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Multicriteria Portfolio Management

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Preface

The globalization of financial markets, the intensifying competition among financial institutions and organizations, and rapid economic and technological changes have led to increasing uncertainty and instability in financial and business environments. Within this new context, financial engineering—that is, the formulation of creative solutions to financial decision-making problems and the development and implementation of innovative financial instruments—has become more essential than ever before.

The classic financial theory provides the necessary theoretical framework for understanding the operation and behavior of financial institutions and financial markets. It constitutes the founding basis for modeling the decisions taken within these entities. During the early 1950s, with the work of Markowitz on portfolio selection, the first attempt was made to apply sophisticated operational tools and approaches to the study of financial decision problems within a more practical context.

Since then, the tools, techniques, and approaches used in financial engineering have been mainly oriented toward modeling financial problems from the optimization point of view (e.g., stochastic optimization, dynamic and nonlinear programming, network optimization). Recently, financial researchers and practitioners and operations researchers have started to exploit the advances in other scientific fields, such as multicriteria decision analysis.

The in-depth study of this new approach led to the development of multicriteria portfolio management, which constitutes a promising approach that enables financial researchers and practitioners to delve into financial decision-making problems within a more realistic, flexible, and integrated context. Following this methodological approach, the aim of this book is to provide a comprehensive presentation of the contribution of multicriteria analysis in all stages of current portfolio management.

The target audience of the proposed book includes a diversified group of readers, such as portfolio managers, financial managers, economists, bankers, accountants,

and venture capitalists as well as management scientists, operations researchers, decision analysts, computer scientists, and risk analysts. The book can also be used as a textbook for graduate courses of finance, business administration and decision sciences.

January 27, 2012

The Authors

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Chapter 1

Introduction

The disastrous impact of the recent worldwide financial crisis in the global economy has shown how vulnerable international markets are to the massive shocks that are, with increasing frequency, afflicting existing financial structures. The insufficiency of our models and tools to effectively intercept the overwhelming consequences of the decline is the starting point for reconsidering and revising the way of thinking and acting we have so far adopted.

Within this new reality, it is necessary for academic researchers and industry practitioners to acknowledge the imperative demand for addressing the profound complexity of financial decision processes through integrated, robust, realistic approaches based on even more productive models and techniques. The intensifying instability and uncertainty that prevail in the markets can be efficiently confronted only if we agree to recognize the need for redesigning and reengineering existing portfolio management (PM) methods and tools while proceeding to the invention of new and more powerful ones.

Under this rationale, three strong necessities become apparent.

1. Enhancement of current PM processes and ontologies.
2. Improvement of the effectiveness of contemporary portfolio engineering models.
3. Augmentation of the operational transparency and compliance within PM practice.

It is obvious that a clear hysteresis exists in totally acknowledging the complexity and singularities of modern PM along with the predicament of the current economic climate. Hence, the financial industry should advocate for the necessity of initializing integrated theoretical and practical frameworks to support both active and passive investment decisions that concern the ill-structured nature of the portfolio engineering process. Overall, it should fortify approaches designed to be fully integrated across all investment functions, from security selection and portfolio construction to performance evaluation and portfolio rebalancing.

The ultimate milestone might be aiming for and engineering portfolios that offer consistent outperformance relative to underlying benchmarks, with strict control of portfolio risk.

The methods, models, and analytics that are presented in this book seek to fulfill the identified necessity and substantially contribute to the global prosperity, acknowledging the complexity and singularities of modern financial decision-making, along with the predicament of the current economic climate.

All of these tools do have, to some extent, a major theoretical issue in common: modern portfolio theory (MPT). A fundamental principle of MPT is that comparisons between portfolios are generally made using two criteria corresponding to the first two moments of return distributions: the expected return and portfolio variance. According to this model and most portfolio models derived from the stochastic dominance approach, the group of portfolios open to comparisons is divided into two parts: (1) efficient portfolios (those that are not dominated by any other portfolio in the group) and (2) dominated portfolios. In other words, these models do not solve for one optimal portfolio but, rather, solve for an efficient set of portfolios, among which the investor must choose, given his or her preference system.

