▼	▼	▼	▼	▼	▼	△	△	△	△	△	△	△
hierarchy costs	▼	▼	▼	▼	▼	▼	▼	△	△	△	△	△	△	△
price pressure (long term)	▼	▼	▼	▼	▼	▼	▼	△	△	△	△	△	△	△

[a] See footnote 537.

measures might be affected by unintentional beta variation. This argument also applies to the following determinants.

If fund flows force the manager to deviate from the intended average market cap of the portfolio holdings, then raw returns and the one-factor alpha are affected, while all remaining alphas control for a tilt in the size exposure. Similarly, an unintentional variation in the average liquidity of the holdings affects all but the liquidity-augmented alpha measures. A decrease in the position liquidity due to inflows, i. e. the ownership ratio of a specific portfolio holding increases because the fund own more stocks of one company after scaling up an existing holding, makes this position more expensive to trade and increases transaction costs. Thus all performance measures that are based on net returns decrease. If outflows result in an increase in the position liquidity, because the ownership ratio in certain stocks is reduced, then this effect reverses.

The last three determinants, a change in the informational advantage, the number of best ideas or the hierarchy costs, all affect true selection skills of the manager, i. e. alpha after accounting for exposures to potential risk factors. Therefore, irrespective of which performance measure is used, inflows will reduce performance while outflows will improve performance. Next, these effect will be analyzed separately for winner and loser funds. However, results on raw returns gross of transaction costs cannot be presented because of a lack of relevant data and one-factor alphas are not presented in order to save space.

7.3 Winner Funds

7.3.1 Single sorting

Winner funds are separated in the formation period by the second sorting into a subgroup with low absolute net inflows, averaging −4.50 million USD per month during the formation period, and a subgroup with high absolute net inflows, averaging 25.78 million USD per month (panel (a) of Table 7.3). This results in a significant difference in fund flows of 30.28 million USD per month in the formation period. This spread is relatively persistent over time, so that high-inflow funds still receive 30.44 million USD higher inflows in the evaluation period (panel (b) of Table 7.3). These results are consistent with the existence of several investor clienteles who respond to past performance with different time lags, some very quickly and others only after a certain period of time.

Table 7.3: Characteristics of winner-fund subgroups

This table presents the characteristics for the winner-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. Panel (a) presents results for the formation period and panel (b) for the evaluation period. See the note to Figure 7.1 for more explanation on the portfolio formation. Column (1) reports the average fund size in millions USD; column (2) reports the average fund age in years; column (3) reports average fees in percent; column (4) reports the average annual portfolio turnover; column (5) reports average monthly absolute net inflows in millions USD; column (6) reports the number of manager changes (MC) per fund. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

(a) Formation period

	Fund size	Fund age	Fees	Turn-over	Net in-flows	MC / fund
Conditional on absolute net inflows (median split point)						
10 low	507.53	10.77	1.75	1.25	−4.50	0.22
10 high	1,041.47	9.00	1.63	1.19	25.78	0.22
10 low − 10 high	−533.95***	1.77***	0.12***	0.06*	−30.28***	–
Conditional on relative net inflows (median split point)						
10 low	816.61	12.74	1.71	1.15	−1.10	0.22
10 high	733.99	7.04	1.67	1.29	22.40	0.22
10 low − 10 high	82.62**	5.70***	0.04***	−0.13***	−23.50***	–
Conditional on manager changes (without / with)						
10 without	785.35	9.45	1.67	1.26	11.59	0.00
10 with	643.56	10.13	1.76	1.16	7.10	1.00
10 without − 10 with	141.79***	−0.68***	−0.09***	0.10***	4.49***	–

(b) Evaluation period

	Fund size	Fund age	Fees	Turn-over	Net in-flows	MC / fund
Conditional on absolute net inflows (median split point)						
10 low	561.27	11.77	1.75	1.18	−0.64	0.19
10 high	1,596.60	10.00	1.60	1.09	29.81	0.21
10 low − 10 high	−1,035.33***	1.77***	0.15***	0.10***	−30.44***	–
Conditional on relative net inflows (median split point)						
10 low	965.45	13.74	1.70	1.09	4.17	0.20
10 high	1,199.03	8.04	1.64	1.19	25.10	0.21
10 low − 10 high	−233.59***	5.70***	0.06***	−0.10***	−20.93***	–
Conditional on manager changes (without / with)						
10 without	1,106.94	10.45	1.65	1.16	15.19	0.20
10 with	866.76	11.13	1.75	1.13	11.79	0.24
10 without − 10 with	240.18***	−0.68***	−0.09***	0.04	3.39***	–

The fraction of managers leaving winner funds is similar for both subgroups. Fees, portfolio turnover and fund age are higher for the low-net-inflow subgroup which, if anything, weakens the predicted relationship. A comparison of the formation- and evaluation-period results reveals that high-inflow funds reduce their fee levels, potentially as a means of attracting even more inflows based on the successful investment performance. Both high- and low-inflow funds reduce their portfolio turnover, possibly in an attempt to lock in their high relative ranking in the sense of strategic tournament behavior.

The fund size of the low-net-inflow subgroup is only about half the size of winner funds with high absolute net inflows at 507.53 million USD compared to 1041.47 million USD, a difference of 533.95 million USD. During the evaluation period, this difference increases to 1,035.33 million USD, mainly due to differences in inflows. If fund size itself is also a determinant of fund performance, this might bias the conclusions. However, based on the relative-net-inflow sorting both subgroups are much closer in size, with the low-net-inflow subgroup being 82.62 million USD larger in the formation period, but 233.59 million USD smaller in the evaluation period. Thus, the relative-fund-flow sorting serves as a robustness test.[538]

Winner funds with and without a manager change are very similar. Funds without a manager change are 141.79 million USD larger, less than a year younger and have 0.09 percentage points lower annual fees. Annual portfolio turnover is higher by 10 percentage points and fund flows are higher by 4.49 million USD (11.59 versus 7.10 million USD) in the formation period. Characteristics in the evaluation period are very similar. None of these difference are expected to affect the performance results.

In terms of investment performance, winner funds which suffer from high absolute net inflows generate negative, though insignificant, monthly alphas of −0.05 percent in the evaluation year (Table 7.4). Winner funds which do not experience large absolute inflows have higher, though still insignificant, alphas in the evaluation year of 0.16 percent per month. The spread between the two subgroups conditioned on absolute net inflows is a significant 0.21 percentage points.

Moreover, comparing the degree of mean reversion, defined as the difference in alphas between the formation and the evaluation period, reveals that the performance of the high-inflow subgroup moves toward the mean by −0.99 percentage

[538] Marginal effects of fund flows and fund size are analyzed in section 7.7 in a regression framework (Table 7.21) and in section 8.4 based on a double sorting on both variables.

Table 7.4: Performance reversals of winner-fund subgroups for single sorts

This table presents the performance and mean reversion in performance for the winner-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.3 for more explanation on the column specification.

	Raw returns			4-factor α		
	r_{t-1}	r_t	$\Delta r_{t-1,t}$	α_{t-1}	α_t	$\Delta\alpha_{t-1,1}$
Conditional on absolute net inflows (median split point)						
10 low	1.41	0.84	−0.58	0.83***	0.16	−0.67***
10 high	1.84	0.66	−1.18**	0.94***	−0.05	−0.99***
10 low − 10 high	−0.43	0.17**	–	−0.11	0.21***	–
Conditional on relative net inflows (median split point)						
10 low	1.40	0.81	−0.59	0.82***	0.13	−0.69***
10 high	1.86	0.69	−1.17**	0.94***	−0.03	−0.97***
10 low − 10 high	−0.46	0.12*	–	−0.12	0.16***	–
Conditional on manager changes (without / with)						
10 without	1.66	0.79	−0.87	0.89***	0.10	−0.79***
10 with	1.60	0.70	−0.90	0.87***	−0.02	−0.89***
10 without − 10 with	0.06	0.09*	–	0.02	0.12**	–

points, from 0.94 to −0.05 percent per month. The low-inflow subgroup reverts by only −0.67 percentage points, from 0.83 to 0.16 percent per month. Thus, high inflows strongly contribute to the mean reversion in winner-fund performance.

Figures 7.2 and 7.3 show this graphically. Figure 7.2 presents the differences between subgroups in the level of evaluation-period alphas when conditioning on fund flows and Figure 7.3 presents the differences in mean reversion from the formation period to the evaluation period. The performance of winner funds (unconditional segment) of 0.07 percent per month can be split into a subgroup with positive abnormal returns of 0.16 (low inflows) and a subgroup with negative abnormal returns of −0.05 (high inflows) by conditioning on net inflows (single-sorting-by-flows segment). Similar differences emerge for the degree of mean reversion in Figure 7.3. Conditioning on fund flows helps to predict both differences in future performance (Figure 7.2) and in the degree of mean reversion (Figure 7.3).[539]

[539] More extreme inflows lead to even stronger results. Specifically, analysis is repeated by

Figure 7.2: Performance of winner funds and winner-fund subgroups

This figure presents monthly risk-adjusted returns based on the four-factor model of Carhart (1997) according to equation (3.23) for winner funds and winner-fund subgroups based on a single sorting and also a double sorting on absolute fund flows and / or manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

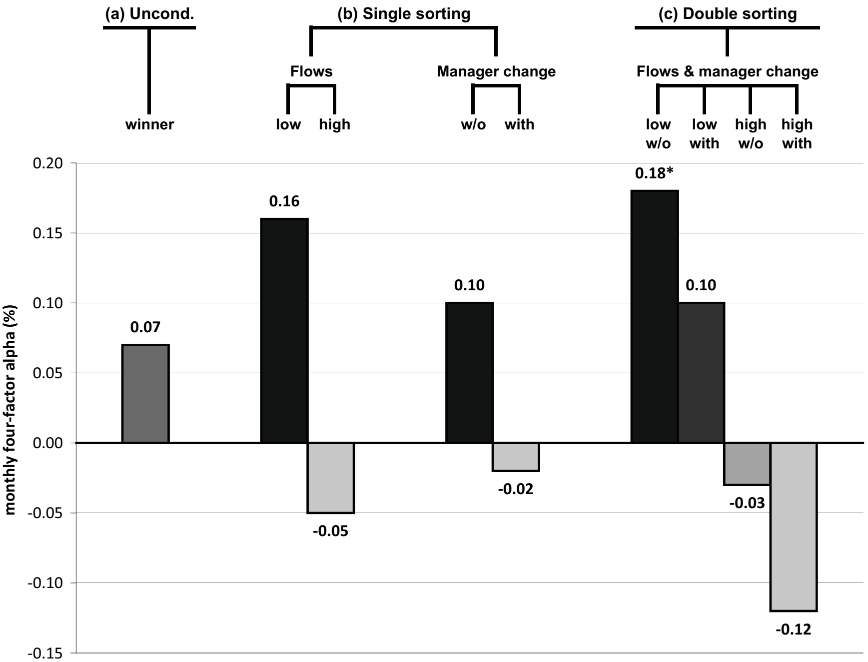
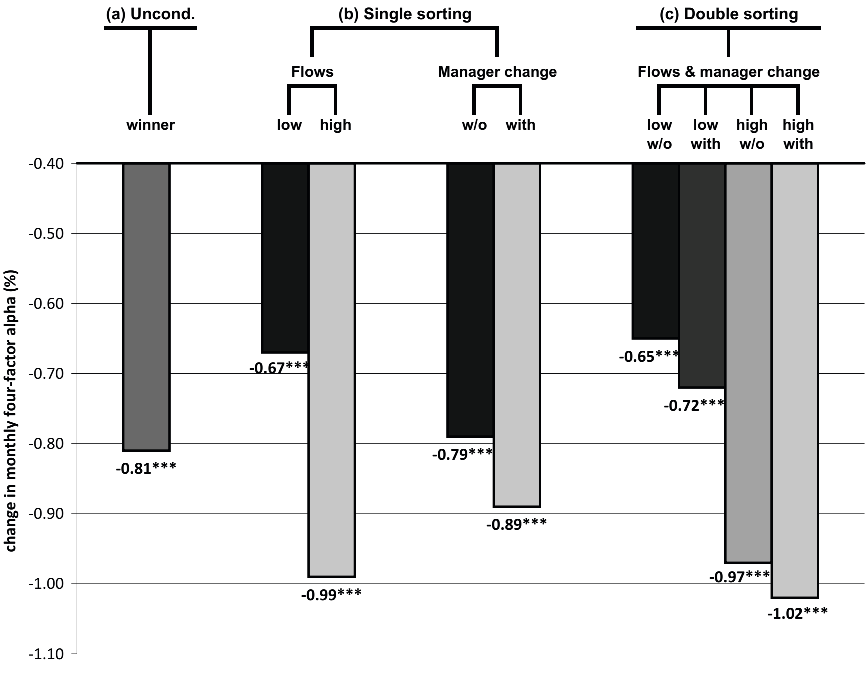


Figure 7.3: Performance reversals of winner funds and winner-fund subgroups

This figure presents the change between the formation and evaluation periods in monthly risk-adjusted returns (Δ alpha) based on the four-factor model of Carhart (1997) according to equation (3.23) for winner funds and winner-fund subgroups based on a single sorting and also a double sorting on absolute fund flows and / or manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.



The mean reversion in raw returns is even more impressive: winner funds with high inflows revert by significant −1.18 percentage points per month, from 1.84 percent monthly returns in the formation periods to only 0.66 percent in the evaluation period. Those winner funds not suffering from high inflows also revert, but by much less. Their raw returns are 1.41 in the formation period and 0.84 percent in the evaluation period, a reduction of only 0.58 percentage points. These 0.84 percent per month of the low-inflow subgroup are still significant 0.17 percentage points above the raw returns of the high-inflow subgroup. The empirical results, therefore, provide clear evidence indicating that fund flows explain the lack of performance persistence among winner funds, confirming the Berk and Green (2004) hypothesis.

As discussed above, winner funds with low absolute net inflows have an average size of 507.53 million USD which is only about half the size of winner funds with high absolute net inflows (1,041.47 million USD). Thus, part of the difference in performance might be explained by differences in size, consistent with the results of Chen, Hong, Huang, and Kubik (2004), rather than by differences in fund flows.[540] To test this, the results from a second sorting based on relative fund flows are analyzed.[541] The two subgroups are now closer in size and the low-relative-inflow subgroup is actually even larger at 816.61 million USD as compared to 733.99 million USD for the high-inflow subgroup. However, the basic conclusions remain the same: the low-net-inflow subgroup outperforms the high-net-inflow subgroup by a significant 0.16 percentage points per month (second panel in Table 7.4). Both absolute and relative capacity constraints seem to matter for winner funds.

defining high-inflow funds as those with net inflows exceeding the 80th percentile and low-inflow funds as those with net inflows below the 20th decile (instead of using the median as the split point) in section 8.3.

[540] Note, however, that funds in the two smallest size groups of Chen, Hong, Huang, and Kubik (2004) have an average fund size of only 4.7 and 22.2 million USD, respectively, indicating that sorting on absolute fund flows leads to quite different results compared to sorting on fund size.

[541] This also serves as a robustness test because it cannot be completely ruled out that the sample used in this study is affected by an incubation bias (Evans, 2010). A potential incubation bias in the data should, if at all, reduce the predicted positive spread between funds with low relative net inflows and high relative net inflows because incubated funds are usually small and attract relatively high net inflows. However, in the case of a sorting on absolute net inflows the effect is ambiguous: it is not clear whether the small size of incubated funds dominates the ranking, implying small absolute net inflows and membership in the small-absolute-net-inflow subgroup, or the large size of net inflows relative to fund size dominate, implying membership in the high-absolute-net-inflow subgroup. A potential influence from mutual fund incubation should, therefore, be kept in mind when interpreting the results.

Bris, Gulen, Kadiyala, and Rau (2007) report that funds which close to new investors after a period of superior performance switch from average four-factor alphas of 0.96 percent per month to 0.15 percent, a significant decrease of 0.81 percentage points. They interpret this result as evidence against their good stewardship hypothesis, which postulates that fund closures are intended to sustain good performance. In contrast, the results of this section indicate that funds sheltered from inflows significantly outperform those experiencing inflows in the subsequent year. Thus, even though mean reversion in performance is present in all funds, the closure of a successful fund to new inflows can still make an important contribution to sustaining their superior performance compared to funds receiving high inflows (at least for another year).

Moreover, evidence supporting the hypothesis relating to manager changes can be documented. Winner-decile-10 funds that lose their skilled manager generate an insignificant average monthly alpha of −0.02 percent. In contrast, winner funds that keep the same manager deliver positive, although still insignificant, alphas of 0.10 percent. The spread of 0.12 percentage points, however, is statistically significant.[542] The degree of mean reversion is also higher at −0.89 percentage points in the case where the manager changes, compared to −0.79 percentage points for the subgroup without a manager change. Thus, manager changes can also partly explain mean reversion among winner funds. Yet, the magnitude of the manager-change mechanism in inducing mean reversion is slightly smaller than that for the inflow mechanism, consistent with the hypothesis above. This is also evident in Figure 7.2. The unconditional performance of winner funds of 0.07 percent per month (unconditional segment) can be split into a subgroup with positive abnormal returns of 0.10 percent per month (without manager change) and a subgroup with negative abnormal returns of −0.02 percent per month (with manager change) by conditioning on manager changes (single-sorting-by-manager-change segment). However, the bars are smaller in magnitude compared to the single-sorting-by-flows segment. Similar conclusions can be drawn from Figure 7.3 which presents the degree of mean reversion in four-factor alphas between the formation and evaluation periods.

[542] Note that this figure might underestimate the true impact of manager changes on performance because neither the reason for a manager change nor the quality of the new manager can be observed. For example, some skilled managers might simply retire and be replaced by a new younger successor in the normal course of events and the investment management companies of successful funds might be able to attract an above-average replacement in such circumstances.

In the case of the manager-change mechanism, the results on raw return are slightly weaker. The evaluation-period spread between winner funds without a manager change and those with a manager change is only weakly significant 0.09 percentage points and the degree of mean reversion in both subgroups is almost equal. This implies that funds without a change in management tend to have lower risks and that a manager change primarily affects selection skills but not risk loadings.

In order to analyze whether the spreads in performance between the individual subgroups can be further explained by other performance determinants, the results of different specifications of the multifactor models are investigated (Table 7.5). Winner funds that do not suffer from high absolute net inflows as well as those not suffering from a manager change generate significantly positive abnormal returns of 0.28 and 0.25 percent, respectively, if judged based on the three-factor model of Fama and French (1993). These alphas are significantly higher compared to those of their peers suffering from inflows or a change in management, which are at insignificant 0.13 and 0.14 percent, respectively, confirming the previous conclusions. Once more factors are added to the performance model, the alphas tend to shrink. This is a consequence of the benchmark becoming stricter once factors are added and might not be surprising.[543] It is interesting, however, that the alphas of the subgroups are affected differently by the addition of factors, especially for the fund-flow subgroups. This provides some insights into the determinants of how fund flows and manager changes affect performance.

In the case of the fund-flow subgroups, the most notable change occurs once the momentum factor is added. The low-inflow subgroup's alpha is reduced by 0.12 percentage points, from significant 0.28 to insignificant 0.16, while that of the high-inflow subgroup is reduced by 0.18 percentage points, from 0.13 to -0.05. Consequently, the spread between low-inflow funds and high-inflow funds increases from 0.15 to 0.21 percentage points once the momentum factor is added to the performance model. An inspection of the different factor loadings explains this result (Table 7.6). High-inflow funds have a higher momentum exposure, presumably because fund managers add the last year's winner stocks when confronted with large sums of money flowing into the fund. The returns from this higher

[543] Note, however, that adding factors does not unambiguously reduce alphas because the effect depends on the sign of the factor loading and the average factor return. In the empirical analysis of loser funds below, adding more factors actually increases alphas.

Table 7.5: Performance of winner-fund subgroups for single sorts

This table presents different performance measures for the winner-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows (median split point)					
10 low	0.84	0.28**	0.16	0.13	0.14
10 high	0.66	0.13	−0.05	−0.08	−0.07
10 low − 10 high	0.17**	0.15**	0.21***	0.21***	0.21***
Conditional on relative net inflows (median split point)					
10 low	0.81	0.26**	0.13	0.11	0.12
10 high	0.69	0.15	−0.03	−0.05	−0.04
10 low − 10 high	0.12*	0.11**	0.16***	0.16***	0.16***
Conditional on manager changes (without / with)					
10 without	0.79	0.25**	0.10	0.08	0.09
10 with	0.70	0.14	−0.02	−0.05	−0.03
10 without − 10 with	0.09*	0.11**	0.12**	0.13**	0.12**

momentum exposure reduce the spread between low-inflow and high-inflow funds when measured based on raw returns or the three-factor model, i. e. the different momentum exposures mask part of the effect of fund flows on selection skills.

Adding the mean-reversion or the liquidity factor results in a parallel downward shift of both subgroups and the spread between low-inflow and high-inflow funds remains constant at 0.21 percentage points. With respect to the factor loadings, high-inflow funds have, contrary to expectations, a higher average market exposure of 1.01 compared to low-inflow funds at 0.97 (Table 7.6). The widespread use of derivatives in recent years, which can be used to equitize cash inflows, potentially explains why higher inflows do not necessarily result in a cash drag. Also in contrast to expectations, high-inflow funds have a significantly higher loading on the small-cap factor implying that winner-fund managers do not respond to inflows by tilting the portfolio toward large-cap stocks. Moreover, high-inflow fund managers seem to more strongly favor growth stocks compared to their low-inflow peers. The expected return column in Table 7.6 summarizes the differences in risk loadings. Recall that it is computed as the product of factor loadings and the

Table 7.6: Factor loadings of winner-fund subgroups for single sorts (4-factor)

This table presents the factor loadings for the winner-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.5 for more explanation on the column specification.

	Factor loadings				$E(r)$	R^2
	β_m	β_{smb}	β_{hml}	β_{mom}		
Conditional on absolute net inflows (median split point)						
10 low	0.97^{***}	0.37^{***}	-0.18^{***}	0.12^{***}	0.68	0.94
10 high	1.01^{***}	0.44^{***}	-0.28^{***}	0.17^{***}	0.72	0.92
10 low − 10 high	-0.04^{*}	-0.07^{***}	0.11^{***}	-0.05^{**}	−0.04	0.38
Conditional on relative net inflows (median split point)						
10 low	0.98^{***}	0.37^{***}	-0.19^{***}	0.12^{***}	0.68	0.94
10 high	1.01^{***}	0.44^{***}	-0.27^{***}	0.16^{***}	0.72	0.92
10 low − 10 high	-0.03^{*}	-0.08^{***}	0.08^{***}	-0.04^{**}	−0.04	0.40
Conditional on manager changes (without / with)						
10 without	0.99^{***}	0.40^{***}	-0.24^{***}	0.14^{***}	0.69	0.93
10 with	1.03^{***}	0.43^{***}	-0.25^{***}	0.15^{***}	0.72	0.92
10 without − 10 with	-0.04^{***}	-0.03^{**}	0.02	−0.01	−0.03	0.16

average risk premiums on the corresponding benchmark factors over the sample period. On aggregate, these different exposures lead to expected returns for the high-inflow subgroup of 0.72 percent per month, 0.04 percentage points higher than the expected returns for the low-inflow subgroup, indicating that high-inflow funds follow riskier strategies.

Both winner-fund subgroups load significantly positively on the mean-reversion factor and have a small but positive loading on the liquidity factor (Table 7.7). Thus, winner-fund managers do not seem to respond to inflows by tilting their portfolio toward more liquid stocks. In conclusion, excessive inflows into winner funds primarily reduce pure security-selection skills, after controlling for several potential risk factors. Transaction costs, a reduction in the information advantage, a lack of best ideas and an increase in hierarchy costs dominate in explaining why net inflows into winner funds have a detrimental impact on their future performance (Table 7.2). In particular, the high momentum exposure of the high-inflow subgroup helps these managers mask part of this negative impact when judged on performance measures that fail to control for momentum exposure.

Table 7.7: Factor loadings of winner-fund subgroups for single sorts (3- and 5- factor)

This table presents the factor loadings for the winner-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.6 for more explanation on the column specification.

	3-factor		5-factor MREV			5-factor LIQ		
	$E(r)$	R^2	β_{mr}	$E(r)$	R^2	β_{l}	$E(r)$	R^2
Conditional on absolute net inflows (median split point)								
10 low	0.56	0.92	0.12^{**}	0.71	0.94	0.02	0.69	0.94
10 high	0.54	0.90	0.12^{*}	0.74	0.92	0.02	0.73	0.92
10 low − 10 high	0.02	0.33	−0.00	−0.04	0.37	−0.00	−0.04	0.37
Conditional on relative net inflows (median split point)								
10 low	0.55	0.92	0.13^{**}	0.71	0.94	0.01	0.69	0.94
10 high	0.54	0.90	0.12^{*}	0.74	0.92	0.02	0.73	0.92
10 low − 10 high	0.01	0.36	0.00	−0.04	0.40	−0.01	−0.04	0.40
Conditional on manager changes (without / with)								
10 without	0.54	0.92	0.11^{*}	0.71	0.93	0.02	0.70	0.93
10 with	0.56	0.91	0.16^{**}	0.75	0.92	0.01	0.73	0.92
10 without − 10 with	−0.02	0.16	-0.05^{*}	−0.04	0.17	0.01	−0.03	0.15

For the manager-change subgroups, adding more factors shifts performance downwards for both subgroups, with and without a manager change, in a parallel fashion. Consequently, the spread between winner funds without a manager change and those with a manager change only varies between 0.11 and 0.13 percentage points when moving from the three-factor model to the five-factor models in Table 7.5. Tables 7.6 and 7.7 confirm this. The factor loadings of both subgroups are very similar. Funds with a manager change have a slightly higher market and small-cap exposure and a slightly lower loading on the mean-reversion factor while the other loadings are not significantly different. Because differences in factor loadings cannot explain the performance spread between the two subgroups, it seems fair to conclude that the same factors as identified for the fund-flow mechanism explain the underperformance of winner funds with a manager change compared to those without a manager change. Specifically, a reduction in the information advantage and a lack of best ideas seem to be important. This is consistent with the view that the fund manager is responsible for the generation of investment ideas rather than in-house buy-side research or even sell-side research, which both are still available to the fund left by the manager.

7.3.2 Double sorting

To examine the joint effects of fund flows and manager changes, a double sort on both equilibrium mechanisms is performed, resulting in four subgroups. Table 7.8 reports raw returns and alphas for winner-decile subgroups conditioned on both mechanisms and the resulting spread portfolios, as well as the degree of mean reversion. Winner funds experiencing neither inflows nor a manager change (weakly) significantly outperform the four-factor benchmark by 0.18 percentage points per month. This corresponds to a mean reversion of only -0.65 percentage points per month between the formation and evaluation periods. In contrast, winner funds suffering from both high inflows and a manager change generate negative, although insignificant, alphas of -0.12 percent per month, a degree of mean reversion of -1.02 percentage points per month. The spread between both subgroups in the evaluation period is highly significant at 0.30 percentage points.

Figure 7.2 shows this graphically: conditioning on both mechanisms simultaneously helps to split up the unconditional winner-fund portfolio, which generates abnormal returns of 0.07 percentage points per month (unconditional segment),

Table 7.8: Performance reversals of winner-fund subgroups for double sorts

This table presents the performance and mean reversion in performance for the winner-fund subgroups and the resulting spread portfolios based on a double sorting on absolute fund flows and manager changes simultaneously. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.3 for more explanation on the column specification.

	Raw returns			4-factor α		
	r_{t-1}	r_t	$\Delta r_{t-1,t}$	α_{t-1}	α_t	$\Delta\alpha_{t-1,1}$
Conditional on absolute net inflows and manager changes						
10 low without	1.42	0.85	−0.56	0.83***	0.18*	−0.65***
10 low with	1.41	0.80	−0.61	0.83***	0.10	−0.72***
10 high without	1.86	0.69	−1.18**	0.94***	−0.03	−0.97***
10 high with	1.78	0.63	−1.15*	0.90***	−0.12	−1.02***
Spread portfolios						
10 low without − 10 high with	−0.36	0.23*	–	−0.08	0.30***	–
10 low without − 10 high without	−0.45	0.17*	–	−0.12	0.21***	–
10 low without − 10 low with	0.01	0.05	–	0.00	0.07	–
10 low with − 10 high without	−0.45	0.12	–	−0.12	0.13*	–
10 low with − 10 high with	−0.37	0.18*	–	−0.08	0.22**	–
10 high without − 10 high with	0.09	0.06	–	0.04	0.09	–

into a subgroup with low net inflows and without a manager change that (weakly) significantly outperforms the four-factor benchmark by 0.18 percentage points (first bar in double-sorting segment) and a subgroup with high net inflows and a manager change that generates negative abnormal returns of −0.12 percentage points (fourth bar in double-sorting segment). In between are the two subgroups that suffer from one but not the other mechanism (second and third bars in double-sorting segment). Figure 7.3 provides evidence on the degree of mean reversion which leads to similar conclusions: suffering from both mechanisms significantly reduces subsequent performance. Winner funds that do not suffer from either of the mechanisms also revert to the mean, but by much less. The equilibrium mechanisms identified can explain a significant fraction of the mean reversion in alphas observed among winner funds. Relating the explained spread of 0.30 percentage points to the unconditional degree of mean reversion of 0.81 percentage points reveals that fund flows and manager changes together might be responsible for 37 percent of the observed mean reversion in winner-fund performance.[544]

The statistically significant spread of 0.30 percentage points per month between the low-without and the high-with subgroups is only slightly lower than the sum of the individual effects.[545] These results indicate that, in the case of winner funds, the two effects are additive and neither magnify nor offset each other in combination. This is consistent with the conclusions from above, that the occurrence of both "events", high inflows and a manager change, are relatively independent from each other (Table 7.1).

For raw returns, the conclusions are similar. Funds not suffering from either of the equilibrium mechanisms experience a modest degree of mean reversion of insignificant −0.56 percentage points while winner funds that suffer from both mechanisms simultaneously revert to the mean by impressive and significant −1.15 percentage points. The return spread between both subgroups is slightly lower compared to the alpha spread at weakly significant 0.23 percentage points.

[544] Specifically, this is the ratio of the evaluation-period four-factor alpha of 0.30 on the "10 low without − 10 high with" spread portfolio (Table 7.8) to the absolute degree of mean reversion in four-factor alphas of 0.81 on winner funds between the formation and evaluation periods (Table 6.3).

[545] The sum of the individual effects is 0.33 and is given by the sum of the evaluation-period alpha of 0.21 on the "10 low − 10 high" spread portfolio (using absolute net inflows) and the evaluation-period alpha of 0.12 on the "10 without − 10 with" spread portfolio (see Table 7.4). Figure 7.2 shows this graphically: 0.30 is the absolute sum of the first and fourth bars in the double-sorting segment; 0.21 is the absolute sum of the two bars in the single-sorting-by-flows segment; and 0.12 is the absolute sum of the two bars in the single-sorting-by-manager-change segment.