One criticism of these models, which has been addressed by both practitioners and academics, is that they fail to embody the objectives of the decision-maker (DM) through the various stages of the decision process. Our purpose in this book is to present an integrated and innovative methodological approach for the construction and selection of equity portfolios. The approach takes into account the inherent multidimensional nature of the problem while allowing the DM to incorporate his or her preferences in the decision process.

According to the conventional theory of finance, maximizing return with minimum risk should be a milestone of every rational investor. Contrary to the theoretical expectations of the conventional theory, however, tests on most financial markets have revealed the existence of other variables. Moreover, behavioral aspects, such as the investor's attitude to solvency or liquidity, are not taken into consideration. Under this rationale, the problem of selecting an attractive portfolio is a multicriteria issue, which should be tackled by using the appropriate techniques.

In financial theory, models allowing the selection of an optimal portfolio are all inspired from the classic theory of Markowitz (1952, 1959), which is exclusively based on the criteria of expected value and variance of the return distribution. In this regard, an investor considers expected return as desirable and variance of return as undesirable. The Markowitz theory describes how we calculate a portfolio that exhibits the highest expected return for a given level of risk or the lowest risk for a given level of expected return (efficient portfolio). According to the theory, the problem of portfolio selection, then, is a single-objective quadratic programming problem that consists in minimizing risk while keeping in mind an expected return, which should be guaranteed. Thus, the solution of the original biobjective model is reduced to the parametric solution of a single objective problem, providing efficient (or Pareto optimal) portfolios.

The fragility of the base hypotheses of the Markowitz model was the starting point for some of the criticisms aimed at this model. In this respect, to obtain the set

of the efficient portfolios within the framework of the mean-variance model, it is important to point out that at least one of the two following hypotheses must be verified: (a) that of a quadratic utility function to represent the investor's preferences, and (b) that of the normal distribution of a stock's returns. The Markowitz model was also a target for other criticisms inherent to the difficulty of its implementation arising from the very high number of parameters it requires. For example, regarding the computation of the correlation matrix, more than 11,000 correlation coefficients should be estimated, when considering, for example, 150 securities. Together with all of these criticisms, one of the model's most serious insufficiencies is that it leads to mathematical problems that are not always representative of reality because (a) the comparison of several possible actions is rarely made according to one single criterion, (b) in many cases, the preferences over a criterion can hardly be modeled by a function, and (c) when there are several objectives, it is impossible to reach them all at once. At this level, the simplification suggested by Sharpe (1963) was obvious, but it generated more serious problems (i.e., the hypothesis of residual independence generates an underevaluation or overevaluation of the variance depending, respectively, on whether the covariances dealt with are positives or negatives).

Multiple criteria decision-making (MCDM)—the field of operational research (OR) that deals with problems that involve multiple criteria—provides a sound methodological basis for resolving the inherent multicriteria nature of portfolio selection problem. As the conventional approach seems necessary but not sufficient to manage portfolio selection efficiently, the main contribution of the MCDM framework is related to the following key issues: (a) When exploiting the MCDM advantage, there is the potential for more realistic models to be built by taking into account, apart of the two basic criteria of return and risk, a number of important other criteria—additional statistical measures of the variation of return, such as the value at risk (VaR) and the skew measures, criteria that are founded in the theory of fundamental analysis, [such as the security's dividend yield and the P/E price to earnings (P/E) ratio] or criteria related to stock market characteristics and behavior of securities, such as the capitalization rate and the b (beta) and a (alpha) coefficients among others. (b) The classic approach imposes a norm on the investor's behavior that can be restrictive as it cannot incorporate his or her individual goals, personal preferences, and attitudes toward risk. The MCDM framework has the advantage of taking into account the specific preference system of any particular investor while allowing for synthesizing in a single procedure all the theoretical and practical aspects of the PM theory.

In this book, we strongly advocate for the necessity of a multicriteria approach to address the problem of portfolio construction and selection, taking into account: (a) the limits related to the Markowitz conventional theory, the results from the estimation of the models, and the philosophy of the single-objective optimization approach; and (b) the behavior of investors, who, in addition to the above-mentioned anomalies, could have additional criteria in mind, beyond risk and return. To address all the above issues effectively, this book presents an integrated and innovative methodological approach, within the frame of MCDM, for constructing and selecting equity portfolios.