The double sorting also allows an analysis of marginal effects. The occurrence of a manager change seems to be independent of fund flows, since on average 22 percent of managers change each year in both subgroups with high and low net inflows (Table 7.3). The difference in fund flows between winner funds without and those with a manager change is statistically significant but economically small at 4.49 million USD. As both mechanisms appear to be independent of each other, controlling for one mechanism should not alter the impact of the other. This is indeed the case. Irrespective of whether the manager changes or not, fund flows have a significantly negative impact on performance of between 0.21 and 0.22 percentage points per month.[546] The spread between winner funds without and with a manager change declines to an insignificant 0.07 percent for the low-inflow subgroup and to an equally insignificant 0.09 percent for the high-inflow subgroup.[547] Thus, the manager-change mechanism is slightly weaker when holding the impact of fund flows fixed. Unreported results, however, indicate that for the high-relative-net-inflow subgroup, the spread between funds without and with a manager change is a significant 0.15 percentage points per month. It seems to be worse for future fund performance when the manager leaves while a lot of money is flowing into the fund as compared to a situation when the fund does not suffer from excessive inflows.

Comparing the subgroups “10 low with” and “10 high without” allows a comparison of the strength of both mechanisms. The statistically significant monthly spread of 0.13 percentage points again confirms that, among winner funds, fund flows are a more important equilibrium mechanism than manager changes. Figure 7.2 also reveals a monotonic decrease in alphas between the two extreme subgroups, with fund flows again having the stronger impact on performance than manager changes (second and third bars in the double-sorting segment).

Turning to the corresponding results based on different specifications of the multifactor models confirms these conclusions. Based on the three-factor model the outperformance of the low-without subgroup is highly significant at 0.29 percent per month. The significant outperformance survives controlling for momentum (0.18 percent) but turns insignificant once the mean-reversion and liquidity factors are added. In contrast, winner funds that suffer from both equilibrium mecha-

[546] This result is based on a comparison of the “10 low without” and “10 high without” subgroups and a comparison of the “10 low with” and “10 high with” subgroups, respectively.
[547] This result is based on a comparison of the “10 low without” and “10 low with” subgroups and a comparison of the “10 high without” and “10 high with” subgroups, respectively.

nisms simultaneously yield alphas which are very close to zero (0.05 percent) based on the three-factor model and even negative (−0.12, −0.14 and −0.12 percent, respectively) for the four- and five-factor benchmarks augmented by mean reversion and liquidity, respectively. Still, the spread between these two subgroups, long in winner funds with lower-than-median net inflows and no manager change and short in winner funds with excessive inflows and a manager change, is highly significant between 0.24 and 0.30 percent per month, depending on the alpha measure employed. Liquidity risk seems to explain 0.02 percentage points of this spread but the majority (0.28 percentage points) are due to transaction costs, a reduction in the information advantage, a lower number of best ideas as well as potential hierarchy costs. These results imply that both, fund flows as suggested by Berk and Green (2004) and manager changes, in combination reduce future winner fund performance.

Table 7.9: Performance of winner-fund subgroups for double sorts

This table presents different performance measures for the winner-fund subgroups and the resulting spread portfolios based on a double sorting on absolute fund flows and manager changes simultaneously. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw returns	Risk-adjusted returns			
		α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows and manager changes					
10 low without	0.85	0.29***	0.18*	0.16	0.17
10 low with	0.80	0.26*	0.10	0.07	0.08
10 high without	0.69	0.16	−0.03	−0.05	−0.05
10 high with	0.63	0.05	−0.12	−0.14	−0.12
Spread portfolios					
10 low without − 10 high with	0.23*	0.24**	0.30***	0.30***	0.28***
10 low without − 10 high without	0.17*	0.13*	0.21***	0.21***	0.22***
10 low without − 10 low with	0.05	0.04	0.07	0.09	0.08
10 low with − 10 high without	0.12	0.10	0.13*	0.12	0.13*
10 low with − 10 high with	0.18*	0.21*	0.22**	0.21**	0.20*
10 high without − 10 high with	0.06	0.11	0.09	0.09	0.07

7.4 Loser Funds

7.4.1 Single Sorting

Loser funds are separated in the formation period by the second sorting into into a subgroup with low net inflows, experiencing average monthly net inflows of −10.72 million USD, and a subgroup with high net inflows of 8.15 million USD (panel (a) of Table 7.10). Consequently, the difference in fund flows between both groups is 18.87 million USD which is only slightly less than two-thirds of the spread of 30.28 million USD between the high- and low-inflow subgroups of winner funds (Table 7.3). This observation is consistent with a convex shape of the performance-flow relationship: fund investors chase recent winner funds but are somewhat reluctant to withdraw their money from recent loser funds.[548] Moreover, fund flows of loser funds are less persistent in that the difference in net inflows between the low-inflow and high inflow subgroup is only 10.74 million USD in the evaluation period (panel (b) of Table 7.10).[549] Thus, there are some experienced investors who react relatively quickly on bad performance while a large fraction of investors does not seem to respond on bad performance at all, consistent with the results of Berk and Tonks (2007).

The low-net-inflow funds are larger than the high-net-inflow funds during the formation period, 792.06 million USD compared to 593.03 million USD. This difference is evened out by subsequent differences in fund flows, resulting in a difference in size of only 20.62 million USD in the evaluation period. In the case of the relative-net-inflow sorting, low-inflow funds are smaller than high-inflow funds by 263.20 million USD in the formation period (560.40 versus 823.60 million USD) and by 398.60 million USD in the evaluation period (481.26 versus 897.86 million USD). Low-net-inflow funds, based on the absolute-net-inflow sorting, are significantly older (13.04 years compared to 8.12 years) and have 0.10 percentage points lower annual fees and 34 percentage points lower annual portfolio turnover compared to high-inflow funds. These differences in fees and portfolio turnover might translate into a performance spread between both subgroups and should be kept in mind when interpreting the results. Again, the relative-fund-flow sorting can serve as a robustness test here because low-relative-inflow funds have higher fees and equal portfolio turnover compared to high-relative-inflow funds which, if

[548] Section 4.2.
[549] However, most of this reduction is due to a decay of inflows into the high-inflow subgroup.

Table 7.10: Characteristics of loser-fund subgroups

This table presents the characteristics for the loser-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. Panel (a) presents results for the formation period and panel (b) for the evaluation period. See the note to Figure 7.1 for more explanation on the portfolio formation the note to Table 7.3 for more explanation on the column specification.

(a) Formation period

	Fund size	Fund age	Fees	Turn-over	Net in-flows	MC / fund
Conditional on absolute net inflows (median split point)						
1 low	792.06	13.04	1.83	1.46	−10.72	0.26
1 high	593.03	8.12	1.92	1.80	8.15	0.21
1 low − 1 high	199.04***	4.93***	−0.10***	−0.34***	−18.87***	–
Conditional on relative net inflows (median split point)						
1 low	560.40	12.03	1.91	1.63	−9.66	0.25
1 high	823.60	9.13	1.84	1.63	7.09	0.22
1 low − 1 high	−263.20***	2.90***	0.07***	−0.00	−16.75***	–
Conditional on manager changes (with / without)						
1 with	623.84	10.78	1.98	1.49	−3.31	1.00
1 without	700.88	10.36	1.85	1.68	−0.65	0.00
1 with − 1 without	−77.04*	0.42***	0.13***	−0.19***	−2.66***	–

(b) Evaluation period

	Fund size	Fund age	Fees	Turn-over	Net in-flows	MC / fund
Conditional on absolute net inflows (median split point)						
1 low	674.15	14.04	1.83	1.46	−9.54	0.24
1 high	694.77	9.12	1.93	1.66	1.20	0.18
1 low − 1 high	−20.62	4.93***	−0.10***	−0.20***	−10.74***	–
Conditional on relative net inflows (median split point)						
1 low	481.26	13.03	1.91	1.62	−7.33	0.22
1 high	879.86	10.13	1.86	1.50	−0.99	0.20
1 low − 1 high	−398.60***	2.90***	0.05***	0.12***	−6.34***	–
Conditional on manager changes (with / without)						
1 with	619.84	11.78	1.94	1.53	−3.56	0.23
1 without	688.60	11.36	1.87	1.58	−4.19	0.21
1 with − 1 without	−68.76	0.42***	0.07***	−0.06	0.64	–

anything, weakens the predicted relationship between fund flows and performance among loser funds.[550]

It is interesting to note that the fraction of funds that replace their manager, i. e. exercise internal governance, is higher in the subgroup which experiences outflows, i. e. external governance. This confirms the findings in Table 7.1 above that internal and external governance are complements rather than substitutes. Alternatively, this can be seen as evidence that the loser funds benefiting from both governance mechanisms simultaneously are the ones with the worst performance in the formation period, a hypothesis which will further be investigated in Table 7.15. Fund flows and manager replacements would then be interpreted as independent signals regarding managerial skills based on the market's judgement and the internal judgement of the investment management company, respectively.

There are only minor differences in characteristics between the subgroups with and without a manager change. Fund size is comparable at 623.84 to 700.88 million USD. Fund age of both subgroups is between 10 and 11 years on average. Average fees are slightly higher for funds with a manager change (198 versus 185 percent) and portfolio turnover is slightly lower (149 versus 168 percent). However, funds with a change in management increase their portfolio turnover in the subsequent year (evaluation period) to 153 percent which indicates increased activity after a manager replacement. Those funds without a new manager decrease their portfolio turnover to 158 percent. Thus, based on the trading frequency, it is not continuing loser-fund managers who start to gamble, which would be predicted by the tournament hypothesis, but rather new managers who start to reorganize their portfolio. Consistent with the argument above, loser funds with a manager change experience at the same time outflows that are 2.66 million USD larger than those of loser funds with a manager change (−3.31 versus −0.65 million USD)

Turning to performance and conditioning on absolute fund flows, loser funds with outflows have significant 0.12 percentage points per month higher raw returns in the evaluation period than loser funds with inflows, revealing the impact of external governance (Table 7.11). The degree of mean reversion is much higher for the former, at significant 0.92 percentage points, compared to the latter, which only improve their raw returns by insignificant 0.59 percentage points between the

550 In addition, the regression analysis in section 7.7 (Table 7.21) controls for the impact of fees and portfolio turnover when analyzing the relationship between fund flows and performance.

formation and evaluation periods. Thus, outflows seem to significantly contribute to a performance reversal of loser funds if judged by raw returns. The results for the relative-fund-flow subgroups are similar but slightly weaker and not significant, implying that absolute changes in fund size are more relevant in improving loser-fund performance.

Table 7.11: Performance reversals of loser-fund subgroups for single sorts

This table presents the performance and mean reversion in performance for the loser-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.3 for more explanation on the column specification.

	Raw returns			4-factor α		
	r_{t-1}	r_t	$\Delta r_{t-1,t}$	α_{t-1}	α_t	$\Delta\alpha_{t-1,1}$
Conditional on absolute net inflows (median split point)						
1 low	−0.41	0.51	0.92**	−0.99***	−0.20*	0.79***
1 high	−0.19	0.40	0.59	−0.96***	−0.28**	0.68***
1 low − 1 high	0.21	0.12**	–	−0.03	0.09	–
Conditional on relative net inflows (median split point)						
1 low	−0.41	0.50	0.92**	−0.99***	−0.21**	0.78***
1 high	−0.19	0.41	0.59	−0.95***	−0.27**	0.68***
1 low − 1 high	0.21	0.09	–	−0.04	0.06	–
Conditional on manager changes (with / without)						
1 with	−0.31	0.52	0.83*	−0.97***	−0.18	0.78***
1 without	−0.31	0.42	0.73	−0.97***	−0.26**	0.71***
1 with − 1 without	0.01	0.11***	–	0.01	0.08*	–

However, comparing raw returns with four-factor alphas reveals that the significant return spread between loser funds with low net inflows and those with high net inflows is partly explained by differences in risk exposures, an observation that will be discussed in detail below. In general, loser funds with low inflows, i. e. outflows, revert from highly significantly negative four-factor alphas in the formation period of −0.99 percent to only weakly significant −0.20 percent in the evaluation period, an improvement of 0.79 percentage points, while the performance of those loser funds not benefiting from outflows improves only by 0.68 percentage points from −0.96 to −0.28, both significant. The evaluation-period spread in four-factor alphas between both subgroups is only 0.09, which is positive as expected but insignificant. Figures 7.4 and 7.5 confirm these findings when comparing the two bars in the single-sorting-by-flows segment: conditioning on fund flows does not provide a means to identify significant differences in evaluation-period performance (Figure 7.4) or the degree of mean reversion (Figure 7.5) between loser-fund subgroups. Consequently, the predictions of Berk and Green (2004) on the fund-flow mechanism operating amongst loser funds only finds weak support in the data.

Figure 7.4: Performance of loser funds and loser-fund subgroups

This figure presents monthly risk-adjusted returns based on the four-factor model of Carhart (1997) according to equation (3.23) for loser funds and loser-fund subgroups based on a single sorting and also a double sorting on absolute fund flows and / or manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

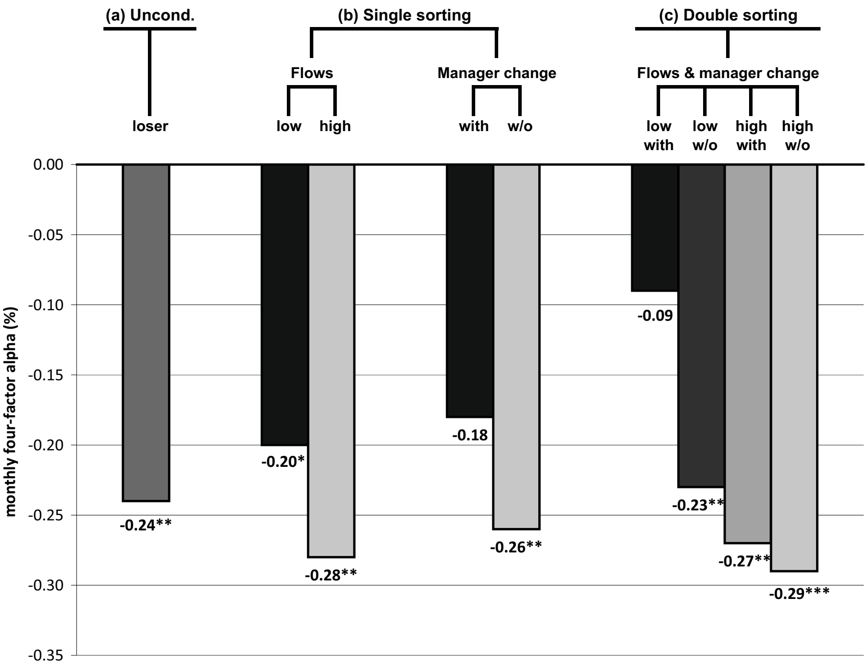
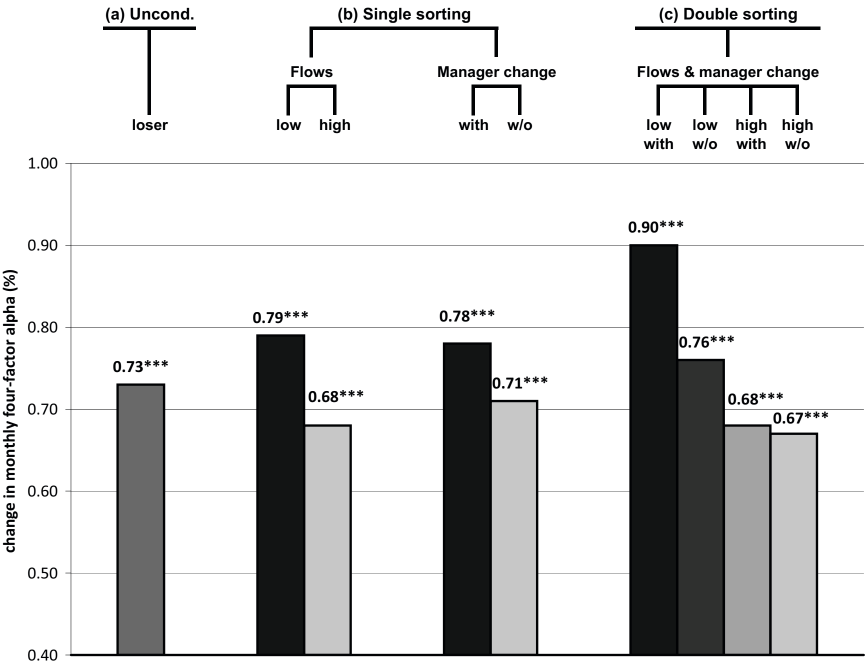


Figure 7.5: Performance reversals of loser funds and loser-fund subgroups

This figure presents the change between the formation and evaluation periods in monthly risk-adjusted returns (Δ alpha) based on the four-factor model of Carhart (1997) according to equation (3.23) for loser funds and loser-fund subgroups based on a single sorting and also a double sorting on absolute fund flows and / or manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.



Turning to manager changes, the hypothesis that bottom funds which fire their fund manager can improve their performance in the following year compared to bottom funds which stick with their presumably unskilled manager is supported by the findings. While loser funds without a change of manager continue to significantly underperform by −0.26 percent per month in the subsequent year, loser funds that replace their manager have insignificant alphas of −0.18 percent per month. This leads to a significant spread in alpha of 0.08 percentage points per month due to the exercise of internal governance and implies that internal governance is effective among loser funds.[551] Additionally, the mean reversion in performance is stronger for loser funds with a manager change at 0.78 percentage points compared to only 0.71 percentage points (both significant) for loser funds that do not experience a manager replacement if judged by four-factor alphas.

The spread in raw returns is even larger at highly significant 0.11 percent, though part of this is explained by differences in factor loadings. Loser funds with a manager change improve their raw returns by weakly significant 0.83 percentage points over the subsequent year while loser funds without a manager change can only generate insignificant 0.73 percentage points higher raw returns compared to the formation period. A new manager, therefore, might contribute to a stronger mean reversion of fund performance toward equilibrium levels by selling off loser stocks and realigning the portfolio. This evidence suggests that manager changes are an important equilibrium mechanism that has both a statistically and economically significant impact on fund performance.

This is also evident in Figure 7.4. Loser funds can be split into a subgroup with insignificantly negative four-factor alphas of −0.18 percent per month (with manager change) and a subgroup with significantly negative abnormal returns of −0.26 percent per month (without manager change) by conditioning on manager changes (single-sorting-by-manager-change segment). Similar conclusions can be drawn from Figure 7.5 which presents the degree of mean reversion in four-factor alphas between the formation and evaluation periods.

As in the case of winner funds, the analysis goes on to investigate the results of different specifications of the multifactor models in order to analyze whether the spreads in performance between the individual subgroups can be further explained by other performance determinants (Table 7.12). The three-factor alphas,

[551] Again, this figure might underestimate the true effect of forced manager replacements on performance, because not all manager changes are performance related.

controlling for a size and value tilt of the portfolio, are significantly negative for all subgroups of loser funds, conditioned on (absolute or relative) net inflows and conditioned on manager replacements. However, the alphas of funds which do not benefit from external governance through outflows and those which do not benefit from internal governance through a manager change are significantly below the alphas of their peers that benefit from either of these two equilibrium mechanisms. Spreads between loser funds with low and high net inflows are significant 0.12 percentage points per month and between loser funds with and without a manager change are significant 0.09 percentage points per month. These results support the hypothesis on fund flows and manager changes as equilibrium mechanism for managerial selection skills. However, for the fund-flow mechanism, part of this result can be explained by differences in factor loadings.

Table 7.12: Performance of loser-fund subgroups for single sorts

This table presents different performance measures for the loser-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows (median split point)					
1 low	0.51	-0.21^{**}	-0.20^{*}	-0.18^{*}	-0.15
1 high	0.40	-0.33^{***}	-0.28^{**}	-0.24^{**}	-0.25^{**}
1 low − 1 high	0.12^{**}	0.12^{**}	0.09	0.06	0.09^{*}
Conditional on relative net inflows (median split point)					
1 low	0.50	-0.21^{**}	-0.21^{**}	-0.20^{*}	-0.18^{*}
1 high	0.41	-0.33^{***}	-0.27^{**}	-0.22^{**}	-0.23^{**}
1 low − 1 high	0.09	0.11^{*}	0.06	0.03	0.05
Conditional on manager changes (with / without)					
1 with	0.52	-0.22^{**}	-0.18	-0.15	-0.14
1 without	0.42	-0.30^{***}	-0.26^{**}	-0.23^{**}	-0.23^{**}
1 with − 1 without	0.11^{***}	0.09^{**}	0.08^{*}	0.08^{**}	0.09^{**}

The alphas of the low-inflow, i. e. high outflow, subgroup improve once more factors are added, from significantly negative −0.21 percent based on the three-factor model to insignificant −0.15 percent based on the liquidity-augmented five-factor model. A similar pattern is evident for the high-inflow subgroup, though all

Table 7.13: Factor loadings of loser-fund subgroups for single sorts (4-factor)

This table presents the factor loadings for the loser-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.5 for more explanation on the column specification.

	Factor loadings				$E(r)$	R^2
	β_m	β_{smb}	β_{hml}	β_{mom}		
Conditional on absolute net inflows (median split point)						
1 low	0.99^{***}	0.18^{***}	0.21^{***}	-0.01	0.71	0.89
1 high	1.02^{***}	0.21^{***}	0.16^{***}	-0.05^{*}	0.68	0.90
1 low − 1 high	-0.03^{*}	-0.02	0.05^{*}	0.04^{**}	0.03	0.16
Conditional on relative net inflows (median split point)						
1 low	0.98^{***}	0.19^{***}	0.21^{***}	-0.00	0.71	0.89
1 high	1.03^{***}	0.20^{***}	0.16^{***}	-0.05^{*}	0.68	0.90
1 low − 1 high	-0.05^{***}	-0.01	0.05	0.05^{***}	0.03	0.23
Conditional on manager changes (with / without)						
1 with	1.03^{***}	0.22^{***}	0.19^{***}	-0.03	0.71	0.90
1 without	1.00^{***}	0.19^{***}	0.18^{***}	-0.04	0.68	0.90
1 with − 1 without	0.02^{**}	0.03^{***}	0.00	0.01	0.03	0.09

alphas remain significantly negative between −0.33 and −0.24 percent per month, depending on the exact model specification. Thus, in the case of loser funds adding more factors to the performance model does not make the benchmark stricter but controls for the negative performance impact of unfavorable factor loadings on some of the risk factors, which in turn makes the benchmark less strict. A comparison of both subgroups shows that loser funds with outflows have a slightly lower loading on the market (weakly significant) and size factors (insignificant), a significantly higher loading on the value factor and also a significantly higher, but still negative, loading on the momentum factor (Table 7.13). On aggregate, this results in higher expected returns for the low-net-inflow subgroup at 0.71 percent per month compared to 0.68 percent per month for the high-net-inflow subgroup. Already the difference in momentum exposure is enough to render the significant three-factor-alpha spread of 0.12 percentage points insignificant at 0.09 percentage points for four-factor alphas. Thus, differences in the momentum loading explain part of the spread between low-inflow and high-inflow loser funds in addition to differences in selection skills.

Controlling for stock-return mean reversion in addition to the momentum exposure reduces even further the spread between loser funds with low net inflows and those with high net inflows. Mean-reversion-augmented five-factor alphas are weakly significant at −0.18 percent per month for the low-inflow subgroup and significantly negative at −0.24 percent for the high inflow subgroup, resulting in an insignificant spread of 0.06 percentage points per month (Table 7.12). This is explained by loser funds with low net inflows having a significantly higher loading on the mean-reversion factor compared to loser funds with high net inflows, though these loadings are negative for both subgroups (Table 7.14). Aggregating all risk loadings based on the mean-reversion-augmented five-factor model results in a spread in expected returns between the low-inflow and high-inflow subgroups of 0.06 percentage points per month.[552] These results indicate that loser funds with outflows appear to hold on to momentum loser stocks, which continue to underperform, and long-term winner stocks, which exhibit mean reversion, to a much smaller extent than loser funds without significant outflows. Both improves the raw returns of the former compared to the latter but has no impact on mean-reversion-augmented five-factor alphas. Manager inertia, or a disposition effect, seems to be much more prevalent in the case of loser funds that do not benefit from outflows. Put differently, significant outflows seem to help loser funds managers to dispose of momentum loser stocks and mean reverting winner stocks.

This result is in contrast to winner funds where fund flows primarily affected security selection skills. Furthermore, it suggests that loser-fund managers do not suffer from capacity constraints of their once successful strategies, such as a reduction in the information advantage and the number of best ideas that can be generated or an increase in hierarchy costs, which was the dominant reason of mean reversion among winner funds. In fact, it cannot be ruled out completely that loser-fund managers end up in the bottom decile due to bad luck because they hold the last year's loser stocks and the longer-term winner stocks by chance and continue to hold on to them a further year due to some form of inertia, suffering from continued underperformance of the last year's loser stocks and a mean reversion in the performance of long-term winner stocks. Thus, what makes them loser-fund managers is to a lesser extent that they actively pick the wrong

[552] Note that this is not because low-inflow funds have higher positive loadings on the momentum and mean-reversion factors but, quite to the contrary, they have lower negative holdings on both factors.

Table 7.14: Factor loadings of loser-fund subgroups for single sorts (3- and 5- factor)

This table presents the factor loadings for the loser-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.6 for more explanation on the column specification.

	3-factor		5-factor MREV			5-factor LIQ		
	$E(r)$	R^2	β_{mr}	$E(r)$	R^2	β_{l}	$E(r)$	R^2
Conditional on absolute net inflows (median split point)								
1 low	0.72	0.89	−0.08	0.69	0.89	-0.06^{**}	0.67	0.89
1 high	0.73	0.90	-0.21^{***}	0.64	0.91	-0.05^{*}	0.64	0.90
1 low − 1 high	−0.01	0.12	0.13^{***}	0.06	0.26	−0.01	0.02	0.16
Conditional on relative net inflows (median split point)								
1 low	0.71	0.89	−0.07	0.70	0.89	-0.05^{*}	0.68	0.89
1 high	0.74	0.90	-0.23^{***}	0.63	0.91	-0.06^{**}	0.64	0.90
1 low − 1 high	−0.02	0.16	0.16^{***}	0.06	0.34	0.01	0.04	0.23
Conditional on manager changes (with / without)								
1 with	0.74	0.90	-0.17^{***}	0.68	0.90	-0.07^{**}	0.67	0.90
1 without	0.72	0.90	-0.15^{**}	0.65	0.91	-0.05^{*}	0.65	0.91
1 with − 1 without	0.02	0.09	−0.02	0.02	0.09	−0.01	0.02	0.09

stocks but to a greater extent that they remain passive and do not actively sell these underperforming stocks once they realize their harmful investment decisions of the past.

If loser-fund managers consistently picked the wrong stocks in each year, then there should not be any difference in three-, four- or mean-reversion-augmented five-factor alphas.[553] This is what can be observed among loser funds with outflows, where alphas only improve by 0.03 percentage points when moving from three- to mean-reversion-augmented five-factor alphas (−0.21 versus −0.18). These fund managers have utilized the outflows to reduce their momentum and mean-reversion exposures to insignificant −0.01 and −0.08, respectively. The remaining underperformance of −0.18 is due to bad selection skills.[554] Alphas of loser-fund managers that do not benefit from outflows increase by 0.09 percentage points per month when moving from three- to mean-reversion-augmented five-factor alphas (−0.33 versus −0.24). These managers seem to remain in their rigor and have significantly negative loadings on the momentum factor of −0.05 and on the mean-reversion factor of even −0.21. Thus, −0.24 percentage points of their underperformance based on the mean-reversion-augmented 5-factor model is due to bad stock selection but 0.09 percentage points, i. e. the difference between 3-factor and mean-reversion-augmented 5-factor alphas, are accounted for by their inertia. Fund flows play an important role in releasing managers from their inertia but cannot significantly explain the difference in true selection skills.

An analysis of the liquidity-augmented five-factor model reveals that loser funds tend in general to hold more liquid assets, as indicated by a negative loading on the liquidity factor, which does not allow them to earn an illiquidity premium. This is even slightly more the case for low-inflow loser funds with a loading on the liquidity factor of significant −0.06 compared to only weakly significant −0.05 for loser funds with high net inflows. Once controlled for liquidity risk, loser funds that benefit from outflows still generate negative yet insignificant alphas of −0.15 percent per month compared to significantly negative −0.25 percent for the high-inflow subgroup. The spread between both is weakly significant at 0.09 percentage points per month. Based on the liquidity-augmented five-factor model,

[553] Because the underperformance could not be explained by these funds suffering from continued underperformance of the last year's loser stocks and a mean reversion in the performance of long-term winner stocks but rather by the observation that these funds tend to hold this year's underperforming stocks.

[554] Without taking liquidity risk into account. See below.

the results provide weak support for the Berk and Green (2004) hypothesis among loser funds.

Taken all together, the evidence on loser funds provides a mixed picture on whether fund flows qualify as equilibrium mechanism explaining mean reversion in true selection skills of fund managers. The empirical results clearly provide evidence that raw returns (and even three-factor alphas) are significantly affected by fund flows. Based on these measures, the performance of loser funds with outflows significantly improves as predicted by Berk and Green (2004). However, moving on to the factor models that control for momentum and mean reversion reveals that outflows are basically used by fund managers to reduce their negative loadings on the last year's loser stocks and the long-term winner stocks, which were both responsible for their prior underperformance. Thus, the performance improvement does not follow from mean reversion in true selection skills as predicted by Berk and Green (2004). Taking liquidity risk into account again reverses the picture slightly in favor of the Berk and Green (2004) story because the alpha spread between low-inflow and high-inflow loser funds becomes significantly positive again, implying some form of mean reversion in stock selection skills.

An important aspect, which is a potential further explanation for the weak support for the Berk and Green (2004) hypothesis for loser funds, is that a large fraction of investors are reluctant to withdraw money from these funds.[555] Indeed, the difference in average fund flows between the low- and high-fund-flow subgroups of loser funds is only less than two-thirds as large as the same difference for winner funds (18.87 million USD versus 30.28 million USD, Tables 7.10 and 7.3).[556] Therefore, the external incentive for poorly performing fund managers to change their portfolios and improve performance is not a powerful one.[557] This behavior is consistent with a disposition effect also on the side of the fund investors, whereby investors are hesitant to realize losses and stay invested in the fund, maybe hoping that the fund price eventually returns to the original purchase price. Perhaps investors hope that the equilibrium mechanisms will work without them having to incur any additional effort or costs and try to "free ride" on the actions of others. This might be because they anticipate either a

[555] Sirri and Tufano (1998), Lynch and Musto (2003), Berk and Tonks (2007), and section 4.2.

[556] Median differences are not reported in the tables but reveal a similar picture.

[557] Berk and Tonks (2007) compare this with the repayment behavior of mortgage borrowers. Some borrowers are sensitive to changes in the interest rate and refinance their mortgage whenever it is beneficial, while a significant proportion is reluctant to refinance.

strategy change or the firing of a poorly performing manager by the investment management company. Furthermore, transaction costs and the costs involved in gathering information about alternative funds might reduce the mobility of capital. The consequence is that the equilibrium mechanism involving fund flows is weak in underperforming funds and poor performance can persist (Carhart, 1997; Berk and Tonks, 2007). In the presence of transaction costs and some degree of mean reversion, only a few investors might be willing to be early sellers. However, the results show that staying invested in loser funds is a sub-optimal strategy, since performance remains negative, even if internal and external governance are applied, while investors could alternatively earn 0.18 percent abnormal monthly returns by switching to previous-year winner funds with lower inflows and no manager change, an additional return likely to be sufficient to cover switching costs.

Consequently, two separate disposition effects might reinforce each other in explaining average underperformance of loser funds, one on the side of the fund managers and one on the side of the fund investors. Fund manager inertia explains why loser funds hold on to the last year's loser stocks that continue to underperform and to long-term winner stocks that revert to the mean. The results show that significant outflows could trigger fund managers to dispose of some of these stocks which would contribute to an improvement in performance, at least if measured by raw returns and three-factor alphas. However, due to fund investor inertia, most loser funds do not even experience large outflows which does not push fund managers to take action. To test whether a stronger response by investors would improve loser-fund performance by more, the above analysis is repeated by focusing only on loser funds in the highest or lowest net-inflow quintiles instead of using the median as a split point. See section 8.3 for results.

A potential third explanation for the weak support of the Berk and Green (2004) hypothesis in the case of loser funds is the short-term impact of forced asset sales. When loser-fund managers sell off existing holdings, this induces transaction costs and results in a negative market impact. Coval and Stafford (2007) even document that loser funds in distress, i. e. experiencing extremely large outflows, suffer from other investors predicting the forced asset sales of these loser funds and gaining by trading against them. This makes it an even harder task for the fund manager to bring back performance to average levels. In the case of winner funds, these trading expenses worked in the same direction as the equilibrium mechanisms, reenforcing their impact on performance. However, for loser funds trading expenses are in the opposite direction of the mean reversion mechanisms, weakening their beneficial impact on subsequent fund performance.

Turning to the multifactor-model results for loser funds with a change in management confirms the previous results based on the four-factor model. While loser funds without a manager change continue to significantly underperform by −0.30 to −0.23 percent per month in the subsequent year, depending on the performance measure, loser funds that replace their manager have alphas between −0.22 and −0.14 percent per month which are insignificant in three out of four cases. This leads to a significant spread in alpha resulting from the exercise of internal governance of 0.08 to 0.09 percent per month based on risk-adjusted returns, irrespective of which performance measure is used. The spread in raw returns is even larger at highly significant 0.11 percentage points, but is merely explained by new managers choosing higher loadings on the risk factors. In particular, the market and size exposures are significantly higher for loser funds with a manager change by 0.02 (1.03 versus 1.00) and by 0.03 (0.22 versus 0.19), respectively. The loadings on the value, momentum, mean-reversion and liquidity factors are not significantly different between both manager-change subgroups. A new manager, therefore, might contribute to a stronger mean reversion of fund performance to neutral levels and might reduce poor performance persistence by bringing in true stock selection skills which the previous fund manager lacked. In contrast to the fund-flow channel, manager changes do not seem to affect risk loadings by much.

7.4.2 Double Sorting

An investment management company might fire an underperforming manager to avoid the risk of investors withdrawing funds. A comparison of the composition (Table 7.1) and characteristics (Table 7.10) of the subgroups reveals that the internal and external governance mechanisms interact positively: funds with outflows have a higher fraction of manager changes than funds with positive net inflows and funds with a manager change have larger outflows than funds without. Table 7.15 investigates the interaction and dependency between the two equilibrium mechanisms and fund performance. Funds that experience both mechanisms, internal and external governance, have insignificant alphas of −0.09 percent per month in the evaluation period. This investment performance is even superior compared to the unconditional performance of decile-7 funds (Table 6.3) and corresponds to an impressive degree of mean reversion of 0.90 percentage points per month. Some loser funds benefit from both mechanisms operating simultaneously and, when this happens, strongly revert to the mean, with little sign of poor performance persisting.[558] In contrast, funds without either form of governance mechanism continue to significantly underperform by −0.29 percent per month, regressing to the mean by only 0.67 percentage points per month. Thus, the alpha spread between both subgroups is a highly significant 0.20 percentage points per month. Similar conclusions can be drawn for raw returns where the spread between both extreme subgroups is even a highly significant 0.23 percentage points per month.

Figure 7.4 shows this graphically for risk-adjusted returns: conditioning on both mechanisms simultaneously helps to split up the unconditional loser-fund portfolio, which generates abnormal returns of significant −0.24 percentage points per month (unconditional segment) into a subgroup with low net inflows and with a manager change that generates insignificant four-factor alphas of −0.09 percentage points (first bar in double-sorting segment) and a subgroup with high net inflows and no manager change that generates significantly negative abnormal returns of −0.29 percentage points (fourth bar in double-sorting segment). An analysis of the degree of mean reversion leads to similar conclusions, as can be seen from an examination of Figure 7.5. Benefiting from both mechanisms significantly improves subsequent performance. Loser funds that do not experience either one of the mechanisms revert to the mean by only 0.67 percentage points, much less than the 0.90 percentage points of loser funds benefiting from both mechanisms. The equilibrium mechanisms identified can explain a significant fraction of the mean reversion in alphas observed among loser funds. Relating the explained spread of 0.20 percentage points to the unconditional degree of mean reversion of 0.73 percentage points reveals that fund flows and manager changes might be responsible for 27 percent of the observed mean reversion in loser-fund performance.[559]

If internal and external governance were independent of each other, their combined impact on fund performance would be expected to be the sum of the individual effects. However, the alpha spread between both extreme subgroups, the

[558] Note, however, that on average less than 12 percent of all loser funds benefit from a combination of both governance mechanisms (Table 7.1), explaining why studies not conditioning on fund flows and manager changes report, on average, persistent underperformance.

[559] Specifically, this is the ratio of the evaluation-period four-factor alpha of 0.20 on the "1 low with − 1 high without" spread portfolio (Table 7.15) to the absolute degree of mean reversion of 0.73 on loser funds between the formation and evaluation periods (Table 6.3).

Table 7.15: Performance reversals of loser-fund subgroups for double sorts

This table presents the performance and mean reversion in performance for the loser-fund subgroups and the resulting spread portfolios based on a double sorting on absolute fund flows and manager changes simultaneously. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.3 for more explanation on the column specification.

	Raw returns			4-factor α		
	r_{t-1}	r_t	$\Delta r_{t-1,t}$	α_{t-1}	α_t	$\Delta\alpha_{t-1,1}$
Conditional on absolute net inflows and manager changes						
1 low with	−0.40	0.61	1.02**	−0.98***	−0.09	0.90***
1 low without	−0.40	0.48	0.89**	−0.99***	−0.23**	0.76***
1 high with	−0.19	0.44	0.63	−0.95***	−0.27**	0.68***
1 high without	−0.20	0.38	0.58	−0.96***	−0.29***	0.67***
Spread portfolios						
1 low with − 1 high without	−0.20	0.23***	–	−0.02	0.20***	–
1 low with − 1 high with	−0.21	0.17*	–	−0.03	0.18**	–
1 low with − 1 low without	0.01	0.13*	–	0.01	0.15**	–
1 low without − 1 high without	−0.20	0.11*	–	−0.02	0.06	–
1 low without − 1 high with	−0.21	0.04	–	−0.04	0.04	–
1 high with − 1 high without	0.01	0.06	–	0.02	0.02	–

one benefiting from outflows and a manager replacement and the one not benefiting from either of these mechanisms, of 0.20 percentage points is larger than the sum of the individual effects.[560] This implies that the internal and external governance mechanisms are magnified when they operate jointly in loser funds, which has important implications for the governance of underperforming funds.

Turning to marginal effects supports this conclusion. Interestingly, within the group of loser funds with a change in management, i. e. measuring the marginal effect of fund flows when keeping the impact of manager changes fixed, those funds that experience large absolute outflows have alphas that are significantly higher by 0.18 percentage points per month compared to those without outflows (insignificant −0.09 versus significant −0.27 percentage points per month). The same difference for loser funds without a manger change is only insignificant 0.06 percentage points (−0.23 versus −0.29 percentage points, both significant). Thus, the poor effectiveness of the fund-flow mechanism based on the single sorting is almost entirely explained by the subgroup without a manager change. Within the subgroup of funds with outflows, those with a manager change have a significant 0.15 percentage points higher average alpha than those without a manager change, while the difference for the funds without outflows is close to zero at insignificant 0.02. These results once more strongly support that the interaction between internal and external governance is essential in bringing loser-fund performance back to neutral levels. Again, an explanation for this behavior could be a disposition effect among loser-fund managers. Even if loser funds benefit from outflows, fund managers who stay aboard the loser fund do not seem to use these outflows to reorganize their portfolio, but merely scale down existing investments. Similarly, even if loser funds benefit from a replacement of their manager, this new manager only takes action to reorganize the portfolio if simultaneous outflows force him to do so while he does not seem to alter the portfolio weights if fund size remains relatively constant.

Next, the importance of each mechanism is compared. Note that the raw returns of both subgroups with outflows significantly revert to mean levels by 1.02

[560] The sum of the individual effects is 0.17 and is given by the sum of the evaluation-period alpha of 0.09 on the "1 low - 1 high" spread portfolio (using absolute net inflows) and the evaluation-period alpha of 0.08 on the "1 with - 1 without" spread portfolio (see Table 7.11). Figure 7.4 shows this graphically: 0.20 is the difference between the first and fourth bars in the double-sorting segment; 0.09 is the difference between the two bars in the single-sorting-by-flows segment; and 0.08 is the absolute sum of the two bars in the single-sorting-by-manager-change segment.

percentage points for the low-with subgroup and by 0.89 percentage points for the low-without subgroup while both high-net-inflow subgroups experience only insignificant mean reversion by 0.63 percentage points for the high-with subgroup and by 0.58 percentage points for the high-without subgroup. A comparison of evaluation-period raw returns between the low-without and the high-with subgroups reveals only a modest spread of 0.04 percentage points per month (0.48 versus 0.44 percent). However, the mean reversion is significant at 0.89 percentage points for the former but only insignificant 0.63 percentage points for the latter. This directly points toward the higher importance of fund flows to improve loser-fund performance as compared to manager replacements. The picture for alphas is similar. Mean reversion is also higher for loser funds benefiting from outflows but not from a manager change at 0.76 percentage points compared to 0.68 percentage points for loser funds benefiting from a replacement of their manager but not from outflows (both significant). The level of alpha is, again, higher for loser funds with outflows but no manager replacement at −0.23 percent compared to the subgroup with a manager change but without outflows at −0.27 percent, an insignificant spread of 0.04 percentage points. Based on these comparisons, fund flows seem to be slightly more important than a manager change for an improvement in loser-fund performance. This result is different compared to the conclusion from the single-sorting results and seems to be dominated by the interaction between the fund-flow and the manager-change mechanism. Figure 7.4 also reveals a monotonic decrease in alphas between the two extreme subgroups, with fund flows again having the stronger impact on performance than manager changes (second and third bars in the double-sorting segment).

All of the above conclusions are robust when controlling for additional risk factors (Table 7.9). The performance of the low-with loser-fund subgroup is insignificant for all alpha-measures and increases when moving from the three-factor to the liquidity-augmented five-factor model from −0.11 to −0.04. The performance of the high-without loser-fund subgroup, being significantly negative for all alpha-measures, increases in a similar fashion from −0.34 to −0.26, when going from the three-factor to the liquidity-augmented five-factor model. Thus, the spread between both extreme subgroups is relatively constant between 0.19 and 0.23 for the different factor models and remains significant in all cases. The observation that the spread in mean-reversion-augmented five-factor alpha (0.19 percentage points) is smaller than the spread in three-factor alphas (0.23 percentage points) implies that part of the spread between loser funds benefiting from both governance mechanisms and those that do not is explained by loadings on the momentum and mean-reversion factors. Consistent with the above conclusions, loser funds without outflows and a manager replacement seem to hold on to momentum loser stocks and long-term winner stocks to a larger degree. If the manager is replaced the new manager improves performance by bringing in new investment ideas and, to a smaller degree, by selling the momentum losers and long-term winners which he inherited from his predecessor, something he does not seem to be willing to do if there are no outflows which force him to sell some of the existing portfolio positions, maybe due to a disposition effect.[561] Thus, if the new manager is forced by outflows he seems to be doing the right thing: He not only sells momentum losers and long-term winners, which affects factor loadings, but he also avoids other stocks with unfavorable future prospects, which improves alpha. However, the loser funds not benefiting from either of the mechanisms also hold more liquid stocks than loser funds benefiting from both mechanisms, as implied by the observation that the spread between both subgroups in liquidity-augmented five-factor alpha (0.22 percentage points) is larger than the corresponding spread in four-factor alphas (0.20 percentage points). An important result is that outflows alone predominantly affect factor loadings while in combination with a manager replacement the dominant source of the return reversal is an improvement in selection skills.

Also the conclusions on the marginal impact of governance mechanisms remain unchanged. Only raw returns and three-factor alphas provide weak evidence that even in the case of no manager replacement outflows are beneficial for subsequent fund performance. This is based on a comparison of the low-without and high-without subgroup, which yields a (weakly) significant spread of 0.11 percentage points (raw returns) and 0.10 percentage points (three-factor alphas), respectively. However, this spread seems to be largely a result of differences in momentum and mean-reversion loadings and, when appropriately accounted for these effects, reduces to 0.03 based on the mean-reversion-augmented five-factor alphas. Again, this also confirms the relevance of outflows for breaking up fund managers' inertia.

[561] Jin and Scherbina (2010) also document that bringing in a new managers increases the likelihood that this new manager will dispose of momentum-loser stocks at a higher rate than continuing managers. However, slightly in contrast to the results of this section, they also provide evidence that this result holds in the presence of inflows.

Table 7.16: Performance of loser-fund subgroups for double sorts

This table presents different performance measures for the loser-fund subgroups and the resulting spread portfolios based on a double sorting on absolute fund flows and manager changes simultaneously. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows and manager changes					
1 low with	0.61	−0.11	−0.09	−0.06	−0.04
1 low without	0.48	-0.24^{**}	-0.23^{**}	-0.22^{**}	-0.19^{*}
1 high with	0.44	-0.32^{***}	-0.27^{**}	-0.23^{*}	-0.24^{*}
1 high without	0.38	-0.34^{***}	-0.29^{***}	-0.25^{**}	-0.26^{**}
Spread portfolios					
1 low with − 1 high without	0.23^{***}	0.23^{***}	0.20^{***}	0.19^{***}	0.22^{***}
1 low with − 1 high with	0.17^{*}	0.22^{**}	0.18^{**}	0.17^{*}	0.20^{**}
1 low with − 1 low without	0.13^{*}	0.13^{**}	0.15^{**}	0.16^{**}	0.16^{**}
1 low without − 1 high without	0.11^{*}	0.10^{*}	0.06	0.03	0.06
1 low without − 1 high with	0.04	0.08	0.04	0.01	0.04
1 high with − 1 high without	0.06	0.02	0.02	0.02	0.02

7.5 Winner-Minus-Loser Spread

So far the focus has been on first separating winner and loser funds and then analyzing the impact of fund flows and manager changes, i. e. the effects of the two equilibrium mechanism, on future fund performance. The results may offer additional insights and may become even more pronounced when taking an alternative perspective, i. e. first distinguishing between an environment with and one without both market mechanisms and then analyzing the different impact on winner and loser funds. If funds flows and manager changes will force the market back into its equilibrium, i. e. insignificant fund alphas, then one could expect to observe mean reversion and close to zero performance differences between winner and loser funds in the evaluation period. Without the effects of the two mechanisms, it seems more likely to find some positive and negative performance persistence, although the magnitude of the alphas may be smaller relative to the formation period. So far, the empirical results have revealed an only weakly significant spread in four-factor alphas between the winner and the loser portfolio of 0.32 percentage points per month for the 12-month evaluation period (Table 6.3). This spread roughly corresponds to the winner-minus-loser spread of 0.29 percentage points in the study of Carhart (1997). It will be analyzed in the next step how this spread is affected by the equilibrium mechanisms. Specifically, the performance of the winner and loser portfolios is compared in six different scenarios, which are defined in panel (a) of Table 7.17. Panel (b) reports the corresponding four-factor alphas. In the first column, funds do not experience either one of the equilibrium mechanisms. Specifically, winner funds do not suffer from inflows or a manager change and loser funds do not benefit from outflows or a manager change. Based on the hypotheses outlined above the highest level of positive and negative performance persistence is expected to be found among these funds. The next two columns focus on one of these mechanisms individually, not conditioning on the other one. The fourth column reports the unconditional winner-minus-loser spread, not taking fund flows or manager changes into account. The next two columns report the results for funds that experience either one of the mechanisms, without conditioning on the other one. In the last column both mechanisms operate simultaneously. In this, the strongest tendency of fund performance to revert to the mean should be observed according to the equilibrium mechanisms.

Interestingly, focusing only on winner and loser funds that do not experience either of the equilibrium mechanisms yield a winner-minus-loser spread of 0.47 percentage points per month which is highly significant at the one percent level. This spread continuously falls once we condition only on funds not experiencing one of the equilibrium mechanisms but not conditioning on the other one (Figure 7.6). If funds are not exposed to the fund-flow mechanism, not taking the manager-change mechanism into account, the spread is reduced to 0.44 percentage points, still significant at the five percent level. Funds that do not experience a manager change, not taking fund flows into account, yield a winner-minus-loser spread of 0.37 percentage points, still weakly significant at the ten percent level. For the unconditional winner-minus-loser spread portfolio, alphas turn out to be also weakly significant at 0.32 percentage points. This spread decreases further when concentrating only on funds that experience either the manager-change mechanism or the fund-flow mechanism to insignificant 0.16 and 0.14 percentage points, respectively. Analyzing only winner and loser funds that experience both equilibrium mechanisms simultaneously, we find an insignificant spread between winner and loser funds of −0.03 percentage points. Thus, if both mechanisms are at work, winner funds suffer from inflows and a manager replacement while

Table 7.17: Performance of winner-minus-loser spread portfolios

This table presents monthly risk-adjusted returns based on the four-factor model of Carhart (1997) according to equation (3.23) for the winner- and loser-fund subgroups and the resulting spread portfolios based on a single sorting and also a double sorting on absolute fund flows and / or manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White's heteroscedasticity-consistent standard errors are used for the regression coefficients.

	Without equilibrium mechanisms			Uncondi-	With equilibrium mechanisms		
	Both	Flows	Manager	tional	Manager	Flows	Both
(a) Portfolio formation							
Winner funds							
Inflows	low	low	–	–	–	high	high
Manager ch.	without	–	without	–	with	–	with
Loser funds							
Inflows	high	high	–	–	–	low	low
Manager ch.	without	–	without	–	with	–	with
(b) Four-factor alphas in evaluation period (α_t)							
Winner	0.18*	0.16	0.10	0.07	−0.02	−0.05	−0.12
Loser	−0.29***	−0.28**	−0.26**	−0.24**	−0.18	−0.20*	−0.09
Winner − loser	0.47***	0.44**	0.37*	0.32*	0.16	0.14	−0.03

loser funds benefit from outflows and a newly hired manager, any spread between previously outperforming and previously underperforming funds is eliminated and even slightly reversed. Thus, when investors and mangers take advantage of outperformance or react to underperformance in the previous period, the equilibrium processes forces the spread between previous winner and loser funds to become virtually zero in the evaluation period. In contrast, if funds are not exposed to these mechanisms, the spread is still significant 0.47 percentage points. Thus, the equilibrium mechanisms seem to be able to explain the 0.50 percentage point difference per months or 6.00 percent per year of the winner-minus-loser spread. This strongly highlights the importance of fund flows and manager changes in explaining mean reversion in mutual fund performance or why fund performance cannot persist in efficient markets.

7.6 Before-Fee Analysis

The evidence presented above in the case of winner funds is consistent with efforts by winner-fund managers to maximize their fees by increasing their assets under management either at the same fund (i. e. higher-than-median inflows) or by moving to another fund (i. e. manager change), as discussed in section 7.1. But winner-fund managers might also strategically adjust fee levels to past performance. In contrast, loser funds experiencing a high degree of both internal and external governance might charge lower fees to reflect their lower skills.[562] To investigate these aspects, the above analysis is repeated using pre-fee returns.[563] Simply adding back fees to the results based on net-of-fee returns would lead to biased conclusions since the sorting into decile portfolio (and decile-portfolio subgroups) is also affected by differences in fee levels.

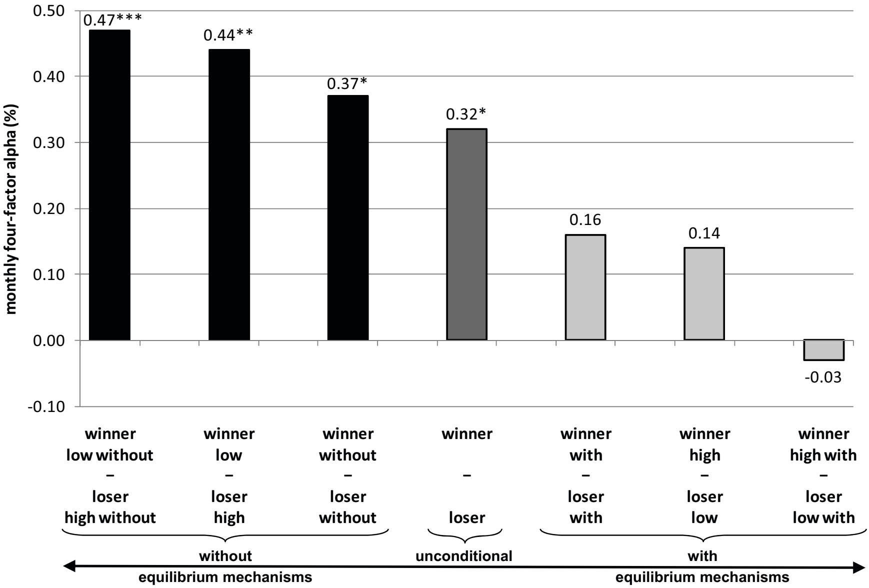
Table 7.18 presents the unconditional results for winner and loser funds and the resulting spread portfolio. The main conclusions do not change compared to the net-of-fee results in Table 6.4. Recent winner funds continue to significantly

[562] In addition to fees, cross-sectional differences in trading costs might explain part of the spreads between the different deciles and decile subgroups. However, even though information on portfolio turnover is available, the differences in the levels of transaction costs are not known and these might be large across funds depending on the investment style, especially with respect to a small-cap tilt. Thus, the data does not allow controlling for cross-sectional differences in total trading costs. However, the regression test controls simultaneously for differences in fees and turnover (section 7.7).

[563] Unlike the definition of fees used in the characteristics tables only annual management fees are added back to compute gross returns but not front- or back-end loads.

Figure 7.6: Winner-minus-loser spread

This figure presents monthly risk-adjusted returns based on the four-factor model of Carhart (1997) according to equation (3.23) for the winner-minus-loser spread portfolio based on a single sorting and also a double sorting on absolute fund flows and / or manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.



outperform the three-factor benchmark by 0.32 percent per month but this outperformance is rendered insignificant at 0.17 percent once controlled for momentum. Controlling additionally for stock-return mean reversion and the liquidity of the portfolio holdings further reduces this outperformance to 0.14 and 0.18 percent per month, respectively. Loser funds still have negative though insignificant evaluation-period alphas of between −0.14 and −0.08. Hence, the spread between winner and loser funds remains positive for all alpha measures but decreases as compared to the post-fee spreads in Table 6.4. Specifically, the before-fee versus after-fee spread based on three-factor alphas is 0.46 versus 0.51 percentage points, on four-factor alphas 0.28 versus 0.32 percentage points, on mean-reversion-augmented five-factor alphas 0.23 versus 0.26 percentage points and on liquidity-augmented five-factor alphas 0.26 versus 0.27 percentage points.[564] Moreover, the spread in four-factor alphas is no longer significant post fees while both five-factor alphas are not significant before or after fees. Thus, a small fraction of the outperformance of winner funds compared to loser funds is explained by the lower fee levels of the former.

Table 7.18: Before-fee performance of decile portfolios

This table presents different performance measures based on gross-of-fee returns for the decile portfolios 10 (winner) and 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
10 (winner)	0.87	0.32***	0.17	0.14	0.18
1 (loser)	0.58	−0.14	−0.11	−0.08	−0.08
10 − 1	0.29	0.46**	0.28	0.23	0.26

Furthermore, the conclusions based on either single or double sorting on fund flows and manager changes do not change in the case of both winner and loser funds.[565] Before fees, winner funds with lower than median net inflows significantly outperform the multifactor benchmarks by 0.40 percentage points per month for the three-factor model and between 0.25 and 0.28 percentage points per month for the four- and five-factor model. Those winner funds suffering from inflows can only weakly outperform the three-factor benchmark by 0.24 percentage points but have alphas that are indistinguishable from zero based on the four- and five-factor models. The gross-of-fee spread in alphas between winner funds not suffering from inflows and those with higher than median inflows is even consistently higher than the same spread net of fees, irrespective of the performance model applied.[566] In the case of the three-factor model it is 0.17 percentage points per month and between 0.22 and 0.23 percentage points for the four- and five-factor

[564] Compare Tables 7.18 and 6.4.
[565] In the case of the fund-flow sorting, only the results based on absolute fund flows are presented and, in the case of the double sorting, only the results for the extreme subgroups either suffering from both or none of the equilibrium mechanisms are discussed.
[566] Compare Tables 7.19 and 7.5.

Table 7.19: Before-fee performance of winner-fund subgroups

This table presents different performance measures based on gross-of-fee returns for the winner-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows (median split point)					
10 low	0.97	0.40***	0.28***	0.25**	0.27**
10 high	0.77	0.24*	0.06	0.03	0.04
10 low − 10 high	0.20**	0.17**	0.22***	0.22***	0.23***
Conditional on manager changes (without / with)					
10 without	0.91	0.36***	0.21*	0.19*	0.21*
10 with	0.83	0.26*	0.10	0.07	0.09
10 without − 10 with	0.07	0.10**	0.11**	0.12**	0.11**
Interaction effects between absolute net inflows and manager changes					
10 low without	0.98	0.41***	0.30***	0.28***	0.29***
10 high with	0.74	0.16	−0.01	−0.03	−0.00
10 low without − 10 high with	0.25**	0.25**	0.31***	0.30***	0.30***

models. For the manager-change subgroups a similar picture emerges. Those winner funds that continue to be managed by the same fund manager (weakly) outperform all four multifactor benchmarks, by 0.36 percentage points based on the three-factor model and by between 0.19 and 0.21 percent based on the four- and five-factor models. In contrast, winner funds that suffer from a replacement of their manager can only significantly beat the three-factor benchmark by 0.26 percentage points, but none of the other multifactor benchmarks. The spread between both groups, however, remains significantly positive in all cases between 0.10 and 0.12 percentage points. This is exactly one basis point lower in each case compared to the net-of-fee alphas in Table 7.5. Surprisingly, winner funds with a manager change have higher fees, which should be a reason to stay rather than to leave for successful managers.[567] Thus, higher fund fees do not seem to guarantee the fund manager an adequate compensation package.

The interaction effects between fund flows and manager changes are also robust to potential differences in fee levels among winner funds. The gross outperfor-

[567] This is consistent with the results on fund characteristics in Table 7.3.

mance of those winner funds not suffering from either one of the equilibrium mechanisms is an astonishing 0.28 to 0.41 percent per month, all highly significant. Winner funds suffering from both mechanisms simultaneously continue to underperform the multifactor benchmarks even before costs, with the exception of the three-factor benchmark. Thus, the spread between both groups remains significantly positive at 0.25 percentage points per month based on the three-factor model and between 0.30 and 0.31 percentage points for the four- and five-factor models and is equal, or in most cases even higher, compared to the corresponding net-of-fee spread.[568] Just to give an impression of the economic relevance of the equilibrium mechanisms: Unconditional winner funds outperform the four-factor benchmark by insignificant 0.17 percent per month before fees (Table 7.18) while conditioned on both equilibrium mechanisms the low-without subgroup of winner funds outperforms the four-factor benchmark after fees by (weakly) significant 0.18 percent per month (Table 7.9). The benefits from the equilibrium mechanisms are, thus, even larger in economic magnitude than the fees earned by the investment management company.

In the case of a single sorting on loser funds, the significance of the underperformance vanishes for all subgroups and all alpha measures but the three-factor alpha for loser funds with high net inflows or without a manager change. All other single-sorting subgroups generate alphas that are still negative but indistinguishable from zero. The gross spreads between the low-net-inflow and the high-net-inflow subgroups are also slightly reduced to weakly significant 0.10 and insignificant 0.06, 0.04 and 0.07 percentage points per month compared to net-of-fee spreads of significant 0.12, insignificant 0.09, 0.06 and weakly significant 0.09 percentage points based on the three-, four, mean-reversion-augmented five- and liquidity-augmented five factor model.[569] There seems to be some negative relationship between external governance and the fee level, consistent with better governed funds charging lower fees. In the case of manager changes, this relationship is not evident. With the exception of a difference of 1 basis point for the liquidity-augmented five factor model the spreads between loser funds with a manager change and those without remain the same before and after fees. Thus, differences in fee levels are not an explanation for the spread between those loser funds with internal governance applied and those without.

[568] Compare Tables 7.19 and 7.9.
[569] Compare Tables 7.20 and 7.12.

Table 7.20: Before-fee performance of loser-fund subgroups

This table presents different performance measures based on gross-of-fee returns for the loser-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows, on relative fund flows or on manager changes. See the note to Figure 7.1 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw returns	Risk-adjusted returns α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows (median split point)					
1 low	0.63	−0.09	−0.08	−0.06	−0.04
1 high	0.54	−0.19*	−0.14	−0.10	−0.11
1 low − 1 high	0.09*	0.10*	0.06	0.04	0.07
Conditional on manager changes (with / without)					
1 with	0.66	−0.08	−0.06	−0.03	−0.02
1 without	0.55	−0.17*	−0.13	−0.10	−0.10
1 with − 1 without	0.11**	0.09**	0.08*	0.08*	0.08*
Interaction effects between absolute net inflows and manager changes					
1 low with	0.75	0.04	0.06	0.08	0.11
1 high without	0.53	−0.19*	−0.14	−0.10	−0.11
1 low with − 1 high without	0.22***	0.23***	0.20***	0.18**	0.22***

In the case of a double sorting on internal and external governance simultaneously, loser funds can be identified that generate even positive before-fee alphas of between 0.04 and 0.11 percent per month, irrespective of the performance model used. Those loser funds not benefiting from either one of the governance mechanisms continue to underperform by −0.19 to −0.10 percent per month, significant only for the three-factor model. The before-fee spread between both extreme subgroups is almost identical to the net-of-fee spread, with two exceptions where both spreads differ by 1 basis point per month, and are highly significant in all cases between 0.18 and 0.23 percentage points per month.[570] Furthermore, based on a comparison of gross and net returns and the magnitude of the performance impact of both equilibrium mechanisms, it seems reasonable to conclude that the equilibrium mechanisms are more relevant in explaining below-average performance than the impact of fees. Specifically, the unconditional four-factor alpha of loser funds before fees is −0.11 (Table 7.18) while conditioning on both equilibrium mechanisms identifies the loser-fund subgroup with outflows and a manager change

[570] Compare Tables 7.20 and 7.16.

that has a corresponding four-factor alpha after fees of −0.09 percent per month. Thus, adding back fees improves the unconditional net alpha of loser funds from significant −0.24 percent per month (Table 6.3) to insignificant −0.11 before fees while the simultaneous application of internal and external governance would even improve it to insignificant −0.09 percent per month. Assuming the (admittedly unrealistic) case that at the end of each year the regulator would step in and force all decile-1 funds to hand back all of the collected fees to their investors, an extreme form of a performance-based fee, investors would benefit less from this action than from firing the manager and withdrawing money. Thus, the governance mechanisms identified here are of high economic relevance.