The book proceeds as follows. In Chap. 2 we present the fundamental issues that govern the conjoint field of multicriteria decision-making framework and portfolio management. In Chaps. 3–5, we delve into the three most significant phases of portfolio management (i.e., stock evaluation, portfolio optimization, and portfolio performance evaluation phases). In Chap. 6, we develop the basic principles exploited in professional asset management. Finally, the conclusions are given in Chap. 7.

Chapter 2

Multicriteria Portfolio Management

2.1 Introduction

The portfolio management process is an integrated set of steps undertaken in a consistent manner to create and maintain an appropriate portfolio (combination of assets) to meet clients' stated goals (Maginn et al. 2007). The three fundamental elements in managing any business process are planning, execution, and feedback. The same steps form the basis for the portfolio management (PM) process. During the planning step, investment objectives and policies are formulated, capital market expectations are formed, and strategic asset allocations are established. During the execution step, the manager constructs the portfolio and integrates investment strategies with capital market expectations to select specific assets for the portfolio. Finally, during the feedback step, the manager monitors and evaluates the portfolio compared with the plan. Any changes suggested by the feedback must be examined carefully to ensure that they represent long-run considerations. It is profound that the portfolio management process has several dimensions. As will be proved, the framework of multiple criteria decision-making (MCDM) provides a solid methodological basis for resolving the inherent multicriteria nature of this problem.

The emphasis in this chapter is on a detailed literature review of the studies in the field of PM within the MCDM framework. The chapter proceeds as follows: We first set up the problem by analyzing the PM process, stressing the need to model the problem using multicriteria analysis. We then summarize some of the most important MCDM methodological frameworks, followed by providing an elaborate review of the coherent studies relevant to the PM problem in the MCDM context. We conclude the chapter by discussing the benefits of exploiting the MCDM modeling approach.

2.2 Problem Setting

2.2.1 *Modern Portfolio Theory*

Modern portfolio theory (MPT) is a theory of investment that attempts to maximize portfolio expected return for a given amount of portfolio risk or, equivalently, minimize risk for a given level of expected return, by carefully choosing the proportions of various assets. Although MPT is widely used in practice in the financial industry, in recent years the basic assumptions of MPT have been widely challenged by such fields as behavioral economics.

The MPT is a mathematical formulation of the concept of diversification in investing, with the aim of selecting a collection of investment assets that has collectively lower risk than any individual asset. That this is possible can be seen intuitively because different types of assets often change in value in opposite ways. For example, to the extent prices in the stock market move differently from prices in the bond market, a collection of both types of assets can in theory face lower overall risk than either individually. However, diversification lowers risk even if assets' returns are not negatively correlated.

More technically, MPT models an asset's return as a normally distributed function (or more generally as an elliptically distributed random variable), defines risk as the standard deviation of return, and models a portfolio as a weighted combination of assets so that the return of a portfolio is the weighted combination of the assets' returns. By combining different assets whose returns are not perfectly positively correlated, MPT seeks to reduce the total variance of the portfolio return. MPT also assumes that investors are rational, and markets are efficient.

The MPT, developed during the 1950s through the early 1970s, was considered an important advance in the mathematical modeling of finance. Since then, many theoretical and practical criticisms have been leveled against it. They include the fact that financial returns do not follow a Gaussian distribution or indeed any symmetrical distribution, and that correlations between asset classes are not fixed but can vary depending on external events (especially during crises). There is also growing evidence that investors are not rational, and markets are not efficient.

The fundamental concept behind MPT is that the assets in an investment portfolio should not be selected individually, each on its own merits. Rather, it is important to consider how each asset changes in price relative to how every other asset in the portfolio changes in price. Investing is a trade-off between risk and expected return. In general, assets with higher expected returns are riskier. For a given amount of risk, MPT describes how to select a portfolio with the highest possible expected return. Alternatively, for a given expected return, MPT explains how to select a portfolio with the lowest possible risk (the targeted expected return cannot be more than the highest-returning available security, of course, unless negative holdings of assets are possible). Therefore, MPT is a form of diversification. Under certain assumptions and for specific quantitative definitions of risk and return, MPT explains how to find the best possible diversification strategy.