In conclusion, winner-fund managers do not seem to attempt to maximize their fee income by actively adjusting the fee levels to their expected performance and that the benefits of outflows and manager changes among both winner and loser funds are not related to differences in fees. This demonstrates that the performance impact of the equilibrium mechanisms documented in the previous section is robust to potential differences in fee levels.

7.7 Regression Analysis

7.7.1 Model Specification

In this section, the output from a pooled regression of the change in annualized Bayesian four-factor alphas between the formation and evaluation periods is examined. The explanatory variables are relative net inflows, manager changes and a set of other control variables documented in the literature as having an impact on performance.[571] Relative net inflows are used in this section because they are more comparable across funds. The aims are threefold: (1) by controlling for other determinants of mutual fund performance, it is possible to measure the marginal impact of fund flows and manager changes, as well as the interaction with other control variables; (2) it allows an analysis of the performance impact of both equilibrium mechanisms over time, i. e. whether they lead to mean reversion, in contrast to the cross-sectional results in the previous sections using ranked portfolio tests; (3) it serves as a robustness test.

[571] Following French (2008), all variables are winsorized at the 1st and 99th percentile to avoid any bias resulting from extreme outliers.

In the first model, the following additional control variables are included: fund size (total net assets), fund fees, fund age and the portfolio turnover ratio.[572] Because there is a strong tendency for the extremes in fund performance to revert to the mean, two dummy variables that indicate whether a fund is currently in decile 10 or decile 1 based on previous year performance are added to the regression. These dummies capture the pure mean reversion effect and ensure that the other coefficients are not biased. The key variables of interest are net inflows and the manager-change dummy. Additionally, an interaction term between fund flows and the decile-10 and decile-1 dummies are included in order to analyze the differential effects of fund flows on performance in the top and bottom funds. Similarly, a manager-change dummy indicating whether the fund manager has been replaced during the previous year and an interaction term between manager changes and the decile-10 and decile-1 dummies is used.

The second model analyzes the impact of being a small-cap or a sector fund on performance and the marginal impact of fund flows on winner and loser funds that belong to these two investment-style categories. Capacity constraints are anticipated to be more prevalent in narrow and illiquid markets and, as a result, fund flows are expected to have a stronger impact on performance in these investment categories. A third model investigates the interaction effect between a change in the manager of a winner or loser fund and the fund being a member of a large fund family. Gervais, Lynch, and Musto (2005) argue that the replacement of an underperforming manager in a large fund family reveals more information than the replacement of a manager in a small fund family. A fund is assigned to the large-family group if the number of funds offered by its fund family at the end of the previous year is higher than the 70th percentile. A fourth model assesses the interaction between the manager-change and fund-flow mechanisms. Specifically, a dummy for winner funds that have higher-than-median net inflows and a manager change and a dummy for loser funds that have lower-than-median net inflows, i. e. high net outflows, and a manager change are included.[573]

[572] Chen, Hong, Huang, and Kubik (2004) and Cremers and Petajisto (2009) find a negative effect of fund size on performance, Carhart (1997) documents a negative effect from fees, Huij and Verbeek (2007) and Karoui and Meier (2009) report an outperformance of young funds. Results on turnover are ambiguous. Elton, Gruber, Sanjiv, and Hvlaka (1993) and Carhart (1997) find a negative relationship, Wermers (2000) documents that turnover is not associated with fund performance and Dahlquist, Engström, and Söderlind (2000) and Chen, Jegadeesh, and Wermers (2000) find a positive relationship.

[573] In an additional unreported regression, year dummies are included in the analysis. However, as the alphas are already adjusted for general market movements, the results are not

7.7.2 Results

Table 7.21 presents the results for the four model specifications. As the change in performance between consecutive years is measured, a significant coefficient on one of the control variables would indicate that there was a trend in performance over time. An examination of the first four regressors in Table 7.21 indicates that, across all models, only fund size (as measured by total net assets) is statistically significant. The decile-1 and decile-10 dummies are both highly significant and indicate that loser funds improve their alphas by between 7.93 and 7.94 percentage points in the following year, depending on the model, while the alphas of winner funds deteriorate by between 8.21 and 8.31 percentage points in the following year, before conditioning on any other variable. These findings indicating strong mean reversion are consistent with the results of the portfolio tests.

In line with the hypothesis of Berk and Green (2004), a significant negative relationship is documented between relative net inflows and subsequent performance. A 100 percentage points increase in relative net inflows during the previous year decreases four-factor alphas for all funds by 1.06 percentage points on average in the following year. Model 1 reveals that the decrease becomes 1.48 percentage points for winner funds which confirms the results of the ranked portfolio test. Controlling for a fund's market segment shows that performance decreases by an additional 0.86 percentage points if the winner fund is a small-cap or sector fund and receives high inflows (Models 2 to 4). This supports the notion that capacity constraints are partly driven by transaction costs.

A manager change does not have a significant impact on the average fund, but if the manager of a winner-decile-10 fund changes, performance subsequently deteriorates by a significant 1.15 to 1.30 percentage points in the following year, according to Models 1 to 3. The more sophisticated Model 4 shows that the effect operates through fund flows. Winner funds that lose their manager, while also experiencing above-median net inflows, experience an average deterioration in performance of 2.29 percentage points in the following year. If the star manager of a large fund family leaves, the effect is not significantly different from the case in which the manager of a small fund family leaves, implying that not even large fund families have access to the fund management skills that would prevent the deterioration in performance following the loss of a talented manager.

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qualitatively different. Furthermore, using standard errors according to Newey and West (1987) does not alter the conclusions. These results are available on request.

Table 7.21: Pooled regressions for change in fund performance

This table presents the results of a pooled regression for the change in annualized Bayesian four-factor alphas between the formation and evaluation years. The explanatory variables are defined as follows: TNA_{t-1} is the fund size in billion USD; $fees_{t-1}$ are annual fees in percent; age_{t-1} is the fund age in years (multiplied by 100); $turnover_{t-1}$ is portfolio turnover; $dec10_t$ and $dec1_t$ are two dummies indicating whether the fund is currently ranked in decile 10 or 1, respectively, based on previous year performance; $flows_{t-1}$ are relative net inflows; SC/SEC is a dummy variable indicating whether the fund is a small-cap or sector fund; mgr_ch_{t-1} is a dummy variable indicating whether the manager changed during the previous year; lfam is a dummy variable indicating whether the fund belongs to a large fund family and hi fl_{t-1} and lo fl_{t-1} are two dummy variables indicating whether the fund had higher- or lower-than-median net inflows during the previous year, respectively.

	Model			
	(1)	(2)	(3)	(4)
constant	0.37*	0.36*	0.36*	0.37*
TNA_{t-1} (bn USD)	−0.13***	−0.13***	−0.13***	−0.13***
$fees_{t-1}$ (%)	−0.09	−0.08	−0.08	−0.08
age_{t-1} (·100)	−0.52	−0.52	−0.53	−0.60
$turnover_{t-1}$	−0.02	−0.01	−0.01	−0.01
$dec10_t$	−8.21***	−8.25***	−8.25***	−8.31***
$dec1_t$	7.94***	7.94***	7.94***	7.93***
$flows_{t-1}$	−1.06***	−1.06***	−1.06***	−1.06***
$flows_{t-1} \cdot dec10_t$	−0.42***	0.05	0.05	0.12
$flows_{t-1} \cdot dec1_t$	−0.15	0.08	0.10	0.21
SC/SEC	–	−0.02	−0.02	−0.03
$flows_{t-1}$ · SC/SEC · $dec10_t$	–	−0.86***	−0.86***	−0.86***
$flows_{t-1}$ · SC/SEC · $dec1_t$	–	−0.46	−0.52	−0.45
mgr_ch_{t-1}	0.15	0.15	0.15	0.15
$mgr\_ch_{t-1} \cdot dec10_t$	−1.21**	−1.15**	−1.30**	−0.22
$mgr\_ch_{t-1} \cdot dec1_t$	0.76	0.78	−0.43	−1.80**
mgr_ch_{t-1} · lfam · $dec10_t$	–	–	0.41	0.41
mgr_ch_{t-1} · lfam · $dec1_t$	–	–	2.92***	2.71***
mgr_ch_{t-1} · hi fl_{t-1} · $dec10_t$	–	–	–	−2.29**
mgr_ch_{t-1} · lo fl_{t-1} · $dec1_t$	–	–	–	3.00***
# observations (fund-years)	21,403	21,403	21,403	21,403
R^2	0.15	0.15	0.15	0.15

For loser funds, the improvement in alpha following an increase in relative outflows is not significantly different from the general performance improvement for average-performing funds (Model 1), implying that the performance of loser funds is less sensitive to a change in net flows of the same magnitude than the performance of winner funds. Further, being a small-cap or sector fund has little effect on the relationship between outflows and subsequent performance (Model 2). The improvement in performance following a manager change, although positive, is insignificant for a typical loser fund, according to Models 1 and 2. However, the more sophisticated Models 3 and 4 reveal that replacing an underperforming manager in a fund belonging to a large fund family improves performance significantly by an additional 2.71 to 2.92 percentage points in the following year. This result supports the predictions of Gervais, Lynch, and Musto (2005) that manager replacement in a large family contains more information, particularly if it is associated with an underperforming manager. Additionally, model 4 shows a strong interaction between the two equilibrium mechanisms. If loser funds fire their manager, while also experiencing above-median outflows, they experience an aggregate performance improvement of 3.00 percentage points the following year, although this is attenuated by a deterioration of 1.80 percentage points as a result of the pure effect of a manager change in a bottom-performing fund. This supports the findings from the ranked portfolio tests.

The results in this section strongly confirm the Berk and Green (2004) hypothesis for fund flows as a predictor of mean reversion in performance over time for winner funds, but not for loser funds. The effect of manager changes is driven by the interaction with high net inflows for winner funds, and by the interactions with outflows and fund family size for loser funds. These interaction effects suggest that a manager change has a magnified impact on performance in combination with fund flows, reinforcing the evidence from the ranked portfolio tests. All four models imply that, by itself, a manager change has no effect on performance: it is only in combination with fund flows that a manager change has an impact. In contrast, relative fund flows have an independent negative impact on performance.

7.8 Discussion

In this section, the role of fund flows and manager changes in explaining the lack of persistence in mutual fund performance has been examined. Using a CRSP sample of 3,946 actively managed U. S. equity mutual funds over the period from 1992 to 2007, the empirical evidence implies that both mean reversion in winner-fund performance and mean reversion in loser-fund performance can be explained by these two equilibrium mechanisms.

To summarize, the results for winner funds lend strong support to the hypothesis of Berk and Green (2004) that fund flows are a key mechanism bringing active mutual fund outperformance back into equilibrium where expected abnormal returns are zero. However, another equilibrium mechanism, manager changes, also contributes to this effect. Winner funds subject to both mechanisms simultaneously experience the largest performance deterioration. Conditioning on both mechanisms explains 37 percent of the unconditional mean reversion of winner funds. Importantly, this mean reversion can be attributed entirely to differences in true selection skills across fund managers that belong to both subgroups. Differences in factor loadings are in favor of funds suffering from both mechanisms and even reduce this spread. Fund flows are, however, a more important equilibrium mechanism than manager changes. Nevertheless, the two effects are additive.

In the case of loser funds, the empirical support for the Berk and Green (2004) hypothesis is rather weak when considering fund flows as the sole equilibrium mechanism. However, manager changes both separately and jointly with outflows play an important role in the governance process, leading to a significant improvement in the performance of loser funds. Applying internal and external governance at the same time not only brings performance levels back to equilibrium (−0.09) in the evaluation period, but also explains 27 percent of the unconditional mean reversion among loser funds. However, differences in mean reversion between both subgroups are even larger based on raw returns but differences in factor loadings explain much of this spread, indicating that internal and external governance mainly result in changes with respect to the factor loadings but have only a smaller impact on true selection skills. Individually, manager changes are a more effective governance tool than withdrawing money, especially when transaction costs associated with the latter are taken into account. However, in combination both mechanisms are highly complementary and the effects are magnified. These equilibrium mechanisms are more important in explaining below-average performance than, for example, the impact of fees. Thus, the higher persistence observed among loser funds is partly due to their higher fees as concluded by Carhart (1997) but also due to the fact that governance is only applied at less than 12 percent of all loser funds. The inertia of mutual fund investors to withdraw money from loser funds, maybe due to a disposition effect, seems to play an important role in explaining continued underperformance of these funds.

Taking an alternative perspective and focusing on the spread in four-factor alphas between winner and loser funds, this study provides further insights into the equilibrium mechanism that are partially responsible for mean reversion in fund performance. The unconditional spread of winner-minus-loser funds reverts from 1.86 percentage points per month in the formation period to 0.32 percentage points in the evaluation period, consistent with earlier studies. Conditioning only on winner and loser funds that do not experience the equilibrium mechanisms, yields a highly significant winner-minus-loser spread of 0.47 percentage points per month in the evaluation periods. Thus, even though mean reversion over time still dominates, winner funds continue to significantly outperform loser funds if the equilibrium mechanisms are not at work. In contrast, when conditioning only on winner and loser funds that experience both equilibrium mechanisms, the corresponding spread narrows to an insignificant −0.03 percentage points and is virtually zero, meaning that the spread between winner and loser funds in the formation period is totally eliminated in the next period. These results strongly indicates that, on the one hand, the combination of both equilibrium mechanisms explains a significant part of mean reversion in performance and therefore the lack of performance persistence, and that, on the other hand, positive and negative performance may persist, although to a lower degree, if the funds are not exposed to shifts in funds flows and manager changes.

What are the potential implications of these findings? First of all, investors should pay close attention to fund flows and the resulting changes in fund size, as well as to the career paths of individual fund managers amongst different funds. According to the results of this chapter, past performance is only an indicator of future performance if the manager is not replaced and fund flows do not eliminate the persistence. It would be valuable for investors if investment management companies were required to publish information on fund flows on a regular basis and on manager changes immediately. Moreover, an improved investor education or independent recommendations from financial advisors and mutual fund rating agencies might be beneficial for investors' long-term investment decisions.

Second, investment management companies should make their best efforts to retain skilled managers. While this is an obvious statement to make, it implies that a stronger alignment of performance with remuneration might be necessary to avoid the high turnover of talented managers. Das and Sundaram (2002) have questioned the usefulness of U.S. restrictions permitting only fulcrum fees as performance-related fee contracts. Hedge fund industry practice, which typically combines asymmetric performance fees with personal stakes by the fund manager, provides valuable lessons for the mutual fund industry. After a fund has been soft-closed by the investment management company after a period of excessive inflows, it might be appropriate to allow the fund to switch from size-based fees to performance-based fees. Nohel, Wang, and Zheng (2010) discuss the implications of allowing side-by-side management of hedge funds and mutual funds by the same manager as a way of retaining star fund managers. This privilege is usually only granted to the best performing managers and any agency conflicts do not seem to reduce mutual fund performance. Still, any improvement in the rewards to star fund managers will be at the expense of investors, again making it difficult for investors to benefit from any performance persistence. An important message from findings in this chapter is that star fund managers extract their skill-rents one way or another, even if that means changing jobs.

Finally, with respect to loser funds, the investment management company needs to respond more promptly in the face of poor performance. Since losing fund managers seem to be incapable of extricating themselves from their losing positions, maybe due to a disposition effect also on their side, the investment management company needs to replace them much sooner than hitherto: the fund-flow mechanism is much less effective at loser funds if not accompanied by a change in the fund manager.

8 Time Effects, Extreme Flows and Capacity Constraints

8.1 Research Questions and Hypotheses

In the previous chapter 7, the empirical evidence indicates that fund flows and manager changes are important equilibrium mechanisms explaining mean reversion in mutual fund performance. In this chapter, these effects are analyzed in more detail, first, with respect to the relevant time dimension and, second, with respect to the relationship between the magnitude of fund flows and the associated performance reversal. Both approaches can be interpreted as an analysis of what effect a larger difference in cumulated fund flows has on subsequent performance. This larger difference, however, can be achieved by two ways: either the time interval over which fund flows are accumulated is extended to a longer period or the sorting into subgroups is based on more extreme split points by setting a stricter condition for the inclusion of funds in the high- or low-inflow subgroups.

So far, the analysis was based on 12-month formation and 12-month evaluation periods. Thus, the first question to be investigated is whether the effects that have been observed depend on the length of the time interval studied (section 8.2). For example, it might be of interest whether it is possible that fund performance reacts more quickly to manager changes than on fund flows. In addition, this additional analysis serves as a robustness test. Because fund flows occur and accumulate over time, a stronger response of performance to past fund flows would be expected when the formation period is longer, both for winner and loser funds. In the case of winner funds, a relatively immediate negative reaction of performance on positive net inflows is expected for short evaluation periods because the transaction costs associated with liquidity-induced trading are already a drag on fund performance. However, in the very short run, winner funds with strong inflows might benefit from price pressure of their own stock purchases in positions they already own in their portfolio (Bernhardt and Davies, 2009). In the case of loser funds, the transaction costs associated with liquidity-induced trading are a drag on performance in the short term as documented by Edelen (1999). Thus, the beneficial impact of a reduced asset base on fund performance probably sets in

P. Lückoff, *Mutual Fund Performance and Performance Persistence,*
DOI 10.1007/ 978-3-8349-6527-1_9,

only with a time delay, if at all.[574] In the case of manager replacements, a new manager would first shift the portfolio to a neutral position and then start investing according to his assessment, especially among loser funds. Thus, in both cases the reaction of performance to manager changes should be relatively immediate. A stronger response is expected for short formation periods and for evaluation periods with short to medium length.

After having analyzed the impact of the time dimension on the response of fund performance to the equilibrium mechanisms, the empirical analysis goes on to focus only on the fund-flow mechanism. Specifically, the question is raised how the reaction of fund performance is related to the magnitude of fund flows (section 8.3). This is especially interesting for loser funds because three potential explanations for the weak support of the Berk and Green (2004) hypothesis among loser funds reported in section 7.4.1 can be identified: (1) the negative short-term impact of transaction costs from liquidity-induced trading; (2) a disposition effect among fund managers, i. e. managers do not respond to outflows by reorganizing the portfolio; (3) a disposition effect among fund investors, i. e. due to their hesitant response to past underperformance outflows are just not large enough to positively affect fund performance in the sense of Berk and Green (2004). It is the third explanation which is analyzed explicitly in section 8.3 by focusing only on loser funds that do in fact experience large outflows.

In order to investigate how the level of fund flows is related to the performance reversal, a similar analysis as that in chapter 7 is performed. However, instead of using median net inflows as the split point between the decile subgroups with high and low net inflows, the upper and lower quintiles are used as the split points. Thus, high-inflow funds are those with the highest 20 percent of net inflows, i. e. above the 80th percentile, and low-inflow funds are those with the lowest 20 percent of net inflows of each decile, i. e. below the 20th percentile. If higher levels of inflows and outflows have a stronger impact on investment performance as compared to lower levels, then the performance reversals observed in this chapter should be larger than those observed in chapter 7.

In addition to the sorting on more extreme fund flows, a sorting on fund size is performed in section 8.3, which is based on the following reasoning. Two assumptions are crucial for the hypothesis of Berk and Green (2004). First, investors

[574] Note that based on a single sorting loser funds could not benefit significantly from outflows (section 7.4.1).

respond to past performance and, second, the resulting change in fund size, an increase in the case of winner funds and a decrease in the case of loser funds, leads to performance reversals due to capacity constraints in active management. The previous analysis based on the fund-flow sorting has tested both of these assumptions simultaneously. To gain a more detailed understanding of the mechanisms behind the Berk and Green (2004) hypothesis, the fund-size sorting only focuses on the second assumption of Berk and Green (2004), namely the existence of capacity constraints in active management or, more technically, of decreasing returns to scale. Based on this assumption, small funds should outperform large funds. In fact, previous studies have documented a negative relationship between fund size and fund performance (e. g. Chen, Hong, Huang, and Kubik, 2004; Yan, 2008).[575] The empirical analysis of section 8.3 extends the study of Chen, Hong, Huang, and Kubik (2004) and Yan (2008) in two ways. First, capacity constraints are separately analyzed for winner and loser funds. Second, empirical evidence based on a real-time trading strategy is provided that analyzes whether the regression results of Chen, Hong, Huang, and Kubik (2004) and Yan (2008) can be applied in reality to earn abnormal returns, i. e. the economic value of the size effect among funds is assessed. Furthermore, the direct analysis of capacity constraints especially relevant in the case of loser funds because the results in section 7.4 have revealed that the weak support of the Berk and Green (2004) hypothesis for loser funds might be due to the reluctance of investors to withdraw money. Thus, the analysis of size effects among loser funds is a potential approach to investigate whether the Berk and Green (2004) would hold if investors withdrew larger amounts of money from underperforming funds.

The question how these two mechanisms, fund size and fund flows, are related in explaining fund performance is analyzed in the last section 8.4 of this chapter.[576] In the case of winner funds, it is interesting to investigate whether large funds or small funds suffer more from inflows. On the one hand, one might expect that large funds are better in accommodating a certain level of inflows because

[575] Note that these studies should not be interpreted as empirical evidence in favor of the Berk and Green (2004) hypothesis because only the change in fund size that is due to the response of investors to past performance qualifies as an equilibrium mechanism in the sense of Berk and Green (2004).

[576] It would also be interesting to investigate how all three mechanisms, fund flows, manager changes, and fund size, interact. However, this would require a three-dimensional sort resulting in fund portfolios with only a small number of funds, making conclusions very sensitive to the specific composition of the portfolios. The pooled regression in section 7.7 controls for all three variables simultaneously.

their models and investment strategies are optimized for a certain level of size and returns to scale might decrease in a convex shape. On the other hand, small funds might still find enough profitable investment targets and transaction costs from liquidity-induced trading are smaller due to smaller absolute trade sizes. Thus, the exact relationship between fund size and fund flows as equilibrium mechanisms is an empirical question. In the case of loser funds, the corresponding research question is whether large or small funds benefit more from outflows. Again, this depends on the shape of the decreasing returns to scale and is an empirical question. In addition, this section serves as an additional robustness test for whether the results for the sorting on fund flows in chapter 7 were in part explained by differences in fund size that resulted from the one-dimensional sort. Clearly, inflows result in an increase in fund size and outflows result in a decrease in fund size. This relationship can only be controlled for when analyzing both variables simultaneously. This issue will be discussed below.

The following itemization summarizes the research questions that are being analyzed in this chapter in order to deepen the understanding of the equilibrium mechanisms:

- What is the "reaction time" of fund performance on fund flows and manager changes (section 8.2)?

- Does a higher level of inflows into winner funds result in a stronger performance reversal (section 8.3)?

- Does a higher level of outflows out of loser funds result in a (stronger) subsequent performance improvement, i. e. can the weak empirical support of the Berk and Green (2004) hypothesis documented in section 7.4.1 be explained by the reluctance of loser-fund investors to withdraw significant amounts of money (section 8.3)?

- Do large winner funds suffer from inflows to the same degree as small winner funds (section 8.4)?

- Do large loser funds benefit from outflows to the same degree as small loser funds (section 8.4)?

8.2 Alternative Formation and Evaluation Periods

8.2.1 Winner Funds

Table 8.1 presents the monthly four-factor alphas of different winner-fund spread portfolios for a variety of formation and evaluation periods. An analysis of different time periods used for portfolio formation and evaluation in section 6.4 has already revealed that performance persistence decays over time.[577] Based on the hypotheses outlined above, this is due to more money flowing into the last year's winner funds in combination with decreasing returns to scale in active management or because the skilled fund manager leaves to a better paid job. For the 12-month formation periods, a drop in performance persistence is especially evident when going from the 6-month evaluation period (12/6) to the 12 months evaluation period (12/12). Specifically, the alpha spread between winner and loser funds ($10 - 1$) drops from highly significant 0.56 percentage points per month to only weakly significant 0.32 percentage points per month. An analysis of the fund-flow subgroups (10 low $-$ 10 high) reveals for both the sorting on absolute net inflows and the sorting on relative net inflows an inversely U-shaped pattern of the alpha spread. For relatively short and relatively long evaluation periods, fund flows only seem to have a small impact on the performance of winner funds. However, for exactly the 12 months evaluation period (12/12), i. e. when the drop in performance persistence is large, the impact of fund flows on winner-fund performance seems to peak out at 0.21 percentage points for absolute flows and 0.16 percentage points for relative flows. This indicates that both observations, the decay in performance persistence and the impact of fund flows, are closely related.

Moving to 24-month formation periods reveals that the accumulation of fund flows over time is an important determinant of its impact on fund performance. Irrespective of the length of the evaluation period the spread between winner funds with low net inflows and those with high net inflows is significantly positive, for both absolute and relative fund flows. The maximum is reached for 6-month evaluation periods (24/6) with an alpha spread of 0.33 percentage points for absolute flows and 0.20 percentage points for relative flows.[578] It seems that, due to the

[577] The corresponding columns (4) and (6) for 12-month and 24-month formation periods, respectively, and four-factor alphas used as evaluation measure of panel (c) in Table 6.17 are reproduced in column (1) of Table 8.1.

[578] In the case of absolute fund flows, the same alpha spread can be documented already for a 3-month evaluation period (24/3).

Table 8.1: Performance of winner-fund spread portfolios for alternative formation and evaluation periods

This table presents monthly risk-adjusted returns based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23) for the following spread portfolios using alternative lengths of the formation and evaluation periods: long in decile-10 funds and short in decile-1 funds (10 − 1), long in decile-10 funds with low absolute net inflows and short in decile-10 funds with high absolute net inflows (10 low − 10 high), long in decile-10 funds with low relative net inflows and short in decile-10 funds with high relative net inflows (10 low − 10 high), and long in decile-10 funds without a manager change and short in decile-10 funds with a manager change (10 without − with). See the note to Figure 7.1 for more explanation on the portfolio formation. Rows denoted by m/n refer to formation periods of m months and holding periods of n months. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Persistence	Absolute flows	Relative flows	Manager change
	10 − 1	10 low − 10 high	10 low − 10 high	10 without − 10 with
Asymmetric formation and evaluation periods (12 months formation)				
12/1	0.69^{***}	0.06	0.05	0.07
12/3	0.55^{***}	0.11	0.05	0.09^{*}
12/6	0.56^{***}	0.12	0.08	0.09^{*}
12/12	0.32^{*}	0.21^{***}	0.16^{***}	0.12^{**}
12/24	0.12	0.08	0.05	0.08^{*}
12/36	0.28^{**}	0.11^{*}	0.09	0.05
Asymmetric formation and evaluation periods (24 months formation)				
24/1	0.55^{**}	0.27^{***}	0.15^{***}	0.02
24/3	0.45^{**}	0.33^{***}	0.18^{***}	0.06
24/6	0.42^{*}	0.33^{***}	0.20^{***}	0.05
24/12	0.23	0.29^{***}	0.13^{**}	0.07
24/24	−0.03	0.26^{***}	0.11^{**}	−0.01
24/36	−0.16	0.14^{**}	0.07^{*}	−0.00

delayed reaction of some investor clienteles to past performance, the fund-flow mechanism of Berk and Green (2004) takes some time to unfold its full potential. Unreported results even reveal that the spread of 0.33 percentage points for the absolute-fund-flow sorting results from a significant outperformance of the low-inflow subgroup, i. e. winner funds with lower-than-median net inflows significantly outperform the four-factor benchmark after costs by 0.28 percentage points per month based on 24-month formation and 6-month evaluation periods.[579]

However, are these differences in performance only due to differences in the time period considered, i. e. does it take some time until the actions of the fund manager as a response to fund flows translate into performance, or is the higher level of fund flows that accumulates over a longer time period responsible for performance differentials. Thus, it is interesting to analyze whether the pattern in fund size between the different lengths of the formation and evaluation periods corresponds to the pattern in performance differentials between low- and high-inflow funds. Appendix A.4.1 performs this analysis in detail and provides the corresponding tables while the major results are summarized here. If longer time periods would unambiguously result in higher size differentials and, thus, larger performance spreads, then the maximum performance spread would be expected for 24-month formation and 36-month evaluation periods, which does not correspond to the inversely U-shaped pattern for performance observed in Table 8.1. The relationship between the magnitude of fund flows and the size of the performance spread does not seem to be linear. Basically, formation-period fund size and fund flows per month are comparable, irrespective of the length of the formation period. Thus, the change in fund size for 24-month formation periods is roughly twice as large as the change in fund size for 12-month formation periods. As documented in Table 8.1, this larger spread in fund size contributes to larger spreads in performance in the evaluation period between low-inflow and high-inflow funds based on the 24-month formation period compared to 12-month formation period. However, fund flows are relatively persistent in the evaluation period as well such that the size differential between high-inflow and low-inflow funds continues to rise. But performance differentials rather decrease for longer evaluation periods of 24 or 36 months. Thus, the effect of fund flows seems to decay over longer periods. For the relative-fund-flow sorting, the relationship between the pattern in fund size and performance spreads for alternative formation and evaluation periods is even

[579] Results are not reported in the tables but are available on request.

weaker than in the case of the absolute-fund-flow sorting. This supports, that time also play an important role in this relationship independent of the actual levels of accumulated fund flows.

In the case of the manager-change mechanism, the impact on performance is relatively immediate, as expected. For 12-month formation periods, i. e. when the manager changed during the past calendar year, a significant impact on fund performance for 3- to 24-month evaluation periods (12/3 to 12/24) can be documented. Based on 12-month formation and 6-month evaluation periods winner funds without a manager replacement even significantly outperform the four-factor benchmark by 0.21 percentage points per month.[580] Comparable to the fund-flow mechanism, the impact of manager changes on performance follows an inverted U-shape with a peak of 0.12 percentage points per month in the spread between winner funds without a manager change and those with a manager change for 12 months evaluation (12/12). If the manager change occurred any time within the previous 24 months, the spread between winner funds not suffering from a replacement and those suffering from a replacement is positive for evaluation periods of up to 12 months (24/1 to 24/12) yet insignificant and even negative, but also insignificant, for longer evaluation periods (24/24 and 24/36).

In conclusion, one important determinant of how fund flows affect fund performance is the total magnitude of fund flows but the time dimension also plays an important role. If winner-fund subgroups are formed conditional on 24-month instead of only 12-month formation periods, the spread between low-inflow and high-inflow winner funds is considerably larger and significant for all lengths of the evaluation period. Thus, steady inflows over longer periods are even worse for future investment performance than inflows over shorter periods. It will be further analyzed below whether this is due to a higher level of fund flows that accumulates over a longer time period or if the time period itself also plays an important role in this context. Specifically, it is analyzed in section 8.3 if similar levels of fund flows as in the case of 24-month formation periods also reduce fund performance to a comparable degree if these flows occur over shorter periods of only 12 months. To be precise, in this section larger spreads in fund flows resulted from a longer accumulation period (24 versus 12 months) while in section 8.3 the length of the formation period is 12 months but a more extreme split point is used to determine high-inflow and low-inflow funds.

[580] Results are not reported in the tables but are available on request.

8.2.2 Loser Funds

For loser funds, Table 8.2 reveals that there is no significant relationship between fund outflows and performance reversals for any of the formation and evaluation periods, neither for absolute nor for relative flows.[581] The strongest result is obtained for 12-month formation and 12 months evaluation periods. However, as already discussed in section 7.4, it is not statistically significant. Thus, even if outflows accumulate over longer periods, they do not have the beneficial impact on subsequent performance as predicted by Berk and Green (2004).

However, an analysis of differences in fund size and fund flows reveals, that, based on the absolute-fund-flow sorting, low-inflow loser funds tend to be much larger in fund size compared to high-inflow loser funds and differences in fund flows are not large enough to narrow this gap significantly. Thus, the resulting size differentials might just not be large enough for the Berk and Green (2004) mechanism to work. Based on the relative-fund-flow sorting, the picture reverses and low-inflow funds are indeed smaller than high-inflow funds. However, as discussed above, this still does not translate into significant performance differentials. Thus, it does not only seem to be the reluctant response of investors to poor past performance that explains why loser fund performance does not improve subsequently to outflow but other reasons might be responsible for this observation as well. See appendix A.4.2 for a more detailed analysis of fund flows and fund size of the loser-fund subgroups.

For manager changes there is only a small band of 6 to 12 months based on the 12-month formation periods during which a significant impact on subsequent performance can be observed. The spread in performance between loser funds with a manager replacement and those without is significant at 0.09 (12/6) and 0.08 percentage points per month (12/12), respectively. Thus, a manager replacement does not have an immediate impact on the performance spread between the loser-fund subgroups, presumably because the reorganization of the portfolio requires some time. For longer evaluation periods, the beneficial impact of a new manager compared to loser funds that kept their old manager decays. This might be

[581] The significantly negative alpha of −0.14 percentage point on the spread between loser funds with low relative net inflows and high relative net inflows for 12-month formation and 36-month evaluation periods (12/36) seems to be partly explained by the extremely small fund size of loser funds with low relative net inflows of only 370.49 million USD (Table A.7 in appendix A.4.2) and the observation that in the case of loser funds small funds tend to underperform large funds (Table 8.3).

Table 8.2: Performance of loser-fund spread portfolios for alternative formation and evaluation periods

This table presents monthly risk-adjusted returns based on a Bayesian version of the four-factor model of Carhart (1997) according to equation (3.23) for the following spread portfolios using alternative lengths of the formation and evaluation periods: long in decile-10 funds and short in decile-1 funds (10 − 1), long in decile-1 funds with low absolute net inflows and short in decile-1 funds with high absolute net inflows (1 low − 1 high), long in decile-1 funds with low relative net inflows and short in decile-1 funds with high relative net inflows (1 low − 1 high), and long in decile-1 funds with a manager change and short in decile-1 funds without a manager change (1 with − without). See the note to Figure 7.1 for more explanation on the portfolio formation. Rows denoted by m/n refer to formation periods of m months and holding periods of n months. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Persistence	Absolute flows	Relative flows	Manager change
	10 − 1	1 low − 1 high	1 low − 1 high	1 with − 1 without
Asymmetric formation and evaluation periods (12 months formation)				
12/1	0.69***	0.01	0.01	0.02
12/3	0.55***	−0.00	0.06	0.01
12/6	0.56***	0.00	0.03	0.09**
12/12	0.32*	0.09	0.06	0.08*
12/24	0.12	0.05	0.00	−0.03
12/36	0.28**	−0.07	−0.14**	0.01
Asymmetric formation and evaluation periods (24 months formation)				
24/1	0.55**	0.00	0.01	0.02
24/3	0.45**	0.00	0.01	0.03
24/6	0.42*	0.05	0.06	0.01
24/12	0.23	0.03	0.01	−0.03
24/24	−0.03	0.05	−0.01	−0.08
24/36	−0.16	0.02	−0.06	−0.07

explained by the other loser funds also starting to take action by altering the investment strategy or even replacing the manager as well. Precisely, the longer the evaluation period the higher the likelihood that the results are contaminated by overlapping events.[582] If the manager was replaced some time during the previous 24 months, no noticeable difference in performance between the two subgroups of loser funds can be documented. The pattern for manager changes among loser funds is similar to the one among winner funds. It requires a certain but short period of time until a new manager can improve fund performance compared to loser funds without a manager replacement but this effect does not last very long.

In the case of loser funds, neither the time dimension nor the magnitude of fund flows significantly improves the effectiveness of the fund-flow mechanism as a form of external governance that improves subsequent fund performance. Specifically, one might expect that due to the negative short-term effects of liquidity-induced trading on fund performance a longer period is required for loser funds to improve performance after a reduction in the asset base. However, an analysis of evaluation periods of up to 36 months does not support this hypothesis. Moreover, constructing portfolios based on 24-month formation periods, which allows outflows to accumulate over a longer period and to reach a larger total magnitude, also does not improve the results. Thus, the fund-flow mechanism, if applied individually, remains weak. This also suggests that the underlying performance determinants differ between winner and loser funds because the negative effect of inflows into winner funds cannot be undone by outflows out of loser funds. Thus, fund flows have a different impact on performance depending on the level of managerial skill.

8.3 Extreme Fund Flows and Fund Size

8.3.1 Portfolio Formation

In this section, the analysis of chapter 7 for the fund-flow mechanism is repeated but concentrates on extreme levels of fund flows. The question is whether stronger

[582] For example, when the 12-month formation and 24-month evaluation periods are used it might happen that investment management companies decide in month 13, i. e. the first month of the evaluation period, to replace the manager. This fund, however, will still belong to the no-manager-change subgroup because the portfolio formation, also with respect to assigning funds to decile subgroups, is only based on the formation period.

fund flows result in a stronger performance reversal, or, in the case of loser funds, a performance reversal at all. The portfolio formation is similar to the approach outlined in section 7.2.1. Specifically, after ranking funds into deciles based on the previous year performance, subgroups of the winner and loser deciles are formed based on a single sorting on fund flows (panel (a) of Figure 8.1). In contrast to the earlier results, the upper and lower quintiles of net inflows are used instead of the median as the split point between the low-inflow and high-inflow subgroups. Specifically, low-net-inflow funds are defined as funds with net inflows below the 20th percentile of net inflows of all other funds in the same decile during the formation period. Accordingly, high-net-inflow funds are defined as funds with net inflows exceeding the 80th percentile of net inflows of all other funds in the same decile during the formation period. Both a ranking on relative net inflows and a ranking on absolute net inflows is used for portfolio formation. While the previous section 8.2 focused on the effects of higher levels of fund flows by allowing flows to accumulate over longer formation periods, this section focuses on an analysis of higher levels of fund flows due to more extreme split points between the high-inflows and low-inflow subgroups.

Decreasing returns to scale in active management, commonly referred to as capacity constraints and analyzed, for example, by Chen, Hong, Huang, and Kubik (2004) and Yan (2008), are at the core of the Berk and Green (2004) hypothesis. However, usually only the fraction of the change in fund size that is due to the response of investors to past performance is relevant in the context of equilibrium mechanisms. This is why the previous analysis has focused on the implications of fund flows instead of fund size on performance persistence. In order to allow for a more fundamental analysis of capacity constraints, this section also analyzes the impact of fund size on the performance of recent winner and loser funds. Thus, , subgroups of the winner and loser deciles are formed based on a single sorting on fund size (panel (b) of Figure 8.1).

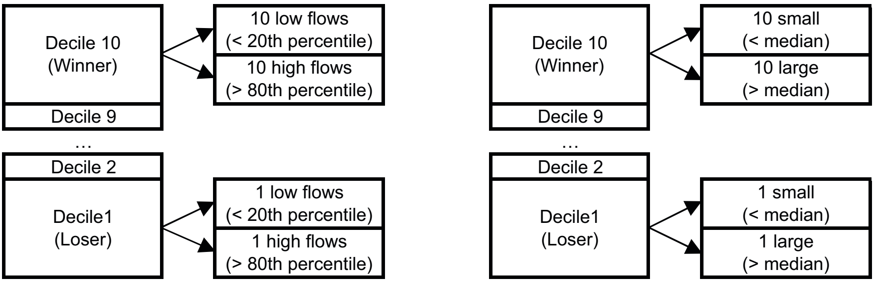
8.3.2 Winner Funds

This section analyzes the relationship between the total level of inflows and the corresponding performance impact, i. e. a more extreme split point is applied for the sorting on fund flows with high-inflow funds being those exceeding the 80th percentile of net inflows of all winner funds and low-inflow funds being those with

Figure 8.1: Portfolio formation based on extreme fund flows or fund size

This figure presents the methodology applied to construct the subgroup portfolios based on extreme fund flows or fund size. Funds are first sorted into deciles based on their performance in the formation period. Then, the decile-10 (winner) and decile-1 (loser) funds are further divided into: (a) a low-net-inflow (low) or high-net-inflow (high) subgroup based on whether their net inflows during the formation period are lower than the 20th percentile or higher than the 80th percentile of net inflows of all other funds in the same decile (using either absolute net inflows or relative net inflows and presenting the results for both); (b) a small-fund-size (small) or large-fund-size (large) subgroup based on whether their fund size during the formation period is lower or higher than the median fund size of all other funds in the same decile.

(a) Extreme absolute / relative flows (b) Fund size



net inflows below the 20th percentile of net inflows into all winner funds. In contrast to section 8.2, where a higher level of fund flows resulted from a longer formation period, in this section the formation period is kept at 12 months but a more extreme split point is applied. Based on the absolute-fund-flow sorting, this results in a difference in fund flows between the low-inflow and high-inflow subgroups which is about 1.5 times as large as the corresponding figure when using the median as the split point.[583]

As a result of the more extreme inflows, the performance of high-inflow funds is further reduced compared to the median split point based on the absolute-fund-flow sorting. For example, the four-factor alpha of high-inflow funds is reduced to an insignificant −0.11 percent (Table 8.3) compared to −0.05 percent for the median split point (Table 7.5). For the other performance measures the picture

[583] See appendix A.5.1 for a more detailed discussion.

is very similar. Performance is between 0.05 and 0.06 percentage points lower for high-inflow funds based on the quintile split point as compared to the median split point, depending on the specific performance measure used. Thus, the additional 11.36 million USD net inflows into high-inflow winner funds compared to the median split point (37.14 versus 25.78 million USD) contribute to an additional reduction of fund performance due to decreasing returns to scale in active management consistent with the hypothesis of Berk and Green (2004). The corresponding four-factor alpha for high-inflow funds based on 24-month formation periods is an insignificant −0.13 percent per month, yet slightly lower compared to the quintile breakpoint and a 12-month formation period.[584] This is in line with the expectation that larger total inflows that accumulate over the formation period lead to a stronger subsequent performance reversal. In conclusion, the total amount of net inflows that accumulates over a certain period seems to be relevant in predicting future fund performance irrespective of the length of this formation period.

Interestingly, for the low-inflow subgroup, the more extreme split point also reduces the performance compared to the median split point. Specifically, the four-factor alpha of low-inflow funds is 0.13 percent per month based on the quintile split point while the same figure is 0.16 percent based on the median split point (Table 7.5). The other performance measures for low-inflow funds based on the quintile split point are also between 0.03 and 0.06 percentage points below the corresponding figures for the median split point. A potential explanation for this result is that low-inflow funds do not suffer from positive net inflows anyway, neither based on the median split point nor on the quintile split point. In fact, both subgroups experience outflows which can be interpreted as a signal of informed investors in the sense of smart money.[585] These investors would only withdraw large amounts of money from recent winner funds if they have some information about negative future prospects for these funds which are stronger than the positive signal from past outperformance.[586] Thus, larger outflows, as in the case of the quintile split point, are a more negative signal for future performance. Due to the performance reduction for both high-inflow and low-inflow winner funds when

584 This result is not reported in the tables but available on request. Together with an alpha of 0.17 percent per month this results in a spread between low-inflow and high-inflow funds of 0.29 percentage points per month as reported in Table 8.1 in the 24/12 row.

585 Section 3.7.3.

586 Assuming that withdrawals due to liquidity needs of investors are evenly distributed across all funds because they are not related to past performance.

Table 8.3: Performance of winner-fund subgroups (extreme flows)

This table presents different performance measures for the winner-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows (quintile split point), on relative fund flows (quintile split point) or on fund size. See the note to Figure 8.1 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows (quintile split point)					
10 low	0.79	0.22*	0.13	0.10	0.11
10 high	0.61	0.08	−0.11	−0.13	−0.13
10 low − 10 high	0.18*	0.13	0.24***	0.23***	0.24***
Conditional on relative net inflows (quintile split point)					
10 low	0.82	0.25**	0.16	0.12	0.13
10 high	0.71	0.18	0.00	−0.02	−0.02
10 low − 10 high	0.11	0.07	0.15**	0.14**	0.15**
Conditional on fund size (median split point)					
10 small	0.85	0.30**	0.16	0.13	0.15
10 large	0.67	0.13	−0.03	−0.05	−0.05
10 small − 10 large	0.19***	0.18***	0.19***	0.18***	0.20***

using the quintile split point, the spread between low-inflow and high-inflow funds increases for the quintile split point compared to the median split point for all performance measures but the three-factor alpha, but not by much. For example, based on the four-factor alpha it is 0.24 percentage points per month compared to 0.21 percentage points for the median split point.

For the sorting on relative net inflows, an analysis of the characteristics of the fund groups reveals that absolute inflows into the high-inflow subgroup are comparable in size to the median split point.[587] Consequently, no significant differences in performance can be detected when comparing the results for the quintile and the median split points in Tables 8.3 and 7.5. Performance for the high-inflow subgroup based on the quintile split point is 0.02 to 0.03 percentage points higher compared to the median split point, depending on the performance measure used. The four-factor alpha, for example, is 0.00 percent per month if portfolios are formed on quintiles of fund flows while the corresponding alpha is only −0.03 percent per month when the median is used. This is attributed to

[587] See appendix A.5.1 for a more detailed discussion.

random effects as, based on the fund-flow hypothesis and given that formation-period fund flows are comparable, it cannot be expected to detect any difference. In contrast, more pronounced differences in fund flows can be observed between the low-inflow subgroups for the quintile and median split points with 8.03 million of outflows for the former and only 1.10 million USD of outflows for the latter. Performance is even slightly higher by 0.01 to 0.03 percentage points for the winner funds with more extreme outflows (quintile split point) compared to the less extreme, i. e. median, split point, with the exception of a 0.01 percentage points lower three-factor alpha. The four-factor alpha is 0.16 percent per month for the quintile split point and 0.13 percent per month for the median split point. The low-minus-high-inflow spread for the relative-fund-flow sorting is insignificant for the three factor alpha at 0.07 percentage points per month, compared to significant 0.11 percentage points for the median split point, while the four- and five-factor alpha spreads vary between significant 0.14 and 0.15 percentage points for the median split point, compared to significant 0.16 percentage points for the median split point. Thus, differences are quite small and stronger relative fund flows do not necessarily result in a stronger subsequent performance response.

Sorting on past fund size generates subgroups that differ substantially in their characteristics. Most notably, small winner funds are only 41.09 million USD in size on average while large winner funds have an average asset base of 4,168.21 million USD. Absolute inflows into small winner funds are much smaller compared to absolute inflows into large winner funds but relative to initial fund size, small winner funds tend to grow at a rate almost three times as high as the growth rate of large winner funds.[588] Interestingly, sorting on past fund size yields significant performance spreads between small and large winner funds (Table 8.3). This is consistent with the more general results of Chen, Hong, Huang, and Kubik (2004) and Yan (2008) that, on average, small funds outperform large funds. Small winner funds generate the highest raw returns of all of the subgroups at 0.85 percent per month. However, adjusting for market risk as well as potential size and value tilts of the portfolio, this performance is reduced to a still significant three-factor alpha of 0.30 percent per month. Significance does not survive the additional incorporation of a momentum factor to the benchmark and performance is further reduced to 0.16 percent per month based on the four-factor model. The corresponding five-factor alphas are 0.13 when controlling for mean reversion and 0.15

[588] See appendix A.5.1 for a more detailed discussion.

when controlling for illiquidity risk, both not significant. Large winner funds, in contrast, have insignificant three-factor alphas of 0.13 percent per month and even negative four- and five-factor alphas of between -0.05 and -0.03 percent per month. The performance spread between small and large winner funds is in the range of 0.18 to 0.20 percentage points per month, depending on the performance model, and highly significant in all cases. For the four- and five factor models, this spread is smaller than the corresponding performance spread between low-inflow and high-inflow winner funds based on the absolute-fund-flow sorting, irrespective of whether the median or the quintile split points are used in the latter case (Tables 7.5 and 8.3). Moreover, when using the median split point, low-inflow winner funds have almost identical four and five-factor alphas as small winner funds of between 0.13 and 0.16 percent per month, yet none of these alphas is significant. Thus, the fund-flow mechanism seems equally important in predicting future fund performance as the fund-size mechanism documented by Chen, Hong, Huang, and Kubik (2004) even though the funds in both subgroups differ considerably with respect to the size and flow characteristics (Table A.8 in appendix A.5.1). Moreover, sorting on past performance and fund size does not yield significantly positive alphas even though the regression-based evidence in Chen, Hong, Huang, and Kubik (2004) strongly indicates that fund size is an important performance determinant. Thus, despite the relationship between both variables being highly significant in a regression framework, this does not necessarily translate into abnormal returns of investment strategies that are based on this relationship. This underscores the importance of using the ranked portfolio test, i. e. replicating a real-time trading strategy, in order to assess the economic significance of a relationship between fund characteristics and investment performance.

The factor loadings of the different subgroups based on the extreme-fund-flow sorting and the fund size sorting do not differ much an cannot explain the performance differentials to a large degree. Details on the factor loadings are discussed in appendix A.5.1.

Summarizing these findings, the results based on the more extreme fund-flow split point are not very strong. The empirical evidence indicates that larger absolute net inflows into winner funds reduce their performance even further but the differences for the relative-net-inflow subgroups are rather small and do not even have the expected sign. Thus, if more capital on an absolute scale is flowing into winner funds this further reduces their performance while larger relative growth does not further hurt subsequent investment results. Sorting on fund size, which should yield the most extreme results of capacity constraints if these constraints only depend on the size of the asset base, generates significant spreads between small and large winner funds. However, these spreads are comparable in size to the spreads between low-inflow and high-inflow winner funds even though both subgroups, those from a fund-size sorting and those from a net-inflow sorting, differ in their characteristics. Specifically, the performance spread when sorting on net inflows does not seem to be explained by differences in funds size. Both mechanisms, fund flows and fund size, are important in explaining and predicting future fund performance and their interaction will be analyzed in more detail in section 8.4. However, it is somewhat surprising that, despite the strong results of Chen, Hong, Huang, and Kubik (2004) and Yan (2008) that small funds outperform large funds, an investment strategy based on past performance and fund size cannot capture the positive effect of a small fund size on performance in the form of a significantly positive alpha for this strategy. Neither does a strategy based on past performance and past fund flows.

8.3.3 Loser Funds

Compared to the results based on the median split point, sorting loser funds based on the more extreme quintile split points yields subgroups with different characteristics. Most importantly, outflows out of the low-inflow subgroup of loser funds are 43 percent larger for the quintile split point compared to the median split point. Thus, if the weak support of the Berk and Green (2004) in section 7.4 with respect to a performance reversal was due to the reluctance of investors to withdraw significant amounts of money, then the performance improvement following the more substantial outflows when using the quintile split point should generate larger performance reversals of the low-inflow subgroup.[589]

Indeed, larger outflows when using the quintile split point as compared to the median split point are beneficial for loser funds' performance (Table 8.4). Low-inflow loser funds based on the absolute fund flow sorting and using the quintile split point generate raw returns and risk-adjusted returns that are 0.03 percentage point higher compared to the same subgroup using the median split point (Table 7.12). Moreover, while three out of the four alpha measures for low-inflow

[589] See appendix A.5.2 for a more detailed discussion.

funds are significantly negative when using the median split point, all four are insignificantly different from zero between -0.12 and -0.18 percent per month when using the quintile split point, depending on the exact model specification. Thus, when outflows are larger, the performance improvement is also larger, consistent with the predictions of Berk and Green (2004). However, the spread between low-inflow and high-inflow loser funds remains insignificant for all but the three-factor model, even when using the more extreme quintile split point. Specifically, the low-minus-high spread is highly significant 0.19 percentage points per month for the three-factor model but approximately one third of this spread ($0.19 - 0.12 = 0.07$ percentage points) can be explained by the momentum factor and another sixth ($0.12 - 0.09 = 0.03$ percentage points) by the mean-reversion factor. Thus, the poor performance of loser funds that do not benefit from large outflows is explained to a large degree by their unfavorable loading on the last year's loser stocks and the long-term winner stocks that tend to revert to the mean. Differences in managerial skill, as measured by the idiosyncratic return component after controlling for momentum and mean reversion effects, can only explain an insignificant spread between low-inflow and high-inflow loser funds of 0.09 percentage points per month. Thus, the overall support for the Berk and Green (2004) hypothesis among loser funds is rather weak, even if the analysis concentrates only on the 20 percent of loser funds with the largest outflows.

Interestingly, comparing the results for the 12-month formation period and the quintile split point with the results based on the 24-month formation period and the median split point reveals that the total amount of money flowing out of the fund does not seem to be the dominant explanation for the performance reversal. For the 12-month formation period and the quintile split point 183.48 million USD ($12 \cdot 15.29$ million USD) are flowing out of the loser funds over the formation period (Table A.10 in appendix A.5.2) compared to 239.52 million USD ($24 \cdot 9.98$ million USD) for the 24-month formation period and the median split point (Table A.6 in appendix A.4.2). Nevertheless, the spread between low-inflow and high-inflow funds based on the former approach is 0.12 percent per month compared to only 0.03 percent per month for the latter approach according to the four-factor model (Table 8.2). This result indicates that rapid outflows are more helpful in improving loser-fund performance than money flowing out of the fund over a longer period but on a slower and steadier rate. A potential reason for this might be that the large outflows per month are more effective in arousing

Table 8.4: Performance of loser-fund subgroups (extreme flows)

This table presents different performance measures for the loser-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows (quintile split point), on relative fund flows (quintile split point) or on fund size. See the note to Figure 8.1 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows (quintile split point)					
1 low	0.54	−0.18	−0.17	−0.15	−0.12
1 high	0.39	-0.37^{***}	-0.29^{**}	-0.24^{*}	-0.24^{*}
1 low − 1 high	0.15^{**}	0.19^{***}	0.12	0.09	0.12
Conditional on relative net inflows (quintile split point)					
1 low	0.51	-0.21^{**}	-0.21^{**}	-0.20^{*}	-0.17^{*}
1 high	0.39	-0.35^{***}	-0.28^{**}	-0.23^{*}	-0.24^{*}
1 low − 1 high	0.11	0.14^{**}	0.07	0.03	0.07
Conditional on fund size (median split point)					
1 small	0.45	-0.28^{***}	-0.24^{**}	-0.22^{**}	-0.22^{**}
1 large	0.45	-0.28^{***}	-0.23^{**}	-0.20^{*}	-0.19^{*}
1 small − 1 large	0.00	−0.00	−0.01	−0.03	−0.03

the fund manager from his inertia while he can more easily ignore continued but smaller outflows. Thus, the fund manager might need a clear signal to overcome his inertia and to take action in reorganizing the portfolio.

For the relative-fund-flow sorting, the results are similar to the absolute-fund-flow sorting though slightly weaker. Larger outflows when using the quintile split point also slightly improve the performance of loser funds with outflows compared to the median split point, though absolute differences are small.[590]

The analysis of small and large loser funds reveals an interesting result. According to the arguments of Berk and Green (2004) a reduction in the fund size should, ceteris paribus, result in an improvement in investment performance due to decreasing returns to scale. Consistent with this theoretical argument, Chen, Hong, Huang, and Kubik (2004) provide strong empirical evidence that on average small funds outperform large funds, which is mainly explained by a positive relationship between fund size and average trading expenses as well as hierarchy

[590] Compare Tables 7.12 and 8.4 and see appendix A.5.2 for a discussion of fund characteristics.

costs. However, this relationship does not seem to hold for loser funds. Specifically, small loser funds have almost identical performance as large loser funds even though they are much smaller in size with an asset based of 38.67 million USD compared to 1,329.18 million USD for large loser funds.[591] Raw returns in both cases are 0.45 percent per month. The alphas of small loser funds are in a range of -0.28 to -0.22 while the corresponding alphas for large loser funds are between -0.28 and -0.19, equal or even higher compared to the alphas of small loser funds, though none of the differences are significant. This is a clear indication that the underperformance of loser funds cannot be explained by fund size or capacity effects. If a large fund size were responsible for loser funds' underperformance, which might be concluded from the results of Chen, Hong, Huang, and Kubik (2004), then it would be reasonable to believe that a smaller fund size could alleviate this disadvantage and fund performance would improve. This does not seem to hold for conditioning on past performance in the first step and concentrating only on those funds that underperformed during the previous year. Other reasons, such as a general lack of investment skills, seem to be more important in explaining loser-fund underperformance. Moreover, fund size is a static measure and an inspection of Table A.10 in appendix A.5.2 indicates that the characteristics of loser funds, and especially the size of their asset base, do not seem to change much from the formation to the evaluation period. In contrast, the results in section 7.4 have revealed that outflows, a more dynamic measure of a change in fund size, can improve loser-fund performance, especially if they are accompanied by a manager change.

Thus, it does not seem to be the same mechanism that explains improvements in loser-fund performance which also explains a deterioration of winner-fund performance. In the case of winner funds, differences in size and resulting capacity constraints explain differences in performance and the last year's fund flows contribute to such differences in size. In the case of loser funds, in contrast, the role of outflows rather seems to trigger activity of the fund manager who suffers from inertia, similar to the case of a manager replacement. At least, a mere reduction in capacity constraints, as measured by a smaller fund size, does not seem to improve loser-fund performance.

As in the case of winner funds, the factor loadings of the different loser-fund subgroups based on the extreme-fund-flow sorting and the fund size sorting do

[591] See appendix A.5.2 for a more detailed discussion.

not differ much an cannot explain the performance differentials to a large degree. Details on the factor loadings are discussed in appendix A.5.2.

Summarizing the findings based on more extreme split points, the general conclusion remains the same as in the case of the median split point. Thus, even if investors do withdraw significant amounts of money from loser funds, little support can be found for the Berk and Green (2004) hypothesis. The reason seems to be a failure of the manager to take appropriate actions. In addition, the higher transaction costs associated with forced asset sales is likely to contribute to the weak performance reversal after outflows. Moreover, this implies that the underperformance of loser funds is explained by a lack of good ideas, rather than the level of average transaction costs, because the latter should be reduced after a decrease in fund size. This effect is amplified by the reluctance of fund investors to withdraw money. Thus, this section confirms that loser funds suffer from a double disposition effect: manager inertia and investor inertia. However, this section also provides evidence that even if investors do respond more strongly to past performance, though absolute levels of outflows out of loser funds are still smaller than absolute levels of inflows into winner funds, loser-fund performance does not improve by significantly more than when their response to past performance is more modest. This indicates that fund manager inertia is more responsible for continued loser-fund underperformance than the weak performance-flow relationship among loser funds.

8.4 Interaction of Fund Flows and Fund Size

8.4.1 Portfolio Formation

In the case of winner funds both, a large fund size and excessive inflows, seem to be detrimental for superior performance. In the case of loser funds, fund size does not seem to affect investment performance while outflows are weakly, and in combination with a manager replacement strongly, beneficial for subsequent investment returns. It is obvious, however, that fund flows directly affect fund size. Thus, the conclusions of the previous sections based on single sorts on either fund flows or fund size might be affected by the interaction of both variables. In this section, the aim is to disentangle both effects by applying a bivariate sorting procedure that allows an analysis of one effect while holding the other one constant. The portfolio formation is presented in Figure 8.2. In the first step, funds are allocated to decile portfolios based on their previous year performance, as measured by a Bayesian version of four-factor alphas. In the second step, funds are further subdivided into subgroups based on a double sorting on net inflows (absolute or relative) and fund size depending on whether net inflows and fund size during the formation period are above or below the median net inflows and fund size of all other funds in the same decile, respectively. This procedure yields four subgroups of each of the winner and loser deciles: large funds with high net inflows and low net inflows and small funds with high net inflows and low net inflows. A further complication arises because large funds tend to have higher absolute levels of inflows or outflows, i. e. net inflows of +100 million USD or −100 million USD are more likely for a fund with a size of 1 billion USD than for a fund with a size of 200 million USD. On the other hand, small funds tend to have higher relative levels of inflows and outflows, i. e. net inflows of +100 percent or −80 percent are more likely for a fund with a size of 50 million USD than for a fund with 1 billion USD. In order to deal with this problem, portfolios are formed on both, absolute and relative net inflows, separately. Details on the composition of the portfolios are presented in appendix A.6.

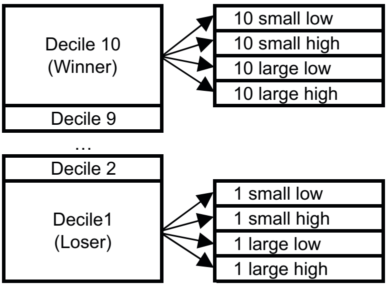
8.4.2 Winner Funds

Based on the hypothesis regarding capacity constraints, small winner funds that do not suffer from excessive inflows should provide the best investment results. Indeed, the subgroup of winner funds that are smaller than the median and have low absolute inflows generates the highest raw returns of all winner-fund subgroups of 0.90 percent per month (Table 8.5).[592] Even controlling for the market exposure as well as the size, value, momentum, mean-reversion or illiquidity-risk loadings cannot explain these superior returns and all risk-adjusted return measures are significantly positive between 0.20 and 0.35 percent per month, depending on the exact model specification used. Performance measures for small winner funds

[592] Note that the performance based on the single sorting does not equal the simple average of the two subgroups based on the independent double sorting because the subgroups do not contain the same number of funds. For example, the average raw return of small winner funds of 0.85 percent per month (Table 8.3) is not the simple average of the raw returns of small winner funds with low absolute net inflows (0.90 percent) and small winner funds with high net inflows (0.70 percent). Rather, it is closer to the raw returns of small winner funds with low absolute net inflows because a higher fraction of small winner funds receive low absolute net inflows (61 percent) as compared to large absolute net inflows (39 percent) according to Table A.12 in appendix A.6. The remaining difference is due to a small number of funds with missing data on either one of the sorting variables.

Figure 8.2: Portfolio formation based on fund flows and fund size simultaneously

This figure presents the methodology applied to construct the subgroup portfolios based on a double sorting on fund flows and fund size. Funds are first sorted into deciles based on their performance in the formation period. Then, the decile-10 (winner) and decile-1 (loser) funds are further divided into four subgroups combining the following criteria on fund flows and fund size in a double sorting mechanism. Funds are assigned to the low-net-inflow (low) or high-net-inflow (high) subgroup based on whether their net inflows during the formation period are lower or higher than the median net inflows of all other funds in the same decile (using either absolute net inflows or relative net inflows and presenting the results for both). Funds are assigned to the small-fund-size (small) or large-fund-size (large) subgroup based on whether their fund size during the formation period is lower or higher than the median fund size of all other funds in the same decile.



with low relative net inflows are almost identical (Table 8.6). That is, buying recent winner funds that are smaller and receive fewer inflows than the median winner fund generates significantly positive risk-adjusted returns even after fees and transaction costs.[593] These alphas are even higher compared to the alphas of winner funds with low net inflows and no manager change, indicating that capacity constraints are more relevant than the departure of a skilled manager among winner funds (Table 7.9). Consistent with the previous results, all other winner-fund subgroups, small funds with high net inflows and large funds with high or low net inflows, generate risk-adjusted returns that are close to zero or even negative, irrespective of whether absolute or relative net inflows are used for the ranking.[594] Thus, either experiencing large inflows or already being a large

[593] Not taking into account potential loads.