An investor can reduce portfolio risk simply by holding combinations of instruments that are not perfectly positively correlated (correlation coefficient). In other words, investors can reduce their exposure to individual asset risk by holding a diversified portfolio of assets. Diversification may allow for the same portfolio expected return with reduced risk. These ideas started with Markowitz and were reinforced by other economists and mathematicians who have expressed ideas in the limitation of variance through portfolio theory. If all asset pairs have correlations of zero (perfectly uncorrelated), the portfolio's return variance is the sum of all assets of the square of the fraction held in the asset times the asset's return variance (and the portfolio standard deviation is the square root of this sum).

Despite its theoretical importance, critics of MPT question whether it is an ideal investing strategy because its model of financial markets does not match the real world in many ways. Efforts to translate the theoretical foundation into a viable portfolio construction algorithm have been plagued by technical difficulties stemming from the instability of the original optimization problem with respect to the available data. Recent research has shown that instabilities of this type disappear when a regularizing constraint or penalty term is incorporated into the optimization procedure.

The framework of MPT makes many assumptions about investors and markets. Some are explicit in the equations, such as the use of normal distributions to model returns. Others are implicit, such as the neglect of taxes and transaction fees. None of these assumptions is entirely true, and each compromises MPT to some degree. The basic MPT assumptions are as follows.

1. Investors are interested in the optimization problem described above (maximizing the mean for a given variance). In reality, investors have utility functions that may be sensitive to higher moments of the distribution of the returns. For the investors to use the mean variance optimization, one must suppose that the combination of utility and returns make optimization of the utility problem similar to the mean variance optimization problem. A quadratic utility without any assumption about returns is sufficient. Another assumption is to use exponential utility and normal distribution, as discussed below.
2. Asset returns are (jointly) normally distributed random variables. In fact, it is frequently observed that returns in equity and other markets are not normally distributed. Large swings (3–6 standard deviations from the mean) occur in the market far more frequently than the normal distribution assumption would predict. Although the model can also be justified by assuming any return distribution is jointly elliptical, all the joint elliptical distributions are symmetrical whereas asset returns empirically are not.
3. Correlations between assets are fixed and constant forever. Correlations depend on systemic relations between the underlying assets and change when these relations change. Examples include one country declaring war on another or a general market crash. During times of financial crisis, all assets tend to become positively correlated because they all move (down) together. In other words, MPT breaks down precisely when investors are most in need of protection from risk.

4. All investors aim to maximize economic utility (in other words, to make as much money as possible, regardless of any other considerations). This is a key assumption of the efficient market hypothesis, upon which MPT relies.
5. All investors are rational and risk-averse. This is another assumption of the efficient market hypothesis, but we now know from behavioral economics that market participants are not rational. It does not allow for “herd behavior” or investors who will accept lower returns for higher risk. Casino gamblers clearly pay for risk, and it is possible that some stock traders pay for risk as well.
6. All investors have access to the same information at the same time. In fact, real markets contain information asymmetry, insider trading, and those who are simply better informed than others. Moreover, estimating the mean (e.g., there is no consistent estimator of the drift of a Brownian movement when subsampling is between 0 and T) and the covariance matrix of the returns (when the number of assets is of the same order of the number of periods) is a difficult statistical task.
7. Investors have an accurate conception of possible returns; that is, the probability beliefs of investors match the true distribution of returns. A different possibility is that investors’ expectations are biased, causing market prices to be informationally inefficient.
8. There are no taxes or transaction costs. Real financial products are subject both to taxes and transaction costs (e.g., broker fees), and taking these into account alters the composition of the optimum portfolio. These assumptions can be relaxed with more complicated versions of the model.
9. All investors are price takers; that is, their actions do not influence prices. In reality, sufficiently large sales or purchases of individual assets can shift market prices for that asset and others (via cross-elasticity of demand). An investor may not even be able to assemble the theoretically optimal portfolio if the market moves too much while they are buying the required securities.
10. Any investor can lend and borrow an unlimited amount at the risk free rate of interest. In reality, every investor has a credit limit.
11. All securities can be divided into parcels of any size. In reality, fractional shares usually cannot be bought or sold, and some assets have a minimum order size.