[594] With one exception of small winner funds with high relative net inflows, which generate a weakly significantly positive three-factor alpha of 0.26 percent per month. However, most of this abnormal return can be explained by a high momentum exposure and disappears

fund prevents any ability of winner-fund managers to persistently outperform their benchmark. The most extreme results are found at large winner funds that receive high net inflows relative to their asset base: those funds underperform by −0.14 to −0.16 percent per month based on the four- and five-factor benchmarks. This performance is comparable to the investment results of funds in the second or third lowest decile without conditioning on any other variables, i. e. more than 70 percent of all funds in the sample outperform last years' large top-decile funds with high net inflows in the subsequent year (Table 7.5).

Table 8.5: Performance of winner-fund subgroups for double sorts (absolute flows)

This table presents different performance measures for the winner-fund subgroups and the resulting spread portfolios based on a double sorting on absolute fund flows and fund size simultaneously. See the note to Figure 8.2 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows and fund size					
10 small low	0.90	0.35^{***}	0.23^{**}	0.20^{**}	0.22^{**}
10 small high	0.70	0.18	−0.05	−0.09	−0.06
10 large low	0.73	0.18	0.04	0.02	0.02
10 large high	0.65	0.11	−0.05	−0.07	−0.07
Spread portfolios					
10 small low − 10 large high	0.26^{**}	0.24^{***}	0.28^{***}	0.27^{***}	0.29^{***}
10 small low − 10 small high	0.20^{*}	0.17^{*}	0.28^{***}	0.29^{***}	0.27^{***}
10 small low − 10 large low	0.18^{**}	0.18^{**}	0.19^{***}	0.17^{***}	0.19^{***}
10 small high − 10 large high	0.06	0.06	0.00	−0.02	0.02
10 small high − 10 large low	−0.02	0.00	−0.09	-0.12^{*}	−0.08
10 large low − 10 large high	0.08	0.06	0.09	0.09	0.10

Consistent with these conclusions, the spread between both extreme subgroups, long in small winner funds with low net inflows and short in large winner funds with high net inflows (10 small low − 10 large high), is highest at 0.24 to 0.29 percent per month for the sorting on absolute net inflows and even between 0.31 and 0.37 percent per month for the sorting on relative net inflows, highly significant in all cases. Fund size and relative fund flows explain a spread in four-factor alphas of 0.36 percent per month or 4.32 percent per year between the different subgroups of winner funds.

once the benchmark is augmented by a momentum factor.

Table 8.6: Performance of winner-fund subgroups for double sorts (relative flows)

This table presents different performance measures for the winner-fund subgroups and the resulting spread portfolios based on a double sorting on relative fund flows and fund size simultaneously. See the note to Figure 8.2 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw returns	Risk-adjusted returns			
		α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on relative net inflows and fund size					
10 small low	0.90	0.34***	0.22**	0.20**	0.21**
10 small high	0.80	0.26*	0.07	0.03	0.06
10 large low	0.74	0.20	0.05	0.03	0.05
10 large high	0.58	0.03	−0.14	−0.14	−0.16
Spread portfolios					
10 small low − 10 large high	0.32**	0.31***	0.36***	0.34***	0.37***
10 small low − 10 small high	0.10	0.08	0.16**	0.16**	0.15**
10 small low − 10 large low	0.16**	0.14**	0.17**	0.16**	0.16**
10 small high − 10 large high	0.22***	0.23***	0.21***	0.18**	0.23***
10 small high − 10 large low	0.06	0.06	0.02	0.00	0.02
10 large low − 10 large high	0.16**	0.17**	0.19***	0.18**	0.21***

Among small funds, fund flows have a significant marginal impact on subsequent fund performance, which becomes evident from a comparison of small winner funds with low net inflows and small winner funds with high net inflows (10 small low − 10 small high). The corresponding spread in alphas is between 0.17 and 0.29 percentage points per month and significant in all cases for absolute flows and slightly smaller between 0.08 and 0.16 percentage points per month for relative fund flows, significant in three out of four cases. The spread in raw returns and three-factor alphas is slightly smaller compared to the four- and five-factor alphas because small winner funds with high inflows seem to have high loadings on the momentum factor, suggesting that these funds are especially prone to buying recent winner stocks from the new money that is flowing in. Thus, high absolute inflows into small winner funds are detrimental for subsequent performance, especially when controlling for the momentum loading, while high relative inflows, though still placing a curb on future performance, are less harmful. High relative inflows might be used to scale up existing holdings, contributing to high investment performance in the short term by a price-pressure effect while large inflows on an absolute scale into small winner funds might just be too high to be handled efficiently. The results are slightly different for large winner funds, in which case high absolute net inflows affect subsequent performance only on a lower scale. Specifically, the alpha-spread between large winner funds with low absolute net inflows and those with high absolute net inflows (10 large low − 10 large high) is between 0.06 and 0.10 percent per month but not significant. In contrast, large winner funds significantly suffer from high relative net inflows. The corresponding spread in alphas between large winner funds with low and high relative net inflows is between 0.17 and 0.21 percent per month, significant in all cases. Thus, large winner funds are able to cope with net inflows that are large relative to other funds but struggle if they receive inflows that are large relative to their own asset base.

Among winner funds that do not suffer from high net inflows, small funds can clearly outperform large funds (10 small low − 10 large low). In the case of absolute net inflows, the corresponding alpha spread is between 0.17 and 0.19 percent per month while the same figures for relative net inflows are in a similar range at between 0.14 and 0.17 percent per month, all highly significant. Thus, even if a winner fund does not suffer from inflows, the difference in fund size still matters for subsequent performance. In the case of winner funds that receive high absolute net inflows, fund size does not seem to matter as evidenced by the spreads between small and large high-inflow winner funds (10 small high − 10 large high), which are insignificant and close to zero. Specifically, the spread between small and large winner funds with high absolute net inflows is between −0.02 and 0.06 percent per month and not significant for any of the alpha measures. Small winner funds cannot cope any better with a high level of absolute inflows than large winner funds and a small fund size is no longer beneficial for performance once the funds suffer from excessive amounts of new money from investors. A high level of absolute inflows might be worse for small funds compared to large funds, compensating their advantage of a small asset base. In contrast, a small fund size is an advantage with respect future performance if the funds receive high relative net inflows. In this case, small funds outperform large funds by significant 0.18 to 0.23 percent per month. Consequently, if inflows are comparable between small and large winner funds relative to their asset base, small funds have an advantage of handling these inflows. For example, it might be easier for small funds to scale up existing holdings because the ownership ratio, i. e. the fraction of the shares outstanding of a company already held by the fund, is still low. Moreover, small funds tend to hold a lower number of assets in their portfolios which gives them more scope to identify additional profitable investment opportunities compared to large funds that have already moved down their list of best ideas.

A comparison of the magnitude of both mechanisms, fund flows and fund size, reveals that in the case of absolute fund flows, the fund-flow mechanism seems to dominate the fund-size mechanism (10 small high − 10 large low). Winner funds that suffer from a large fund size but only receive small absolute net inflows can outperform winner funds that benefit from a small fund size but receive a high level of absolute net inflows. The alpha spread based on the mean-reversion-augmented five-factor model between those two subgroups is even weakly significant at 0.12 percentage points per month. For relative net inflows, the picture reverses, though none of the alphas are economically large (between 0.00 and 0.06 percentage points per month) or statistically significant. Thus, based on a direct comparison of the fund-flow and size mechanisms, both are highly relevant for subsequent performance but fund flows marginally dominate fund size.

Summarizing these findings on winner funds, it appears important to note that by conditioning on fund flows and fund size simultaneously it is possible to identify those winner funds that continue to significantly outperform all multifactor models used as a benchmark in this study by between 0.20 and 0.35 percentage points per month. However, it remains open whether an investment strategy based on this result can really be implemented in reality due to the small fund size of small winner funds. Funds suffering from capacity constraints, defined either as large funds or those experiencing inflows (or both), generate abnormal returns that are close to zero or even negative. Large inflows are more harmful for small funds as compared to large funds which seem be be better prepared to deal with these inflows. Furthermore, the benefits from a small fund size compared to a large fund size are eradicated once the fund receives high inflows. A comparison of both mechanisms reveals that the negative performance effect of both high inflows and a large fund size is similar in magnitude.

8.4.3 Loser Funds

If loser funds also suffer from capacity constraints then small loser funds with low net inflows, i. e. outflows, would be expected to outperform all other groups of loser funds. However, an inspection of the results for a double sorting on fund size and absolute net inflows (Tables 8.7) or fund size and relative net inflows (Tables 8.7) cannot provide empirical evidence in favor of this conjecture. For example, the four factor alphas of all loser-fund subgroups, small with low or high net inflows and large with low or high net inflows, are significantly negative. This is consistent with the results of the previous sections that neither outflows alone (Table 7.12) nor a small fund size alone (Table 8.4) can significantly improve loser-fund performance. However, for both the absolute-net-inflow sorting and the relative-net-inflow sorting the subgroups with low net inflows have higher performance levels compared to the subgroups with high net inflows. Specifically, for the absolute-net-inflow sorting, small loser funds which experience outflows have four-factor alphas of −0.21 percent per month and large loser funds with outflows of −0.19 percent whereas small loser funds without outflows generate a four-factor alpha of only −0.26 percent per month and large loser funds without outflows generate a four-factor alpha of −0.32 percent. Based on the five-factor models, which are augmented by a mean-reversion factor and a liquidity factor, both small and large loser funds with outflows generate risk-adjusted returns that are still negative but statistically indistinguishable from zero. Thus, part of the underperformance of these funds is due to unfavorable exposures to the longer-term winner stocks and is due even more to a tilt of these funds toward more liquid stocks that prevents them from earning an illiquidity premium. The conclusions based on the relative-net-inflow sorting are fairly similar unless only large loser funds benefit from outflows while small loser funds continue to significantly underperform all multifactor benchmarks.

Based on the absolute-fund-flow sorting the alpha spread between both extreme subgroups, small loser funds with low net inflows and large loser funds with high net inflows (1 small low − 1 large high), is positive between 0.05 and 0.17 percentage points per month, yet insignificant. Within the group of small loser funds, those with outflows consistently generate higher performance than those not benefiting from outflows, though the spread between both subgroups (1 small low − 1 small high) is only significantly positive at 0.13 percent per month for the three-factor alpha and the sorting on relative fund flows. Moreover, in the case of large loser funds, those with outflows seem to weakly benefit compared to those that do not have outflows (1 large low − 1 large high). Specifically, the spread in three-factor alphas is significantly positive at 0.18 percent per month, though most of this spread is explained by a higher, or less negative, loading on

Table 8.7: Performance of loser-fund subgroups for double sorts (absolute flows)

This table presents different performance measures for the loser-fund subgroups and the resulting spread portfolios based on a double sorting on absolute fund flows and fund size simultaneously. See the note to Figure 8.2 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on absolute net inflows and fund size					
1 small low	0.53	-0.22^{*}	-0.21^{*}	-0.20	-0.18
1 small high	0.41	-0.30^{***}	-0.26^{**}	-0.24^{**}	-0.24^{**}
1 large low	0.50	-0.21^{**}	-0.19^{*}	-0.17	-0.14
1 large high	0.37	-0.38^{***}	-0.32^{**}	-0.25^{**}	-0.27^{**}
Spread portfolios					
1 small low − 1 large high	0.17	0.17	0.11	0.05	0.09
1 small low − 1 small high	0.12	0.09	0.06	0.04	0.06
1 small low − 1 large low	0.03	-0.01	-0.02	-0.03	-0.04
1 small high − 1 large high	0.05	0.08	0.05	0.01	0.03
1 small high − 1 large low	-0.09	-0.10	-0.07	-0.07	-0.10^{*}
1 large low − 1 large high	0.14	0.18^{**}	0.13	0.08	0.13^{*}

Table 8.8: Performance of loser-fund subgroups for double sorts (relative flows)

This table presents different performance measures for the loser-fund subgroups and the resulting spread portfolios based on a double sorting on relative fund flows and fund size simultaneously. See the note to Figure 8.2 for more explanation on the portfolio formation and the note to Table 6.4 for more explanation on the column specification.

	Raw	Risk-adjusted returns			
	returns	α_3	α_4	α_5^{mr}	α_5^{l}
Conditional on relative net inflows and fund size					
1 small low	0.51	-0.20^{*}	-0.23^{**}	-0.22^{**}	-0.21^{*}
1 small high	0.40	-0.33^{***}	-0.26^{**}	-0.23^{**}	-0.23^{**}
1 large low	0.50	-0.22^{**}	-0.19^{*}	-0.17	-0.14
1 large high	0.41	-0.33^{***}	-0.29^{**}	-0.23^{*}	-0.24^{*}
Spread portfolios					
1 small low − 1 large high	0.11	0.13	0.06	0.01	0.03
1 small low − 1 small high	0.11	0.13^{*}	0.03	0.01	0.02
1 small low − 1 large low	0.02	0.02	-0.04	-0.05	-0.07
1 small high − 1 large high	-0.00	0.00	0.03	-0.00	0.01
1 small high − 1 large low	-0.09	-0.11^{*}	-0.07	-0.06	-0.09
1 large low − 1 large high	0.09	0.11^{*}	0.10	0.06	0.10

the momentum and mean-reversion factors of large loser funds with outflows. The resulting spread in mean-reversion-augmented five-factor alphas is only 0.08 percent per month and no longer significant, though the spread in liquidity-adjusted five-factor alphas is again weakly significantly positive at 0.13 percent per month. The results for the relative-fund-flow sorting are qualitatively similar but the alpha spreads are slightly smaller in magnitude. Thus, outflows are beneficial for loser-fund performance and this is even more the case among large funds compared to small funds.

A comparison of both effects reveals that in the case of loser funds, outflows are more important in bringing performance levels back to the mean than a small fund size. The investment performance of large loser funds with outflows is better compared to small loser funds not benefiting from outflows by between 0.07 and 0.10 percentage points per month for absolute fund flows and between 0.06 and 0.11 percentage points per month for relative fund flows (1 small high − 1 large low). However, this spread is only weakly significant in two out of eight cases.

To summarize the results of this section on loser funds it seems that capacity constraints are not responsible for the persistent underperformance of decile-1 funds. Neither a small funds size nor (absolute or relative) outflows individually, nor a combination of both, can significantly improve loser-fund performance. Indeed, the four-factor alphas of all subgroups based on single or double sorting remain significantly negative, irrespective of which combinations of fund size and / or fund flows are used for the second sorting (Tables 7.12, 8.4, 8.7 and 8.8). None of these alphas is higher than −0.19 percent per month. In contrast, the alpha of loser funds that experience outflows and at the same time a change in management is insignificant at −0.09 percent per month (Table 7.16). Consequently, only if some change happens at loser funds, i. e. money is flowing out and, more importantly, a new fund manager brings in new investment ideas and a new strategy, subsequent performance tends to improve. This provides evidence that the mechanisms explaining the observed mean reversion in investment performance are quite different among winner and loser funds. While winner funds suffer from size loser funds benefit from change.

Conclusion and Outlook

Summary of the Results

The aim of this study was to analyze the value of active management, specifically of active mutual funds. According to the theoretical analysis in chapter 1 market frictions, asymmetric information in the capital market and economies of scale in information production result in the delegation of private investors' investment decisions to professional portfolio managers. The most important objective of investors is to earn abnormal returns relative to a passive benchmark and accounting for risk. Thus, they aim to benefit from the delegation. However, according to the discussion in chapter 2, this delegation, at the same time, gives rise to a two-layered agency problem, between the investors, the investment management company and the portfolio manager. Both theoretical and empirical evidence is presented that is consistent with significant conflicts of interest in delegated asset management. This involves actions of the portfolio manager that are usually not in line with the objective of return maximization for investors. Rather, portfolio managers aim to optimize their long-term career path and try to maximize compensation. Investment management companies also engage in a variety of distribution and marketing strategies in order to increase the sales of their products which might in some instances involve impure practices. In effect, they might aim to directly affect the purchase decisions of fund investors or try to indirectly increase the fund family's assets by exploiting the performance-flow relationship. Lastly, in some cases third parties are allowed to benefit at the expense of long-term fund investors.

Several measures are employed to mitigate these agency conflicts. First, restrictions with respect to the investment strategy and instruments might be imposed in order to reduce the potential for unintended actions of the portfolio manager. This, however, also reduces the potential to generate alpha. Second, in order to facilitate efficient external governance, measures to increase the transparency and competition between investment management companies can be taken. According to Shleifer and Vishny (1997), one of the most important measures to reduce

P. Lückoff, *Mutual Fund Performance and Performance Persistence,*
DOI 10.1007/ 978-3-8349-6527-1,

agency conflicts is an efficient product market, which in the case of mutual funds is assured through the open-end structure of funds. Thus, fund flows should not be restricted in order to enable market-based control. Third, internal governance through an effective fund board and a real threat of manager replacements should be enabled. Fourth, incentive contracts and co-ownership of the portfolio manager might contribute to a reduction of agency problems.

According to this discussion, investment products can be broadly characterized by their investment style, active versus passive, and by their organizational structure, open-end versus closed-end. Active funds provide the chance to generate positive abnormal returns, i. e. positive alpha, but at the same time face higher agency conflicts compared to passive funds because the portfolio manager of an active fund is less restricted in the investment decisions. Open-end funds further reduce agency costs compared to closed-end funds because they facilitate efficient external governance but at the same time open-end funds suffer from liquidity risk due to unexpected fund flows. Active open-end funds additionally suffer from potential capacity constraints stemming from decreasing returns to scale in active management: once the asset base increases, the potential to generate positive alpha is reduced. Thus, an analysis of the advantages and disadvantages of active versus passive funds needs to consider the performance impact of the open-end versus closed-end structure and the complex tension field between alpha potential, agency costs, liquidity risk and capacity constraints.

The methodological aspects of how to evaluate the skills of portfolio managers as well as the costs from agency conflicts, liquidity risk and capacity constraints are discussed in chapter 3. After giving advice for which performance measure is appropriate for which application, this chapter focuses on recent developments in the area of asset pricing that directly translate into multifactor performance evaluation. The time variability of the investment strategies of funds, which implies time-varying factor loadings, the correct benchmark model specification and a potential estimation error due to the large random component in fund return series are the major issues in performance evaluation. Rolling window regressions, as an alternative to parametric conditional approaches, are suitable to account for time variability. Furthermore, the four-factor model of Carhart (1997) still seems to be a reasonable representation of return factors compared to alternative specifications. Yet, an extension of this model by factors controlling for liquidity risk, stock-return mean reversion and higher-moment risk is recommended. With respect to an efficient estimation procedure, this chapter proposes the Bayesian approach as an alternative to conventional OLS estimation which incorporates additional information into the estimation in order to derive more efficient parameter estimates.

Empirical results on the investment skills of mutual fund managers offer interesting insights. Fund managers are able to generate abnormal performance based on gross returns, not taking into account transaction costs or other expenses while net of these costs mutual funds, on average, tend to underperform their benchmarks. Average investor returns are even below average fund returns due to poor timing decisions made by fund investors. Thus, frictions and the unfavorable investment decisions of investors seem responsible for the unsatisfactory results of the mutual fund industry as a whole. A cross-sectional analysis of which managers are able to outperform their peers reveals that mainly soft factors contribute to a successful investment strategy. In particular, access to certain privileged information sources due to regional or political proximity, social networks, such as a common educational background, and access to internal information from other segments of the financial conglomerate to which the fund family belongs improve fund performance. Moreover, more active funds that follow a concentrated and time-consistent investment strategy provide the highest investment results. Further attributes investors should consider in their decisions are fund size, fund age and the fee level.

The above discussion has already pointed toward external factors that determine the investment performance of mutual funds. Thus, chapter 4 turns to dynamic aspects of mutual fund performance and aims to uncover why a funds' performance is dominated by a strong tendency of mean reversion rather than performance persistence, which should be expected if managerial skills exist. Indeed, according to existing empirical studies it seems that performance persists in the short term but not in the long term, though several methodological and data-related aspects are identified that might render the results of these studies not directly comparable. The key point in this chapter is that the actions of investors, investment management companies and portfolio managers might depend on past performance and, at the same time, might affect future performance. This relationship clearly affects the results of performance persistence studies if not taken into account. In fact, fund investors seem to chase recent winner funds but are slightly more reluctant to sell recent loser funds, even though this passiveness seems to be reduced in recent years. Based on a comprehensive framework, which is derived from a decomposition of total net assets on how portfolio managers can respond to fund flows, potential implications for future performance are derived. In general performance tends to suffer from inflows both in the short and long term and performance tends to benefit from outflows, at least over the longer term, while in the short term the benefits from a reduced asset base might be balanced out by transaction costs associated with liquidity-induced selling pressure. According to these arguments, fund flows are identified as an equilibrium mechanism explaining mean reversion in mutual fund performance.

In addition to fund investors portfolio managers might also respond to past performance. Recent winner-fund managers might pursue better paid opportunities and are replaced by a mediocre manager, resulting in subsequent performance deterioration. Similarly, underperforming managers might be replaced by the investment management company and the newly appointed manager might bring performance back to average levels. Thus, manager changes also serve as an equilibrium mechanism explaining mean reversion in mutual fund performance. There are reasons to believe that both of these mechanisms, fund flows and manager changes, interact and differently affect fund performance if applied simultaneously. Different approaches to reduce the detrimental impact of the equilibrium mechanisms on performance persistence are derived. These include different forms of redemption and creation restrictions, different fee structures, alternative pricing and trading mechanisms as well as changes in the investment strategy and organizational fund structure. However, a critical discussion reveals that some of these measures at the same time reduce the efficiency of the external governance mechanism which might result in higher agency costs. Thus, quantifying the benefits of these measures remains an empirical question.

In the empirical part of this study, performance persistence and determinants of performance persistence are investigated based on a data set that contains all active U. S. mutual funds investing in domestic equity, a total of 3,946 funds. After a presentation of the objectives, data and methodology in chapter 5, chapter 6 goes on to analyze performance persistence based mainly on ranked portfolio tests. That is, decile portfolios are formed based on past performance (formation period) and their performance is analyzed in a subsequent evaluation period. As the ranking measure, Bayesian four-factor alphas are used while raw returns and four-factor alphas are applied to measure performance in the evaluation period.

Additionally, the four-factor model is augmented, first, by a mean-reversion factor in order to distinguish between stock-return mean reversion and mean reversion in manager skills and, second, by a liquidity factor that controls for differences in portfolio liquidity, because funds might be differently exposed to liquidity risk through unexpected fund flows. The results on performance persistence confirm the conclusions of earlier studies on long-term performance persistence: while recent loser funds continue to underperform, though on a much smaller scale, recent winner funds do not offer continued outperformance. Interestingly, adding more factors to the benchmark model further reduces winner-fund performance, because the benchmark is getting stricter, but improves loser-fund performance, because part of their underperformance is explained by unfavorable risk loadings rather than poor stock selection skills.

A special focus of chapter 6 is the question of whether methodological issues can explain why previous studies have documented that short-term persistence exists while long-term persistence does not. These studies differ with respect to the ranking measure, the evaluation measure and the time horizon considered. First, performance persistence is analyzed over identical time horizons but using different ranking measures and different estimation methodologies with respect to performance measurement in the evaluation period, including the approaches used in long-term and short-term studies, respectively. Second, performance persistence is analyzed using identical methodologies but over different time horizons. The results reveal that performance persistence still exists over the short term of up to 12 months but vanishes for longer periods. However, performance persistence is also stronger when using the ranking or performance evaluation methodologies applied in short-term studies. Additionally, persistence is also stronger when the evaluation methodology allows for variation in factor loadings over time and across individual funds, suggesting that not all funds in the same decile are equal with respect to their investment strategy and that this strategy usually changes over time. Thus, the different results between short- and long-term persistence studies are explained by: (1) improved ranking methodologies used by short-term studies; (2) differences in performance evaluation; (3) differences in the time horizon considered. Moreover, the Bayesian version of the four-factor model dominates all other potential ranking measures analyzed in this study and the past 12 months of performance data have more predictive power than longer or shorter ranking periods. Investors can benefit from these results in real time trading strategies.

By using this approach, it is possible to predict the significant outperformance of winner funds for periods of up to 6- or 12-month holding periods, depending on the exact estimation methodology applied. For example, the performance of winner funds is significantly positive between 2.28 and 2.88 percent per year based on this approach (Tables 6.17 and 6.18). Loser-fund performance can also be successfully predicted by this approach, resulting in a significant winner-minus-loser spread of between 6.60 and 6.72 percent per year based on the 6-month evaluation period. An analysis of the migration of funds across deciles and the survival of winner and loser funds in the top and bottom deciles also supports the view that some performance persistence exists among winner and loser funds, at least over shorter periods.

Having established that the observation of performance persistence decaying over time is not a methodological artefact, chapter 7 goes on to analyze whether economic reasons, specifically the equilibrium mechanisms identified in the theoretical part, contribute to this observation. Top- and bottom-decile funds are further split into subgroups based on a single sorting on their past fund flows or whether the manager changed over the previous year and based on a double sorting on both mechanisms simultaneously. For recent winner funds, empirical evidence is provided that fund flows and manager changes are important mechanisms for weakening performance persistence, both individually and in combination. The average four-factor alpha of winner funds that receive high inflows is reduced by 2.52 percentage points in the following year, on average, compared to winner funds that do not experience extreme inflows (Table 7.4). Funds with illiquid investment strategies seem to suffer by even more based on the regression results. The empirical results also suggest that manager changes have a significant impact on the performance persistence of past winner funds. Losing a top-decile manager results in a 1.44 percentage points lower performance in the following year compared to winner funds that keep their star manager. Moreover, the empirical results in this chapter document that both mechanisms help to predict future performance, allowing an identification of those winner funds that continue to significantly outperform the four-factor benchmark. Winner funds not experiencing these mechanisms, i. e. having low net inflows and no manager change, outperform the four-factor benchmark by weakly significant 2.16 percentage points. Yet, this still corresponds to a mean reversion in performance between the formation and evaluation periods of −7.80 percentage points annually (Table 7.8). However, winner funds simultaneously suffering both effects even underperform the four-factor benchmark by 1.44 percentage points in the following year, corresponding to a mean reversion of −12.24 percentage points. Thus, the alpha spread between both groups in the evaluation period is highly significant 3.60 percentage points. This combined effect is approximately equal to the sum of the separate effects, indicating that the equilibrium mechanisms, in the case of winner funds, are additive and neither magnify nor offset each other. About 37 percent of the mean reversion observed among winner funds can be explained by fund flows and manager changes. These results are not driven by differences in fee levels and hold on a gross management fee basis.

The results for losing funds are different. Based on the single sorting and judged by raw returns, loser funds benefiting from outflows outperform those not benefiting from outflows by significant 1.44 percentage points per year, implying that external governance is effective among loser funds (Table 7.11). However, an inspection of risk-adjusted returns reveals that the corresponding four-factor and mean-reversion-augmented five-factor alpha spreads are only 1.08 and 0.72 percentage points, respectively, and that both are not significant. This conflicts with the predictions of the Berk and Green (2004) model for loser funds and implies that outflows are mainly used to adjust factor loadings, i. e. to reduce unfavorable loadings on the last year's loser stocks that continue to underperform and the long-term winner stocks that suffer from stock-return mean reversion, but that outflows do not contribute to a mean reversion in true selection skills. Outflows do not seem to allow the existing fund managers to improve their performance from managing a smaller asset base. Manager changes, on the other hand, play a more important role in the governance of loser funds. Firing an underperforming manager significantly improves loser-fund performance by between 0.96 and 1.08 percentage points, on average, in the following year, depending on the exact model specification, relative to loser funds that keep the same manager. This performance reversal is even stronger when a large fund family fires an underperforming manager according to the regression results. Thus, if applied separately the more important equilibrium mechanism is internal (manager replacement) rather than external governance (outflows).

More important, however, is the finding that both governance mechanisms strongly reinforce each other and are more effective if applied simultaneously. The combined positive effect of 2.40 percentage points higher four-factor alphas compared to funds not benefiting from either governance mechanism is larger than the sum of the individual effects. Investment performance of loser funds benefiting from both effects simultaneously improves by 10.80 percentage points per year from the formation to the evaluation period while the performance of those not benefiting from outflows or a newly appointed manager only improves by 8.04 percentage points, due to the general tendency of mean reversion. This finding indicates that outflows cannot improve performance on their own, but that outflows strongly contribute to performance reversals and, hence, to mean reversion if the manager is also replaced. These results support the conjecture of Dangl, Wu, and Zechner (2008) that it is important to control for manager changes when analyzing the role of external governance (fund flows). Due to this strong interaction between internal and external governance about 27 percent of the observed mean reversion among loser funds can be explained by both mechanisms. Again, neither differences in fee levels nor other variables that affect fund performance can explain these results.

Instead of focusing on winner and loser funds separately, a further analysis focuses on how the equilibrium mechanisms affect the winner-minus-loser spread. Thus, the magnitude of performance persistence with and without changes in fund flows and manager changes is evaluated. The comparison of the winner-minus-loser spread reveals that both equilibrium mechanisms strongly contribute to performance persistence or mean reversion. The unconditional winner-minus-loser spread is 0.32 percentage points and only weakly significant at the ten percent level. However, when conditioning only on those winner and loser funds that are not exposed to both equilibrium mechanisms, the performance spread increases to 0.47 percentage points, highly significant at the one percent level and indicating strong performance persistence. In the case of those winner and loser funds that are exposed to both equilibrium mechanisms simultaneously, the corresponding spread is dramatically reduced to −0.03 and therefore virtually zero, suggesting that these mechanisms are an explanation for mean reversion and why mutual performance does not persist.

Chapter 8 analyzes capacity constraints in greater detail. The performance response of winner funds to manager replacements is documented to be relatively quick with a significant performance reversal over periods of between 3 and 24 months. With respect to fund flows, the strongest response of winner-fund performance to excessive inflows can be observed over holding periods of 12 months.

Interestingly, the fund-flow mechanism is much stronger among winner funds if fund portfolios are formed on past 24-month fund flows as compared to 12-month formation periods, implying that a higher level of accumulated fund flows results in a stronger performance reversal. Moreover, winner-fund performance suffers by more if inflows are higher. Thus, both a longer period of steady inflows and a higher level of inflows further reduce winner-fund performance. Among winner funds, the negative short-term effects of liquidity-induced trading reinforce the negative long-term effects of excessive inflows, leading to a strong impact on performance both over short and longer periods. Looking at how fund size is related to capacity constraints, the results suggest that small winner funds outperform large winner funds, consistent with the conclusions of Chen, Hong, Huang, and Kubik (2004). However, even small winner funds do not significantly beat the four-factor benchmark and the predictive power with respect to future performance of fund size is comparable to that of fund flows. Only if the selection of winner funds is conditioned on low inflows and a small fund size simultaneously, the resulting portfolio of funds outperforms the four-factor benchmark by significant 2.76 percentage points per year (Table 8.5).

The performance of loser funds significantly responds to a manager replacement that occurred over the previous year for holding periods of between 6 and 12 months. However, if the manager has been replaced at any time during the past 24 months, no difference in performance can be observed for loser funds with and without a manager replacement. The fund-flow mechanism remains insignificant for loser funds, irrespective of the length of the formation and evaluation periods. Moreover, even if only those loser funds with extremely high outflows are analyzed, performance still does not significantly improve. This might be explained by the opposing effects of outflows out of loser funds in the short- and long-term term. The negative impact of transaction costs due to liquidity-induced asset sales first has to be recouped before the beneficial impact of a smaller asset base can set in. Interestingly, the capacity effect documented by Chen, Hong, Huang, and Kubik (2004) does not apply to loser funds: small loser funds even slightly underperform large loser funds. Additionally conditioning on fund flows does not improve the results by much. Thus, it seems that capacity constraints, which explain why winner funds do not continue to outperform, cannot explain why loser funds continue to underperform. Only if outflows are combined with a manager replacement does loser-fund performance revert to neutral levels.

Conclusions and Outlook

An important conclusion from this study is that past performance is only an indicator for future performance if the manager is not replaced and if fund flows do not eliminate performance persistence, for both winner and loser funds. In a nutshell, this study provides a theoretical explanation and empirical evidence which is consistent with a lack of performance persistence, even in the presence of managerial skill. True investment skill seems to exist but all parties involved in delegated asset management respond to cross-sectional differences in skill and, by doing so, wipe out superior performance. In particular, capacity constraints seem to hinder superior fund managers' ability to consistently deliver these abnormal returns over time. Taking these factors into account, investment strategies that successfully and significantly beat the four-factor benchmark even after costs can be developed.[595] However, the same mechanisms explaining mean reversion among winner funds do not seem to be responsible for loser-fund underperformance. Rather, it has to be concluded that poor selection skills and some form of inertia, both among fund investors and the portfolio manager, explain why loser funds underperform. Investors are reluctant to withdraw significant amounts of money due to a disposition effect and continuing loser-fund managers are reluctant to use the outflows they experience, if any, to reorganize the portfolio, also due to a disposition effect. A manager replacement helps to release this inertia. Thus, while winner funds suffer from size loser funds benefit from change. However, these results also indicate that the dynamics of winner- and loser-fund performance are still dominated by randomness as indicated by the strongly mean-reverting characteristics of mutual fund performance. In fact, excellent past performance is often the result of something other than skill, namely chance, and extremely poor performance can be attributed to a large degree to bad luck rather than poor skill.

The empirical results of this study contribute to the understanding of the value of active management and even have implications for market efficiency. A fundamental problem of active mutual funds is, as discussed above, that these funds cannot create abnormal value for investors over the longer term, not because fund managers are unskilled but because the equilibrium mechanisms prevent them

[595] Indeed, conditioning on fund flows and manager replacements simultaneously yields risk-adjusted returns of 2.16 percent per year and conditioning on fund flows and fund size simultaneously yields risk-adjusted returns of 2.76 percent. Loads are not taken into account.

from doing so. Thus, the relevant questions for future research are if and how these skills can be translated into persistent abnormal returns for investors without sacrificing too many of the benefits of the open-end fund structure in order to better serve their clients' needs and help them to build up wealth for retirement savings or any other purpose.

With respect to manager changes it seems important to retain skilled managers at winner funds, for example by better aligning compensation to skills. However, too little is currently understood about the reasons or motives of top fund managers to leave, such that no specific recommendations can be given at this point. Because manager replacements are an important determinant of fund performance a requirement for the ad-hoc publication of manager changes might be an important and needed regulatory change. Currently, such information is only disseminated through the publication of (semi-) annual reports. Moreover, there might be a point for allowing the use of a fund manager's track record at a previously managed fund, clearly marked as such, in the marketing material of the fund currently managed by this manager because based on the results of this study, the personal track record might contain relevant information about investment skills. Currently, this is not allowed by the SEC. Future research on mutual fund performance needs to recognize that the fund and the portfolio manager are two separate entities, both contributing to fund performance, instead of treating the whole time series of each fund as one observation even if the fund manager changed several times over the lifetime of the fund. Thus, the construction of better data sets on fund managers might be needed.

In the case of underperforming funds, the benefits from a manager replacement are clear according to results presented in this study. However, the interpretation of this result is not so obvious. One the one hand, the new manager might simply have higher investment skills than the previous manager. On the other hand, the manager replacement might just end a period of manager inertia and even the old manager could have improved fund performance if he had started to react. Two conclusions follow. First, it seems important to improve internal governance mechanisms with respect to the supervision of fund managers. Perhaps the fund board should be given more rights to initiate a manager replacement. Currently, this is the sole responsibility of the investment management company or its management. Second, in the case of underperformance it seems especially important to make underperforming managers aware of potential behavioral biases in their investment decisions, such as a disposition effect, in an attempt to "wake them up". For example, frequently held internal investment committee meetings might put more focus on questioning the fund manager about why he decided to hold on to certain stocks rather than only questioning his "active" decisions of buying or selling stocks.

Finding a solution for the negative performance impact of fund flows is slightly more complicated because restricting flows inevitably reduces the efficiency of external governance which is an important mechanism to reduce agency conflicts present in delegated asset management and, at least theoretically, improves loser-fund performance. Thus, measures that reduce the negative flow impact should not reduce the liquidity of fund shares. One of these measures could be a greater use of derivatives to manage fund flows. Another approach might be to reduce fund flows by transferring part of the trading volume in fund shares to a secondary market such as a fund exchange. However, it is only if a market maker exists who is willing to hold fund shares overnight that the net inflows at the fund level are effectively reduced. This solution does not necessarily require exchange trading of mutual fund shares as long as any third party is willing to provide insurance to the fund against unexpected fund flows. For example, ReFlow provides such services in the U. S. by offering to buy and hold redeemed fund shares for a certain period against the payment of an annual fee by the fund. The exchange-traded fund structure also has some benefits with respect to the liquidity risk of the fund. Specifically, according to the creation and redemption in kind mechanism large inflows or outflows are not handled as a cash transaction but a basket of stocks is transferred between the market maker and the fund avoiding costly liquidity-induced transactions.[596] It is even possible to structure the institutional share class of a fund with in kind creation and redemption while the retail share class uses cash transactions, a solution that is patented by Vanguard.

However, all of these measures might reduce liquidity-induced trading without sacrificing market-based governance but cannot reduce the threat from capacity constraints to a large degree. This can only be done by providing incentives to the investment management company to close or soft-close a successful fund once it exceeds a certain size. A move from size-based to performance-based fees or co-ownership of the mutual fund manager might be needed to better align interests

[596] To be precise, the investors who demand liquidity have to take out these costly transactions so that the corresponding costs are allocated according to the cause.

with respect to fund size. To prevent the fund manager from becoming overly risk averse in the case of co-ownership, because his human capital already has a high loading on the market factor, it might be reasonable to hedge the systematic exposure in a way that his compensation only depends on alpha, in the sense of a “portable alpha”.

In a similar vein, it is questionable if the strict benchmark orientation currently present in the industry is the optimal way to set incentives. It results in a strong tendency to herd and the majority of fund managers do not deviate enough from their benchmark to generate abnormal returns. Usually, the benchmark serves three purposes: (1) it should provide a guide for the investors to understand the risk-return profile of the fund; (2) it should help investors to determine the correlation of the fund with the rest of their portfolio, which is closely related to understanding the risk-return profile; (3) it should allow investors to assess the relative performance of the fund managers. However, a clearly stated investment objective could also serve all of these purposes while still giving fund managers more flexibility in generating abnormal returns within their investment universe. These investment objectives could be defined by the regulator and compliance with the objectives could be monitored based on portfolio holdings that need to be disclosed to the regulator on a regular basis. For example, it would be possible to define very narrow investment objectives such as “European Health Care”, requiring that, for example, 80 percent of the portfolio are invested in European health care stocks, but also relatively flexible investment objectives such as “Global Equity”, only requiring that the fund invests at least 10 percent of its assets in each of at least five different countries or regions. Relative performance evaluation is still available by a comparison of fund performance with the peers in the same investment objective. Funds could be allowed to freely switch between investment objectives after a certain notice period. Moreover, this would avoid tactics such as gaming the benchmark. A drawback of this approach, however, might be that it hinders innovation in areas where no official investment objective exists as of yet. Moreover, an official classification of stocks in industries would be needed, which might be complicated and in some cases arbitrary. However, the same problem is prevalent in the case of the definition of a benchmark.

Behavioral finance, a relatively new research area that has recently gained in prominence, also seems to be important in explaining the dynamics of mutual fund performance, especially among loser funds. Both investors and fund managers do not seem to behave rationally in an economic sense.[597] Investors fail to withdraw money from underperforming funds and the managers of these funds fail to take action in order to restructure the fund. How manager inertia might be released has already been discussed above. However, it is also important to improve the economic behavior of fund investors, especially because a stronger response of investors to past poor performance could help to release fund manager inertia. The irrational behavior of investors might even by able to explain why a service not adding value to them on average in the long term still was able to survive for such a continued period. First and foremost, investors need better education to make well-informed investment decisions. Why not integrate personal finance into the school curriculum? Moreover, better information disclosure might improve investor behavior, for example with respect to fund flows and manager changes but also related to fee levels. However, information needs to be disclosed in a manner that enhances understanding rather than clouding it. For example, Morningstar assigns Stewardship Grades, which are easily comprehensible, taking into account factors such as a firm's corporate culture, the extent to which management owns its own funds, the firm's costs, and the quality of its board. However, based on a study by Choi, Laibson, and Madrian (2010) investors tend to make irrational choices among passive index mutual funds irrespective of whether they are given prospectuses summarizing the fund's risk profile, costs and past performance on a few pages or a detailed prospectus containing lots of information and fine print. Most investors failed to minimize fees which are the dominant performance determinant among index funds. Thus, as long as investors do not have a better financial education, independent and unbiased professional advice might be needed. To assure the unbiasedness of financial advisors, enhanced transparency and new compensation schemes are needed. The fee income of financial advisors needs to be paid directly by investors and not indirectly through kick-backs of the mutual fund they sell as is commonplace in many countries.

On a more general level, the results of this study provide a rationale for the trend to separate alpha and beta sources of performance. Mutual funds are mar-

[597] Tuckett and Taffler (2008, p. 389), drawing on psychoanalytic research, argue that "buying, holding or selling financial assets in conditions of inherent uncertainty and ambiguity [...] necessarily implies an ambivalent emotional and phantasy relationship to them". An unbearable contradiction in the asset management industry emerges from the promise to generate abnormal returns, which is continually reiterated, and the knowledge from academic research and the own academic education that only very few managers succeed in the generation of true alpha. This might explain part of the irrational behavior.

keted on the basis of being able to deliver both a diversified exposure to market risk and a positive alpha. The regulatory and operational environments as well as the resulting incentives, however, make it almost impossible to deliver alpha persistently over time, especially because the open-end structure requires a diversified and highly liquid portfolio. Specifically, active mutual funds cannot serve as an "all-in-one" device suitable for every purpose. One logical consequence is to look for funds that are more flexible to generate diversified and highly liquid market exposure such as exchange-traded funds. Combining these index products as a core with hedge funds as satellites might generate a portfolio with a similar risk-return profile to active mutual funds but with better opportunities to generate alpha for the investor. In this case, investors could satisfy their liquidity demand by selling some of the index funds while the alpha-generating hedge funds could impose redemption restrictions to protect their investment strategies without imposing high costs on their investors. Thus, the conventional active mutual fund is split into two separate portfolios, one regulated and highly liquid portfolio providing only market exposure and one more or less unregulated and less liquid portfolio potentially providing alpha.[598] A combination of both seems optimal for investors who believe in active management. For small retail investors, who face restrictions with respect to the lot size and might not be able to identify and select promising hedge funds, these strategies can be replicated by funds of funds.

Specifically, the level of delegation is higher in funds of funds as compared to single funds. Not only security selection and market timing decisions but also the tactical asset allocation is delegated to the fund manager. Even though the impact of the asset allocation decision on cross-sectional return differentials is lower than claimed by many, if the relevant studies are interpreted correctly, it is nevertheless approximately equally important as security selection. However, in many cases asset allocation decisions are still carelessly neglected by retail investors. Slightly exaggerated, the asset allocation of some retail investors is determined indirectly at the cashier's desk of their main bank, depending on which type of fund is on offer that day, rather than based on a detailed analysis of their personal and financial situation. This might also contribute to the observation that investor returns on average are below fund returns due to the inferior timing or tactical asset allocation decisions of fund investors. Thus, investors also need better advice with respect to the asset allocation. However, it seems important to

[598] Most hedge fund strategies do not separate pure alpha but also assume some market risk.

have separate managers for asset allocation (fund of funds) and security selection (single funds). First of all, both require different skills. For asset allocation decisions the competitive advantage of a successful portfolio manager mainly refers to a sophisticated set of forecasting models based on smaller sets of time series data. In contrast, the required skills of a successful stock picker are rather based on the ability to efficiently handle large sets of cross-sectional data while the forecasting models used tend to be less complex. Second, fund of funds managers might have the incentive to overweight single funds from the same fund family and to "smooth" the family's assets under management. In order to cater to different investor clienteles and to better align the fund's investment strategy with the investment objective of the investor base, it is possible to set up different funds of funds according to different levels of investors' risk tolerance.

The fund of funds structure, however, has the disadvantage that it cannot take into account individual characteristics of the investors, something that financial advisors at banks could theoretically do. Thus, an alternative would be to set up an individual fund of funds for each client with centralized management. Each client has an individual yet standardized account. Depending on certain input parameters such as the client's investment horizon and purpose, risk tolerance, outside risk and available income from other sources as well as the price level at which the client entered the market, the optimal asset allocation can be determined based on a computer algorithm. In this case, it would be possible to provide professional advice to retail clients on a small financial scale not only with respect to security selection but also with respect to the equally important asset allocation decision. The major advantage compared to the current structure, single funds and financial advisors that are mainly employed by banks, is that economies of scale can also be realized in the asset allocation due to the bundling of a very large number of investors.[599] Thus, even retail clients investing only small amounts of money can benefit from the advice of a highly skilled investment professional, something that is currently restricted to high net worth individuals.

This discussion shows that new concepts are needed for the successful future of delegated asset management, both from the perspective of investors and from the perspective of investment management companies. The currently unsatisfactory results of active investment products in most cases are due to the asset manage-

[599] For example, a financial advisor in conventional retail business may have 100 to 200 clients while this figure is around 30 to 40 clients per advisor in wealth management.

ment industry's structure and to a lesser degree due to the people working in the industry. Few active strategies seem to create genuine abnormal returns while the majority of investment products perform worse than passive products over the longer term. For those investors confident in their ability to identify funds of the former group it might still be rational to invest in active funds. All others should choose passive investing.

A Appendix

A.1 Factor-Mimicking Portfolios

Table A.1: Review of the literature on factor-mimicking portfolios

This table presents a review of the literature on risk-based and non-risk-based explanations for the empirical success of the three-factor model of Fama and French (1993) according to equation (3.22) and the four-factor model of Carhart (1997) according to equation (3.23). Studies which develop new factors or methodologies are marked by an asterisk (*).

Economic risk / explanation	References
(a) Risk-based explanations	
Time-varying asset composition	Berk, Green, and Naik (1999)
Business cycle / macroeconomic risk	Fama and French (1993), Chordia and Shivakumar (2002), Vassalou (2003)*, Vassalou and Xing (2004)
Default risk	Vassalou and Xing (2004), Avramov, Chordia, Jostova, and Philipov (2007), Arena, Haggard, and Yan (2008)
Liquidity risk	Amihud (2002), Pástor and Stambaugh (2003)*, Amihud, Mendelson, and Pedersen (2005), Chan and Faff (2005)*, Liu (2006)*, Miralles Marcelo and Miralles Quirós (2006)*, Sadka (2006), Keene and Peterson (2007)*
Higher moments	Ranaldo and Favre (2005)*, Chung, Johnson, and Schill (2006), Kostakis (2009)*
Idiosyncratic volatility	Ali, Hwang, and Trombley (2003), Drew, Naughton, and Veeraraghavan (2004)*, Ali and Trombley (2006), Arena, Haggard, and Yan (2008)
Stochastic expected growth rates	Johnson (2002), Avramov and Hore (2008)
Investments	Berk, Green, and Naik (1999)
Downside risk	Ang, Chen, and Xing (2006)*
Time-varying idiosyncratic volatility	Li, Miffre, Brooks, and O'Sullivan (2008)*
Foreign exchange risk	Kolari, Moorman, and Sorescu (2008)*

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Economic risk / explanation	References
(b) Behavioral explanations	
Extrapolation	Lakonishok, Shleifer, and Vishny (1994)
Underreaction	Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Albuquerque and Miao (2008)
Overreaction	De Bondt and Thaler (1985), De Bondt and Thaler (1987), Daniel, Hirshleifer, and Subrahmanyam (1998)
Fear of reversal	Wang (2008)
Overconfidence (market state)	Huang (2006)
(c) Microstructure / asymmetric information	
Trading volume	Lee and Swaminathan (2000)
Short sale constraints	insitutional ownership: Nagel (2005); idiosyncratic volatility: Ali and Trombley (2006), Arena, Haggard, and Yan (2008)
Transaction costs	Lesmond, Schill, and Zhou (2004), Korajczyk and Sadka (2004), Chelley-Steeley and Siganos (2008)
Analyst coverage	Hong, Lim, and Stein (2000)
(d) Methodological issues	
Micro caps	Fama and French (2008)
Migration	Fama and French (2007b)
Delisting returns	Eisdorfer (2008)
Industry effect	Moskowitz and Grinblatt (1999)
(e) Statistical issues	
Time-varying factor exposure	Ferson and Schadt (1996)*, Ferson and Qian (2005)*, Lewellen and Nagel (2006), Ang and Chen (2007)
Parameter estimation error	Hawawini and Keim (1995)
Spurious regression	Ferson, Sarkissian, and Simin (1999)

A.2 Sample Selection

Table A.2: Classification of investment objectives

This table presents the classification codes used to construct the sample. Lipper codes, Wiesenberger codes and Strategic Insight codes (priority is given in this order if different codes assign funds to different investment categories) are used to classify funds into the following three groups: (1) large- and mid-cap funds; (2) small-cap funds; (3) sector funds.

	Large- and mid-cap	Small-cap	Sector
Lipper	CA, EI, EIEI, G, GI, I, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE	SCCE	FS, H, NR, S, SESE, TK, TL, UT
Wiesenberger	AGG, G, G-I, G-I-S, G-S, G-S-I, GCI, GRI, GRO, I-G, I-G-S, I-S, I-S-G, IEQ, ING, LTG, MCG, S-G, S-G-I, S-I-G, S-I, I[a]	SCG	ENR, FIN, HLT, TCH, UTL
Strategic Insight	AGG, GMC, GRI, GRO, ING	SCG	ENV, FIN, HLT, NTR, SEC, TEC, UTI

[a] Note that Wiesenberger code I for income funds is not restricted to income equity funds but also contains income money market funds, income bond funds etc. Consequently a combination of Wiesenberger code I and policy code CS or I-S or Wiesenberger code I and an allocation to stocks of at least 50 percent is used as condition for funds to be included in the sample.

A.3 Alternative Estimation Methodologies

Table A.3: Factor loadings based on alternative estimation methodologies

This table presents the factor loadings for the decile portfolios 10 (winner) to 1 (loser) and a spread portfolio long in decile-10 funds and short in decile-1 funds for alternative estimation methodologies. Columns (1) to (4) report the factor loadings based on the four-factor model of Carhart (1997) according to equation (3.23). See the note to Table 6.15 for more explanation on the estimation methodologies. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. In the case of the GCT approach, ***, ** and * indicate significant differences from the coefficients of average funds at the 1%, 5%, and 10% levels, respectively. White (1980) heteroscedasticity-consistent standard errors are used for the regression coefficients.

	β_m	β_{smb}	β_{hml}	β_{mom}
Static	0.98^{***}	0.18^{***}	0.04^{***}	0.00
Time-varying (mean)	0.97^{***}	0.21^{***}	-0.01	0.04^{***}
Time-varying (SD)	0.05	0.04	0.08	0.04
10 concatenated	1.00^{***}	0.40^{***}	-0.24^{***}	0.14^{***}
1 concatenated	1.01^{***}	0.20^{***}	0.18^{***}	-0.04
10 GCT (average fund)	0.98^{***}	0.15^{***}	0.08^{***}	-0.01
10 GCT (decile)	1.01	0.40^{***}	-0.24^{***}	0.14^{***}
1 GCT (average fund)	0.98^{***}	0.17^{***}	0.04^{*}	0.00
1 GCT (decile)	1.01	0.19	0.19^{***}	-0.03
10 cross-section (mean)	0.98^{***}	0.22^{***}	0.01	0.01^{***}
10 cross-section (SD)	0.29	0.34	0.46	0.16
1 cross-section (mean)	1.02^{***}	0.25^{***}	0.02^{**}	0.05^{***}
1 cross-section (SD)	0.31	0.36	0.45	0.20
10 Bayesian alphas (mean)	0.99^{***}	0.26^{***}	-0.08^{***}	0.06^{***}
10 Bayesian alphas (SD)	0.27	0.35	0.43	0.19
1 Bayesian alphas (mean)	0.99^{***}	0.29^{***}	0.01^{***}	0.07^{***}
1 Bayesian alphas (SD)	0.29	0.37	0.40	0.20

A.4 Alternative Formation and Evaluation Periods

A.4.1 Winner Funds

To gain a more detailed understanding of how long it takes for fund flows into winner funds to accumulate to an economically significant amount and to determine the resulting difference in fund size between winner funds with higher-than-median inflows and those with lower-than-median inflows, fund flows and fund size are analyzed for the sorting on absolute and relative fund flows, respectively (Tables A.4 and A.5).

Absolute-Fund-Flows Sorting

For the absolute fund-flow sorting and 12-month formation periods, the fund size across the different evaluation periods is, as expected, comparable. Low-inflow funds are between 303.48 (12/36) and 556.21 million USD (12/1) in size and large-inflow funds are between 855.91 (12/36) and 1,106.51 million USD (12/24). This results in size differentials of between 379.28 (12/1) and 580.84 million USD (12/24). Also the differentials in fund flows between the low-inflow and high-inflow subgroups are comparable at between 23.73 (12/36) and 30.28 million USD (12/12) per month. This monthly differential accumulates over 12 months during the formation period but, due to the high persistence of fund flows, also continues to accumulate over the evaluation period. Thus, the longer the evaluation period, the higher the size differentials between low-inflow and high-inflow winner funds. Specifically, the size of low-inflow winner funds remains relatively constant at between 431.73 (12/36) and 561.27 million USD (12/12) in the evaluation period. In contrast, high-inflow funds grow to between 704.93 (12/1) and 1,809.02 million USD (12/36) due to continuing inflows over the evaluation period.

Based on the 24-month formation periods, the spread in fund size in the evaluation period is almost twice as large as the corresponding spread for 12-month formation periods.[600] This results primarily from the fact that in this case fund flows accumulate over 24 months rather than 12 months for the 12-month formation periods because the monthly spreads between low-inflow and high inflow funds are between 25.21 (24/1) and 34.11 million USD (24/24) which is comparable to the corresponding spread based on 12-month formation periods.[601]

[600] Compare the last columns in the upper and lower panels of Table A.4.
[601] Additionally, in the case of the 24-month formation period longer evaluation periods already correspond to larger size differentials in the formation period.

Table A.4: Characteristics of winner funds for alternative formation and evaluation periods (absolute flows)

This table presents the characteristics of decile-10 funds with lower than median absolute net inflows (10 low) and decile-10 funds with higher than median absolute net inflows (10 high) and the resulting spread portfolio. Columns (1) to (3) report the average fund size in millions USD in the formation period; columns (4) to (6) report average monthly absolute net inflows in millions USD in the formation period; Columns (7) to (9) report the average fund size in millions USD in the evaluation period; Rows denoted by m/n refer to formation periods of m months and holding periods of n months. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Formation period						Evaluation period		
	Fund size			Absolute net inflows			Fund size		
	10 low	10 high	10 low − 10 high	10 low	10 high	10 low − 10 high	10 low	10 high	10 low − 10 high
12 months formation									
12/1	556.21	935.49	−379.28***	−4.62	20.89	−25.51***	512.19	1,217.12	−704.93***
12/3	528.15	913.74	−385.59***	−4.68	21.45	−26.14***	522.39	1,235.15	−712.75***
12/6	510.29	931.44	−421.14***	−4.84	21.57	−26.41***	536.84	1,337.39	−800.56***
12/12	507.53	1,041.47	−533.95***	−4.50	25.78	−30.28***	561.27	1,596.60	−1,035.33***
12/24	525.67	1,106.51	−580.84***	−4.30	25.50	−29.81***	553.96	1,766.94	−1,212.98***
12/36	303.48	855.91	−552.43***	−3.15	20.58	−23.73***	431.73	1,809.02	−1,377.29***
24 months formation									
24/1	571.47	1,119.78	−548.31***	−1.37	23.84	−25.21***	546.46	1,958.30	−1,411.84***
24/3	542.77	1,099.06	−556.29***	−1.78	24.69	−26.47***	531.37	2,011.62	−1,480.25***
24/6	507.16	1,173.87	−666.70***	−2.23	26.87	−29.09***	531.02	2,118.93	−1,587.91***
24/12	439.53	1,300.15	−860.63***	−2.77	29.62	−32.39***	540.70	2,392.87	−1,852.16***
24/24	404.25	1,462.44	−1,058.19***	−2.62	31.49	−34.11***	530.74	2,873.90	−2,343.15***
24/36	460.96	1,362.05	−901.09***	−3.55	29.57	−33.12***	563.00	2,613.06	−2,050.06***

Relative-Fund-Flows Sorting

In the case of the relative-fund flow sorting, there is no clear pattern in size differentials in the evaluation period even though the performance pattern is similar to the one observed for absolute fund flows, though slightly weaker (Table A.5). Specifically, winner funds with high relative net inflows tend to be smaller in size during the formation period for all combinations of formation and evaluation periods. This is intuitive because especially small funds tend to attract inflows that are relatively large compared to their actual size.[602] However, across the different lengths of the evaluation periods there is no clear pattern in differentials in fund size or absolute net inflows during the formation period. Consequently, differences in evaluation-period fund size are not meaningful and differences in fund size do not seem to be the only explanation for the performance spread between low-inflow and high-inflow winner funds.

A.4.2 Loser Funds

To gain a more detailed understanding of how long it takes for outflows out of loser funds to accumulate to an economically significant amount and to determine the resulting difference in fund size between loser funds with lower-than-median inflows and those with higher-than-median inflows, fund flows and fund size are analyzed for the sorting on absolute and relative fund flows, respectively (Tables A.6 and A.7).

Absolute-Fund-Flows Sorting

Based on the absolute-fund-flow sorting, all low-inflow loser funds are significantly larger in fund size compared to their large-inflow counterparts during the formation period (Table A.6). Specifically, the fund size of low-absolute-inflow loser funds ranges from 635.95 (12/36) to 967.09 million USD (24/1) while the fund size of high-absolute-inflow loser funds ranges from 248.90 (24/36) to 593.03 million USD (12/12). The resulting size spreads are between 170.71 (12/24) and 690.67 million USD (24/1). Differences in monthly fund flows are between 13.09 (12/36) and 21.52 (12/24) million USD during the formation period. These differences in fund flows are, however, not large enough to reduce the asset base of low-inflow loser funds to a level that is smaller than the asset base of high-inflow

[602] In more technical terms: because absolute fund flows are scaled by fund size to obtain relative fund flows, large funds tend to be associated with low levels of relative fund flows.

Table A.5: Characteristics of winner funds for alternative formation and evaluation periods (relative flows)

This table presents the characteristics of decile-10 funds with lower than median relative net inflows (10 low) and decile-10 funds with higher than median relative net inflows (10 high) and the resulting spread portfolio. See the note to Table A.4 for more explanation.

	Formation period						Evaluation period		
	Fund size			Absolute net inflows			Fund size		
	10 low	10 high	10 low – 10 high	10 low	10 high	10 low – 10 high	10 low	10 high	10 low – 10 high
12 months formation									
12/1	814.03	632.61	181.42***	−0.73	17.49	−18.22***	874.34	858.05	16.29
12/3	791.02	631.79	159.23***	−0.95	18.35	−19.29***	883.10	878.31	4.78
12/6	782.94	658.34	124.60***	−2.12	19.36	−21.48***	924.69	954.77	−30.07
12/12	816.61	733.99	82.62**	−1.10	22.40	−23.50***	965.45	1,199.03	−233.59***
12/24	1,009.17	625.55	383.62***	0.58	20.69	−20.12***	1,297.78	1,046.23	251.55***
12/36	753.33	409.55	343.78***	−0.22	17.73	−17.95***	1,174.84	1,101.82	73.03*
24 months formation									
24/1	1,003.80	561.48	442.32***	5.63	16.35	−10.72***	1,319.98	1,190.23	129.75***
24/3	989.37	568.16	421.21***	5.79	17.22	−11.43***	1,331.76	1,218.70	113.06**
24/6	1,028.75	605.55	423.20***	5.82	19.71	−13.89***	1,379.22	1,278.97	100.24**
24/12	1,032.11	725.73	306.38***	5.29	23.44	−18.15***	1,410.91	1,535.48	−124.57**
24/24	1,075.83	794.34	281.49***	3.51	25.52	−22.01***	1,670.16	1,764.04	−93.88
24/36	967.35	860.61	106.74*	1.34	24.89	−23.55***	1,424.24	1,784.66	−360.42***

loser funds.[603] Thus, the monthly outflows of low-inflow loser funds of between 8.38 (24/1) and 12.16 million USD (12/24) may just not be large enough to make the Berk and Green (2004) mechanism work, even if these fund flows accumulate over 24 months which leads to a reduction in fund size of roughly 240 million USD ($24 \cdot \sim$10 million USD).

Relative-Fund-Flows Sorting

Based on the relative-fund-flow sorting, the picture reverses, especially for the 12-month formation periods (Table A.7). Low-inflow funds are now smaller in size or a of similar size compared to the high-inflow funds in the formation period. Differences in outflows between both groups of between 11.42 (12/36) and 19.71 million USD (12/24) contribute to an increase in this size differential. As a result, low-inflow funds are economically and statistically significantly smaller in the evaluation period compared to their high-inflow counterparts. The differences in size amount to 214.26 (12/1) to 398.60 million USD (12/12). However, as discussed in section 8.2.2, these differences in size do not result in a subsequent significant performance improvement. For the 24-month formation periods there is no systematic pattern in size differentials across the different lengths of the evaluation periods. Monthly differences in fund flows between the low-inflow and high-inflow subgroups amount to 10.33 (24/36) to 14.27 million USD (24/6). Again, low-inflow funds are, in most cases, smaller in the evaluation period than high-inflow funds and their fund size decreases by roughly 216 million USD ($24 \cdot \sim$9 million USD) over the formation period but this does not significantly affect fund performance.

[603] With one exception for 12-month formation and evaluation periods (12/12) where low-inflow funds are statistically and economically insignificant 20.62 million USD smaller than their high-inflow peers.

Table A.6: Characteristics of loser funds for alternative formation and evaluation periods (absolute flows)

This table presents the characteristics of decile-1 funds with lower than median absolute net inflows (1 low) and decile-1 funds with higher than median absolute net inflows (1 high) and the resulting spread portfolio. See the note to Table A.4 for more explanation.