More complex versions of MPT can take into account a more sophisticated model of the world (such as one with nonnormal distributions and taxes), but almost all mathematical models of finance still rely on many unrealistic premises.

2.2.2 Portfolio Management as a Process

After the presentation of MPT fundamental issues, we proceed with defining the PM concept as a process. According to Maginn et al. (2007), PM is an ongoing process in which: (a) investment objectives and constraints are identified and

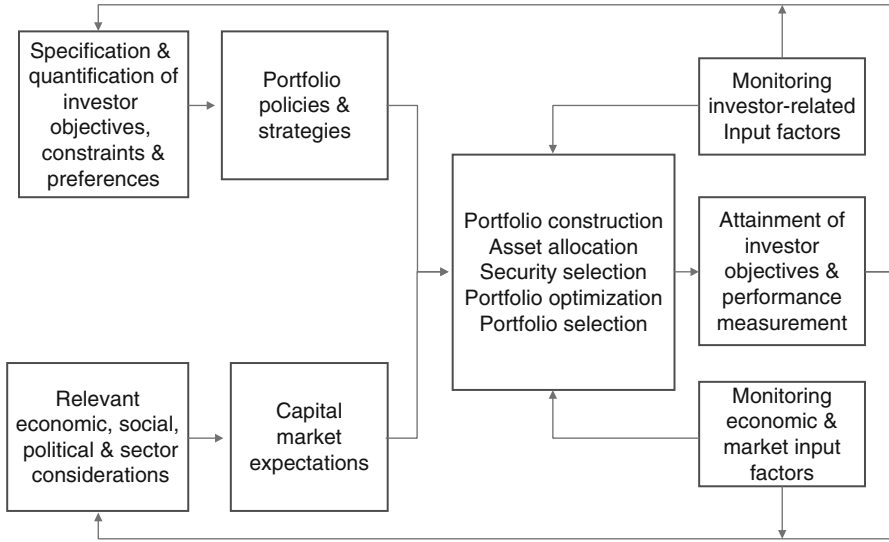


Fig. 2.1 Portfolio management process (Maginn et al. 2007)

specified; (b) investment strategies are developed; (c) portfolio composition is decided in detail; (d) portfolio decisions are initiated by portfolio managers and implemented by traders; (e) portfolio performance is measured and evaluated; (f) investor and market conditions are monitored; and (g) any necessary rebalancing is implemented. As stated previously, the PM process is an integrated set of three steps: planning, execution, and feedback (see Fig. 2.1).

In the planning step, portfolio managers formulate investment objectives and policies, assess capital market expectations, and establish strategic asset allocations. The investment policy statement (IPS) serves as the foundation for the process. The IPT sets out a client’s return objectives and risk tolerance over that client’s relevant time horizon, along with applicable constraints such as liquidity needs, tax considerations, regulatory requirements, and unique circumstances. The IPS must clearly communicate the client’s objectives and constraints. The IPS thereby becomes a plan that can be executed by any adviser or portfolio manager the client might subsequently hire. A properly developed IPS disciplines the portfolio management process and helps ensure against ad hoc revisions in strategy. When combined with capital market expectations, the IPS forms the basis for strategic asset allocation. Capital market expectations concern the risk and return characteristics of capital market instruments such as stocks and bonds. The strategic asset allocation establishes acceptable exposures to IPS-permissible asset classes to achieve the client’s long-run objectives and constraints.

In the execution step, portfolio managers initiate portfolio decisions based on analysts’ inputs, and trading desks then implement these decisions (portfolio implementation decision). Subsequently, the portfolio is revised as investor circumstances or

capital market expectations change. Thus, the execution step interacts constantly with the feedback step. When making the portfolio selection/composition decision, portfolio managers may use the techniques of portfolio optimization. Portfolio optimization—quantitative tools for combining assets efficiently to achieve a set of return and risk objectives—plays a key role in the integration of strategies with expectations.