	Formation period						Evaluation period		
	Fund size			Absolute net inflows			Fund size		
	1 low	1 high	1 low − 1 high	1 low	1 high	1 low − 1 high	1 low	1 high	1 low − 1 high
12 months formation									
12/1	878.44	418.51	459.93***	−9.37	8.77	−18.15***	684.33	493.73	190.60***
12/3	864.89	438.78	426.11***	−9.81	8.69	−18.50***	677.57	522.31	155.27***
12/6	791.76	466.48	325.29***	−10.11	8.54	−18.65***	653.23	545.64	107.59***
12/12	792.06	593.03	199.04***	−10.72	8.15	−18.87***	674.15	694.77	−20.62
12/24	931.76	761.05	170.71**	−12.16	9.36	−21.52***	795.84	707.53	88.31
12/36	635.95	387.16	248.78***	−8.80	4.29	−13.09***	504.74	471.65	33.09**
24 months formation									
24/1	967.09	276.42	690.67***	−8.38	6.24	−14.62***	699.29	373.89	325.39***
24/3	945.17	276.02	669.15***	−9.01	5.94	−14.95***	697.49	374.94	322.55***
24/6	887.38	304.36	583.02***	−9.47	6.52	−15.99***	684.31	422.51	261.81***
24/12	822.49	350.28	472.21***	−9.98	7.09	−17.07***	645.00	458.83	186.17***
24/24	835.24	444.66	390.58***	−11.46	4.99	−16.45***	726.01	392.48	333.53***
24/36	764.54	248.90	515.65***	−11.19	2.76	−13.96***	638.63	413.08	225.55***

Table A.7: Characteristics of loser funds for alternative formation and evaluation periods (relative flows)

This table presents the characteristics of decile-1 funds with lower than median relative net inflows (1 low) and decile-1 funds with higher than median relative net inflows (1 high) and the resulting spread portfolio. See the note to Table A.4 for more explanation.

	Formation period						Evaluation period		
	Fund size			Absolute net inflows			Fund size		
	1 low	1 high	1 low – 1 high	1 low	1 high	1 low – 1 high	1 low	1 high	1 low – 1 high
12 months formation									
12/1	632.24	676.61	−44.37**	−8.89	8.43	−17.32***	480.64	694.91	−214.26***
12/3	618.66	710.72	−92.06***	−9.23	8.08	−17.31***	488.90	706.16	−217.26***
12/6	577.09	704.73	−127.64***	−9.57	7.34	−16.91***	481.03	704.61	−223.58***
12/12	560.40	823.60	−263.20***	−9.66	7.09	−16.75***	481.26	879.86	−398.60***
12/24	689.32	1,003.69	−314.36***	−11.25	8.45	−19.71***	611.61	884.74	−273.13***
12/36	479.88	542.96	−63.08**	−7.97	3.46	−11.42***	370.49	595.24	−224.75***
24 months formation									
24/1	631.05	622.90	8.15	−7.93	5.88	−13.81***	463.65	605.47	−141.82***
24/3	632.38	613.23	19.15	−8.42	5.52	−13.94***	478.24	589.99	−111.76***
24/6	602.76	633.99	−31.22*	−8.69	5.59	−14.27***	472.20	625.53	−153.33***
24/12	599.89	618.60	−18.71	−8.58	5.43	−14.00***	497.44	600.03	−102.60***
24/24	745.61	526.34	219.27***	−9.96	3.98	−13.94***	626.50	492.19	134.30***
24/36	479.81	528.49	−48.68***	−9.76	0.57	−10.33***	407.70	616.98	−209.28***

A.5 Extreme Fund Flows and Fund Size

A.5.1 Winner Funds

Absolute-Fund-Flows Sorting

Based on the absolute-fund-flow sorting, funds in the high-inflow subgroup, on average, experience monthly net inflows of 37.14 million USD compared to −9.90 million USD net inflows for the low-inflow subgroup (Table A.8). Because fund flows tend to be highly persistent, low-inflow funds continue to have outflows of 4.15 million USD per month while high-inflow funds experience the inflow of 40.52 million USD new money per month during the evaluation period. Furthermore, low-inflow funds are smaller in size at 990.10 million USD as compared to 1,465.47 million USD for high-inflow funds in the formation period, a difference of 475.37 million USD. Due to the fund-flow differential, the spread in size increases to 1,160.49 million USD (1,067.35 versus 2,227.84 million USD) during the evaluation period. Manager replacements occur slightly more often in low-inflow funds (25 percent) than in high-inflow funds (23 percent). The remaining characteristics of both subgroups reveal a similar picture, such as in the case of the median split point: low-inflow funds have marginally higher fees (1.69 versus 1.60 percent per year) and portfolio turnover (100 versus 99 percent) and are on average 3.26 years older (14.03 versus 10.77 years).

Sorting on absolute net inflows over the previous 12 months and using the quintile as the split point results in a monthly fund-flow differential between the high-inflow and low-inflow subgroups of 47.03 million USD, more than 1.5 times as large as in the case of using the median as the split point, which results in a fund-flow differential of 30.28 million USD (Table 7.3). Thus, the total fund-flow differential over the 12-month formation period using the median split point is 363.36 million USD (12 · 30.28 million USD) as compared to 564.36 million USD (12 · 47.03 million USD) using the more extreme quintile split point. Using the median as the split point but 24-month formation periods results in a total fund-flow differential accumulated over the 24-month formation period of 777.36 million USD (24 · 32.39 million USD), which is again 38 percent higher as compared to the 12-month formation with the quintile as the split point and more than twice as large when compared to the median split point and 12-month formation (Table A.4). If only the total magnitude but not the time dimension is

Table A.8: Characteristics of winner-fund subgroups (extreme flows)

This table presents the characteristics for the winner-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows (quintile split point), on relative fund flows (quintile split point) or fund size. Panel (a) presents results for the formation period and panel (b) for the evaluation period. See the note to Figure 8.1 for more explanation on the portfolio formation and the note to Table 7.3 for more explanation on the column specification.

(a) Formation period

	Fund size	Fund age	Fees	Turn-over	Net in-flows	MC / fund
Conditional on absolute net inflows (quintile split point)						
10 low	990.10	14.03	1.69	1.00	−9.90	0.25
10 high	1,465.47	10.77	1.60	0.99	37.14	0.23
10 low − 10 high	−475.37***	3.26***	0.09***	0.01	−47.03***	–
Conditional on relative net inflows (quintile split point)						
10 low	650.13	11.90	1.78	1.33	−8.03	0.24
10 high	671.49	3.97	1.69	1.57	23.55	0.21
10 low − 10 high	−21.36	7.93***	0.10***	−0.24***	−31.58***	–
Conditional on fund size (median split point)						
10 small	41.09	6.01	1.79	1.53	1.42	0.19
10 large	1,468.21	13.25	1.60	0.94	19.92	0.23
10 small − 10 large	−1,427.12***	−7.24***	0.19***	0.59***	−18.50***	–

(b) Evaluation period

	Fund size	Fund age	Fees	Turn-over	Net in-flows	MC / fund
Conditional on absolute net inflows (quintile split point)						
10 low	1,067.35	15.04	1.68	0.94	−4.15	0.20
10 high	2,227.84	11.77	1.56	0.87	40.52	0.23
10 low − 10 high	−1,160.49***	3.27***	0.12***	0.08***	−44.67***	–
Conditional on relative net inflows (quintile split point)						
10 low	699.22	12.96	1.78	1.25	−2.50	0.18
10 high	1,109.50	4.97	1.65	1.41	25.23	0.21
10 low − 10 high	−410.28***	7.99***	0.13***	−0.16***	−27.73***	–
Conditional on fund size (median split point)						
10 small	88.71	7.01	1.78	1.43	4.11	0.18
10 large	2,021.08	14.25	1.57	0.87	24.89	0.22
10 small − 10 large	−1,932.37***	−7.24***	0.21***	0.56***	−20.78***	–

relevant in explaining the response of fund performance to past fund flows then the same ranking of the performance spreads between low-inflow and high-inflow funds would be expected for the three different cases.

Relative-Fund-Flows Sorting

For the sorting on relative net inflows, the fund-flow differential between low-inflow and high-inflow funds is slightly smaller compared to the sorting on absolute net inflows. High-inflow funds receive 23.55 million USD new money while low-inflow funds lose on average 8.03 million USD per month, resulting in a spread of 31.58 million USD. Though this spread has increased compared to the corresponding spread of 23.50 million USD for the median split point, most of the increase can be attributed to higher outflows of the low-inflow subgroup while the high-inflow subgroups in both cases receive a similar amount of money per month on average (22.40 million USD for the median split point and 23.55 million USD for the quintile split point). Still, fund flows are highly persistent during the evaluation period. Fund size is similar for low-inflow and high inflow funds during the formation period at 650.13 million USD for the former and 671.49 million USD for the latter, a spread of only 21.36 million USD. However, due to differences in fund flows this size differential increases to 410.28 million USD during the evaluation period. Thus, the sorting on relative net inflows should not be biased by differences in fund size that already exist during the formation period as the resulting size-differential can almost entirely be explained by differences in fund flows as the investors' response to past performance.

Fund-Size Sorting

Sorting funds into subgroups based on fund size yields quite different portfolios. Most notably, small funds are extremely small with only 41.09 million USD fund size on average during the formation period while large funds are on average 1,468.21 million USD in size. Moreover, small winner funds tend to have much lower absolute inflows of only 1.42 million USD per month compared to 19.92 million USD that are flowing into large winner funds. However, relative to the initial fund size, small funds grow by 41 percent (1.42/41.09) while large funds grow by only 16 percent per month (19.92/1,468.21). As a result of these inflows (and capital appreciation), small winner funds grow to 88.71 million USD in the evaluation period, which corresponds to more than a doubling in fund size compared to the formation period. Large winner funds grow to 2,021.08 million USD, an increase of 38 percent compared to the formation period. Note that only part of the difference in fund size between small and large funds of 1,932.37 million USD during the evaluation period can be explained by investors' response to past performance, i. e. fund flows. Most of this difference, 1,427.12 million USD, already existed during the formation period and therefore, the results on a size sorting only serve as a benchmark for a hypothetical extreme scenario of investors' response to past performance but are not a direct test of the Berk and Green (2004) hypothesis.[604] Consistent with the results of Karoui and Meier (2009), small funds tend to be younger on average (6.01 versus 13.25 years), charge higher fees (1.79 versus 1.60 percent) and have a higher portfolio turnover (153 versus 94 percent) compared to large funds. Finally, the replacement of the manager is slightly less likely for small winner funds (19 percent) than for large winner funds (23 percent).

Factor Loadings

An analysis of the factor loadings of the different winner-fund subgroups reveals that based on the fund-flow sorting there are no obvious differences when using the more extreme quintile split point (Table A.9) compared to the median split point (Table 7.6), irrespective of whether absolute or relative net inflows are used for the sorting. Funds with high inflows tend to have slightly lower market exposures than low-inflow winner funds of 1.03 compared to 1.00, consistent with managers holding part of the inflows as cash, when looking at the absolute-inflow sorting.[605] Surprisingly, winner funds with large absolute net inflows have higher small-cap exposures than winner funds with low net inflows (0.42 versus 0.34). This is opposite to the hypothesis that fund managers switch to large-cap stocks as part of the strategy to accommodate inflows because these stocks tend to be more liquid and the same absolute dollar amount makes up a smaller fraction of ownership among large-cap stocks as compared to small-cap stocks (Table 7.2). Furthermore, high-inflow funds are more focused on growth stocks than low-inflow funds with HML loadings of −0.30 compared to −0.17 and tend to hold more momentum winner stocks (0.18 versus 0.08). Presumably, the managers of high-inflow winner funds select past years winner stocks due to a lack of better investment ideas. Because

[604] Specifically, the results might be interpreted as a test of the second part of the Berk and Green (2004), that decreasing returns to scale do exist in active management, but not as a test of the first part that the extent of investors' response to past performance is large enough to explain mean reversion in subsequent fund performance.

[605] Factor loadings for the relative-net-inflow sorting are qualitatively similar. Thus, the following analysis focuses on the absolute-net-inflow sorting.

of the slightly higher risk exposures, high-inflow winner funds face a stronger benchmark, or higher expected returns, of 0.73 percent per month compared to their low-inflow counterparts at 0.67 percent per month. However, compared to the median split point there are no significant differences when using the stricter quintile split point.

Table A.9: Factor loadings of winner-fund subgroups (extreme flows)

This table presents the factor loadings for the winner-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows (quintile split point), on relative fund flows (quintile split point) or on fund size. See the note to Figure 8.1 for more explanation on the portfolio formation and the note to Table 6.5 for more explanation on the column specification.

	Factor loadings				$E(r)$	R^2
	β_m	β_{smb}	β_{hml}	β_{mom}		
Conditional on absolute net inflows (quintile split point)						
10 low	1.00^{***}	0.34^{***}	-0.17^{***}	0.08^{**}	0.67	0.92
10 high	1.03^{***}	0.42^{***}	-0.30^{***}	0.18^{***}	0.73	0.91
10 low − 10 high	−0.03	-0.08^{***}	0.14^{***}	-0.10^{***}	−0.06	0.39
Conditional on relative net inflows (quintile split point)						
10 low	0.99^{***}	0.37^{***}	-0.18^{***}	0.09^{***}	0.67	0.93
10 high	1.00^{***}	0.44^{***}	-0.27^{***}	0.16^{***}	0.71	0.92
10 low − 10 high	−0.01	-0.07^{***}	0.09^{**}	-0.07^{***}	−0.05	0.31
Conditional on fund size (median split point)						
10 small	0.97^{***}	0.41^{***}	-0.20^{***}	0.13^{***}	0.69	0.94
10 large	1.02^{***}	0.39^{***}	-0.27^{***}	0.14^{***}	0.70	0.92
10 small − 10 large	-0.05^{***}	0.02	0.07^{**}	−0.01	−0.01	0.16

Small and large winner funds do not differ much in their factor loadings. Large funds have slightly higher market exposures of 1.02 compared to 0.97 for small winner funds. The SMB loadings are comparable for both subgroups at 0.39 (large) and 0.41 (small). Thus, small funds do not seem to capitalize on their ability to hold more small-cap stocks and to benefit from a size premium if judged based on raw returns compared to funds which suffer from a larger asset base that eventually prevents them from investing in small companies. Moreover, large winner funds are slightly more heavily invested in growth stocks while the momentum loadings are again very similar for both subgroups between 0.13 (small) and 0.14 (large). As a result of the similar factor exposures, the expected returns for small and large winner funds are also comparable at 0.69 percent per month and 0.70 percent per month respectively. Thus, the higher raw returns of small winner funds do not seem to be a result of these funds holding riskier portfolios but rather stem from true selection skills.

A.5.2 Loser Funds

Absolute-Fund-Flows Sorting

Applying the more extreme quintile split point (instead of the median split point) between the high-inflow and low-inflow subgroups to loser funds yields distinct subgroups with larger differences in flows (Table A.10). Specifically, low-inflow loser funds experience outflows of 15.29 million USD per month in the formation period based on the absolute-fund-flow sorting compared to inflows of 12.47 million USD into the high-inflow loser funds. During the evaluation period, outflows out of the low-inflow subgroup are relatively persistent at 13.27 million USD while inflows into the high-inflow subgroup ebb up and are only marginally positive at 1.85 million USD per month. Due to these differences in fund flows low-inflow loser funds shrink in size from an average of 1,101.04 million USD during the formation period to 927.85 million USD during the evaluation period, a reduction of 173.19 million USD, while high-inflow loser funds continue to grow by 140.76 million USD over the same period, from 869.81 to 1,010.57 million USD. Low-inflow funds have a slightly higher likelihood of a manager replacement at 26 percent compared to 24 percent. The remaining characteristics are similar to the case of the median split point. Low-inflow funds are older (15.51 versus 8.62 years), have marginally lower fees (1.76 versus 1.80 percent per year) and significantly lower portfolio turnover (114 versus 179 percent) compared to high-inflow loser funds. Loser funds with extreme outflows seem to increase fee levels slightly by 0.02 percentage points from 1.76 to 1.78 percent per year during the evaluation period, potentially in an attempt to compensate for lost assets under management. Moreover, high-inflow loser funds reduce their portfolio turnover to 164 percent during the evaluation period.

A comparison of the outflows out of loser funds when using the quintile split point compared to the more modest median split point reveals that outflows are about 43 percent larger at 15.29 million USD in the case of the former compared to the latter, when outflows are only 10.72 million USD (Table 7.10). These numbers

Table A.10: Characteristics of loser-fund subgroups (extreme flows)

This table presents the characteristics for the loser-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows (quintile split point), on relative fund flows (quintile split point) or on fund size. Panel (a) presents results for the formation period and panel (b) for the evaluation period. See the note to Figure 8.1 for more explanation on the portfolio formation and the note to Table 7.3 for more explanation on the column specification.

(a) Formation period

	Fund size	Fund age	Fees	Turn-over	Net in-flows	MC / fund
Conditional on absolute net inflows (quintile split point)						
1 low	1,101.04	15.51	1.76	1.14	−15.29	0.26
1 high	869.81	8.62	1.80	1.79	12.47	0.24
1 low − 1 high	231.23***	6.89***	−0.04***	−0.64***	−27.76***	–
Conditional on relative net inflows (quintile split point)						
1 low	547.55	9.40	1.88	2.16	−10.35	0.24
1 high	730.80	5.15	1.82	2.24	11.71	0.24
1 low − 1 high	−183.25***	4.25***	0.06***	−0.08	−22.05***	–
Conditional on fund size (median split point)						
1 small	38.67	7.08	2.03	2.20	−0.19	0.20
1 large	1,329.18	13.86	1.72	1.08	−2.30	0.27
1 small − 1 large	−1,290.51***	−6.79***	0.30***	1.13***	2.11***	–

(b) Evaluation period

	Fund size	Fund age	Fees	Turn-over	Net in-flows	MC / fund
Conditional on absolute net inflows (quintile split point)						
1 low	927.85	16.53	1.78	1.13	−13.27	0.25
1 high	1,010.57	9.63	1.80	1.64	1.85	0.21
1 low − 1 high	−82.72	6.91***	−0.02**	−0.51***	−15.12***	–
Conditional on relative net inflows (quintile split point)						
1 low	460.85	10.57	1.88	2.05	−6.93	0.22
1 high	857.34	6.19	1.80	1.94	2.01	0.20
1 low − 1 high	−396.49***	4.38***	0.08***	0.11	−8.94***	–
Conditional on fund size (median split point)						
1 small	39.33	8.08	2.05	2.06	−0.01	0.16
1 large	1,295.87	14.86	1.72	1.10	−7.96	0.26
1 small − 1 large	−1,256.54***	−6.79***	0.32***	0.95***	7.96***	–

accumulate over the 12-month formation period to total outflows of 183.48 million USD ($12 \cdot 15.29$ million USD) compared to total outflows of 128.64 million USD ($12 \cdot 10.72$ million USD) for the median split point. Using a longer formation period of 24 months and the median as the split point results in total outflows accumulated over this 24-month period of 239.52 million USD ($24 \cdot 9.98$ million USD), which is again 31 percent larger compared to the 12-month formation with the quintile split point and even 86 percent larger compared to the base case with 12-month formation and the median split point. The corresponding fund-flow differentials between low-inflow and high-inflow funds are 266.44 ($12 \cdot 18.87$ million USD) for the base case of 12-month formation and the median split point, 333.12 million USD ($12 \cdot 27.76$ million USD), or 25 percent higher, for 12-month formation and the quintile split point and 409.68 million USD ($24 \cdot 17.07$ million USD), or again 23 percent higher, for 24-month formation and the median split point. Comparable to the argument in the case of winner funds a similar ranking in the performance impact of outflows on loser-fund performance would be expected if only the magnitude of fund flows is relevant in explaining the performance improvement. However, if the time dimension is also relevant, the ranking in performance might differ from the total-fund-flow ranking of the three cases discussed above.

Relative-Fund-Flows Sorting

Using relative net inflows as the variable for the second sorting instead of absolute net inflows reveals a similar picture with respect to most characteristics. Low-net-inflow funds experience outflows of 10.35 million USD per month while high-net-inflow loser funds receive on average 11.71 million USD new money, resulting in a fund-flow differential of 22.05 million USD per month. Though this spread is higher compared to the median split point, which resulted only in a fund flow differential between both subgroups of 16.75 million USD per month, most of this higher spread can be explained by larger inflows into high-inflow funds (11.71 versus 7.09 million USD) rather than larger outflows out of low-inflow funds (10.35 versus 9.66 million USD) (Table 7.10). During the evaluation period, outflows out of low-inflow loser funds based on the quintile split point even drop to 6.93 million USD compared to even higher continuing outflows of 7.33 million USD for the median split point. Again, positive net inflows into high-inflow loser funds significantly drop to only 2.01 million USD during the evaluation period. During the formation period, low-inflow funds are already smaller than high inflow funds by 183.25 million USD (547.55 versus 730.80 million USD). This size differential even widens to 396.49 million USD during the evaluation period due to differences in fund flows, because the asset base of low-inflow funds shrinks to 460.85 million USD while that of high-inflow loser funds increases to 857.34 million USD. Again, low-inflow funds are slightly older (9.40 versus 5.15 years) but charge marginally higher fees (1.88 versus 1.82 percent per year) compared to loser funds with high relative net inflows. Interestingly, the portfolio turnover, though comparable in magnitude across both subgroups, is significantly higher for lower funds with extreme inflows or outflows at 224 and 216 percent, respectively, compared to 163 percent for average loser funds (Table 6.1). This indicates that fund flows induce a high volume of liquidity-induced trades and that the portfolio turnover variable in the CRSP database captures much of this liquidity-induced trading even though it should only provide a measure of discretionary trades according to its definition.[606]

Fund-Size Sorting

Sorting on fund size instead of fund flows results in quite different portfolios. Small loser funds are extremely small at an average size of 38.67 million USD during the formation period while large loser funds have an asset base of on average 1,329.18 million USD. Net inflows are −0.19 million USD for small loser funds and −2.30 million USD for large loser funds, both less than 1 percent of their initial size and therefore negligible. Small loser funds are almost seven years younger (7.08 versus 13.86 years), charge significantly higher annual fees of 2.03 percent compared to 1.72 percent for large funds and also have a portfolio turnover which is more than twice as high as the portfolio turnover of large loser funds (220 versus 108 percent). However, manager replacements occur more often among large loser funds (27 percent) compared to small loser funds (20 percent). These results are indicative of strong governance problems among small loser funds. In general, loser funds are associated with larger fund families compared to winner funds. Specifically, the fund families of loser funds offer on average 26.32 funds in the same segment while families of winner funds only offer 20.51 (Table 6.1). Small loser funds belong to even larger fund families offering on average 29.25 other

[606] For a definition of portfolio turnover see the database guide which is available under http://www.crsp.com/products/mutual_funds.htm.

funds in the same segment.[607] These results are consistent with the argument of Ferris and Yan (2007a) that agency conflicts are less severe in small fund families that are run by the owners.

Factor Loadings

Next, the factor loadings of the different subgroups are discussed (Table A.11). The picture for the fund-flow subgroups is similar to the results based on the median split point for both absolute and relative net inflows. Low-absolute-net-inflow funds have significantly lower market exposures of 1.00 compared to 1.04 for high-inflow funds and significantly higher, i. e. less negative, momentum exposures of insignificant −0.01 compared to significantly negative −0.07, a highly significant spread of 0.06. In particular, the differences in momentum exposures lead to a stricter benchmark for low-inflow funds with an expected return of 0.70 percent per month compared to high-inflow funds that only face an expected return of 0.67 percent per month. This confirms the conclusion from above that loser funds with outflows primarily cut down their exposure to the last year's loser stocks which helps them to improve raw returns but not risk-adjusted returns once controlled for differences in momentum loadings. The same is true in the case of the loading on the mean-reversion factor.[608] For the absolute-fund-flow sorting, low-inflow loser funds have an insignificant loading of only −0.09 while those that do not benefit from outflows have a highly significant loading of −0.27, also a highly significant spread of 0.18. Thus, loser funds without outflows continue to suffer from the mean reversion of formerly outperforming stock holdings while loser funds with outflows have already reduced these holdings to an insignificant position.[609]

There are no obvious differences in factor loadings between small and large loser funds. The former have slightly lower market exposures (0.99 versus 1.02) but slightly higher small-cap loadings (0.22 versus 0.18), consistent with capacity constraints preventing large funds from investments in small-cap stocks. Also the value loading is slightly though insignificantly higher for small loser funds compared to large loser funds (0.21 versus 0.16) while momentum exposures are almost identical (−0.03 versus −0.04). Consequently, expected returns for both

[607] This result is not reported in the tables.
[608] This result is not reported in the tables.
[609] Focusing on the relative-net-inflow subgroups yields a similar impression. The momentum loading of low-inflow funds is neutral at 0.00 while high-inflow funds have a negative loading of −0.06, a significant spread of 0.06. Similarly, the mean-reversion loading of low-inflow funds is insignificant at −0.05 while that of high-inflow funds is significantly negative at −0.26, resulting in a significant spread of 0.21.

Table A.11: Factor loadings of loser-fund subgroups (extreme flows)

This table presents the factor loadings for the loser-fund subgroups and the resulting spread portfolios based on a single sorting on absolute fund flows (quintile split point), on relative fund flows (quintile split point) or on fund size. See the note to Figure 8.1 for more explanation on the portfolio formation and the note to Table 6.5 for more explanation on the column specification.

	Factor loadings				$E(r)$	R^2
	β_m	β_{smb}	β_{hml}	β_{mom}		
Conditional on absolute net inflows (quintile split point)						
1 low	1.00^{***}	0.19^{***}	0.19^{***}	-0.01	0.70	0.89
1 high	1.04^{***}	0.18^{***}	0.18^{***}	-0.07^{**}	0.67	0.88
1 low − 1 high	-0.04^{**}	0.01	0.01	0.06^{***}	0.03	0.14
Conditional on relative net inflows (quintile split point)						
1 low	0.98^{***}	0.20^{***}	0.21^{***}	-0.00	0.71	0.89
1 high	1.03^{***}	0.18^{***}	0.18^{***}	-0.06^{**}	0.67	0.88
1 low − 1 high	-0.05^{**}	0.02	0.03	0.06^{***}	0.04	0.17
Conditional on fund size (median split point)						
1 small	0.99^{***}	0.22^{***}	0.21^{***}	-0.03	0.69	0.89
1 large	1.02^{***}	0.18^{***}	0.16^{***}	-0.04	0.68	0.90
1 small − 1 large	-0.04^{**}	0.04^{*}	0.05	0.01	0.01	0.08

subgroups are also very similar with 0.69 percent per month for small loser funds and 0.68 for large loser funds. These results confirm that fund size is not an important determinant in explaining differences across the loser-fund subgroups based on the fund-size sorting. Neither raw returns nor factor loadings, and as a result risk-adjusted return, differ much between small and large loser funds. Thus, capacity constraints do not seem to be responsible for the underperformance or potential improvements in performance, i. e. the tendency of loser-fund performance to revert to the mean.

A.6 Interaction of Fund Flows and Fund Size

This section analyzes the composition of the individual subgroups. Table A.12 presents in panel (a) how winner funds and in panel (b) how loser funds are allocated to the four subgroups when using absolute fund flows and fund size in the double sorting. Winner funds tend to receive positive net inflows and the larger funds receive higher levels of inflows on an absolute scale. Thus, among winner funds, there are more funds on the main diagonal as compared to the secondary diagonal: 61 percent (31.16/51.16) of the large winner funds at the same time belong to the subgroup with high absolute net inflows while only 39 percent (20.00/51.16) of the large winner funds have low absolute net inflows. Also, 61 percent (29.87/48.84) of the small winner funds belong to the subgroup with low net inflows and only 39 percent (18.97/48.84) of small winner funds receive high absolute net inflows. The results for loser funds are similar, even though more loser funds are on the secondary diagonal as compared to the main diagonal because they experience outflows on average: 62 percent (31.26/50.53) of the large loser funds at the same time experience large absolute outflows, i. e. low absolute net inflows, while 38 percent (19.28/50.53) receive small absolute outflows. Out of the small loser funds, 62 percent (30.84/49.47) have only low absolute outflows, i. e. high absolute net inflows, while the remaining 38 percent (18.63/30.84) of small loser funds have large absolute outflows.

Table A.12: Composition of absolute-fund-flow and fund-size subgroups

This table presents in panel (a) the share of decile-10 funds and in panel (b) the share of decile-1 funds in the low-absolute-fund-flow (low) and high-absolute-fund-flow (high) subgroup and in the small-fund-size (small) and large-fund-size (large) subgroup, respectively, based on the total number of fund months on the sample. See the note to Figure 8.2 for more explanation on the portfolio formation.

(a) Decile-10 funds

Net	Fund size		
inflows	10 small	10 large	Sum
10 low	29.87	20.00	49.87
10 high	18.97	31.16	50.13
Sum	48.84	51.16	100.00

(b) Decile-1 funds

Net	Fund size		
inflows	1 small	1 large	Sum
1 low	18.63	31.26	49.88
1 high	30.84	19.28	50.12
Sum	49.47	50.53	100.00

In the case of the double sorting on relative net inflows and fund size, funds are more evenly allocated to the four categories. This is because both large and small funds are likely to have high or low net inflows relative to their asset base. However, very high levels of relative inflows or outflows are more likely among small funds because fund size is used to scale absolute net inflows in order to compute relative net inflows.[610] Consequently, out of the small winner funds 55 percent (26.96/48.84) have high relative inflows while only 45 percent (21.88/48.84) experience small relative net inflows (Table A.13). In the case of large winner funds, a smaller proportion of only 45 percent (23.17/51.16) receives high relative inflows and 55 percent of the funds receive small relative inflows. Thus, a few more funds are on the secondary diagonal as compared to the main diagonal in panel (a) of Table A.13. Interestingly, the picture slightly reverses for loser funds. Only 48 percent (23.93/49.47) of small loser funds have higher than median relative outflows, i. e. low relative net inflows, while 52 percent (25.54/49.47) of small loser funds have lower than median relative outflows. Thus, among small loser funds the numerator effect, i. e. smaller absolute outflows, seems to dominate the denominator effect of a smaller fund size. Consequently, a higher fraction of large loser funds (51 percent or 25.95/50.53) has high relative outflows, i. e. low relative net inflows, while only 49 percent (24.58/50.53) of large loser funds have low relative outflows.

Table A.13: Composition of relative-fund-flow and fund-size subgroups

This table presents in panel (a) the share of decile-10 funds and in panel (b) the share of decile-1 funds in the low-relative-fund-flow (low) and high-relative-fund-flow (high) subgroup and in the small-fund-size (small) and large-fund-size (large) subgroup, respectively, based on the total number of fund months on the sample. See the note to Figure 8.2 for more explanation on the portfolio formation

(a) Decile-10 funds

Net	Fund size		
inflows	10 small	10 large	Sum
10 low	21.88	27.99	49.87
10 high	26.96	23.17	50.13
Sum	48.84	51.16	100.00

(b) Decile-1 funds

Net	Fund size		
inflows	1 small	1 large	Sum
1 low	23.93	25.95	49.88
1 high	25.54	24.58	50.12
Sum	49.47	50.53	100.00

[610] See equation (4.2) for a definition of relative net inflows.

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