Instead of the “portfolio optimization” terminology, the authors propose the more accurate term “portfolio engineering.” The term portfolio engineering was first introduced in the seminal work of Jacobs and Levy (1995), in which they proposed that equity managers use a unified approach when structuring their portfolios, focusing on the widest possible stock universe, not on preselected groups or particular subsets of equity securities. As an attempt to enforce usage of the terminology and resolve the skepticism that stems from academia or the financial industry, we have provided the following definition (Xidonas et al. 2009b): *Portfolio engineering is a cross-disciplinary field that relies on the techniques and methods of mathematical optimization (single or multiobjective), portfolio theory, and computer science to structure high-yield, well-diversified investment portfolios.*

It must be noted that the portfolio implementation decision is as important as the portfolio selection/composition decision. Poorly managed executions result in transaction costs that reduce performance. Transaction costs include all costs of trading, including explicit and implicit transaction costs and missed trade opportunity costs.

Finally, in the feedback step, managers monitor and evaluate the portfolio. Any changes suggested by the feedback must be examined carefully to ensure that they represent long-run considerations. In any business endeavor, feedback and control are essential elements in reaching a goal. In PM, this step has two components: (a) monitoring and rebalancing and (b) performance evaluation. Monitoring and rebalancing involve the use of feedback to manage ongoing exposures to available investment opportunities so the client’s current objectives and constraints continue to be satisfied. Two types of factor are monitored: investor-related factors (e.g., the investor’s circumstances) and economic and market input factors. Investment performance must be evaluated periodically by the investor in regard to the progress made toward achieving the investment objectives and to assess the skill of the PM manager. Assessment of PM skill has three components. Performance *measurement* involves calculating the portfolio’s rate of return. Performance *attribution* examines why the portfolio performed as it did and involves determining the sources of a portfolio’s performance. Performance *appraisal* is the evaluation of whether the manager is doing a good job based on how the portfolio did relative to a benchmark (a comparison portfolio).

In the spirit of Maginn et al. (2007), but with a more specialized approach, Spronk and Hallerbach (1997) elaborated the relation between the decision context of the investor and the economic environment of the securities. For this reason, they characterized the investment decision process as the following stages: (a) security analysis to determine the relevant characteristics (or attributes) of the investment opportunities; (b) portfolio analysis to delineate the set of nondominated, or efficient, portfolios; (c) portfolio selection to choose the optimal portfolio from the efficient set; and (d) preference analysis.

In recent years, the development of new techniques in operations research and management science, as well as the progress in computer and information technologies, gave rise to new approaches for modeling the portfolio selection problem. Several authors have developed a new approach using MCDM for PM. The multidimensional nature of the problem has been emphasized in many articles (e.g. Xidonas et al. 2010b; Xidonas and Psarras 2009; Steuer et al. 2007a; Zopounidis and Doumpos 2002; Spronk and Hallerbach 1997; Jacquillat 1972). Elaborate and exhaustive justifications are provided in these studies for modeling PM problems within the MCDM framework.

The general idea is that the analysis of the risk nature in PM shows that the latter comes from various origins and its nature is multidimensional. Also, individual goals and investor's preferences cannot be incorporated in these models. MCDM provides the methodological basis to resolve the inherent multicriteria nature of portfolio selection problem. Additionally, it builds realistic models by taking into account—apart of the two basic criteria of return and risk (mean-variance model)—a number of important other criteria. Furthermore, MCDM has the advantage of taking into account the preferences of any particular investor. To manage portfolio selection efficiently, it is necessary to take into account all of the factors that influence the financial markets. Thus, PM is a multicriteria problem. Effectively, multifactor models point out the existence of several factors that influence the determination of stock prices. Furthermore, fundamental analysis models, commonly used in practice, underline that stock prices are dependent on the firm health of the stock and its capacity to pay dividends. The latter itself is a multicriteria problem because to solve it we must appreciate the profitability of the firm, its debt level (in the short and long term), and the quality of management. Finally, in practice, an investor has a personal attitude and particular objectives.

Hurson and Zopounidis (1995, 1997) considered that the classic approach imposes a norm to the investor's behavior that can be restrictive. It cannot take into account the personal attitude and preferences of a real investor confronted with a given risk in a particular situation. However, experience has proved that the classic approach is useful, for instance, concerning the diversification principle and the use of the beta as measure of risk. Thus, the use of the classic approach seems to be necessary but not sufficient to manage portfolio selection efficiently. Some additional criteria must be added to the classic risk–return criteria. In practice, these additional criteria can be found in fundamental analysis or constructed following the personal goals of the investor. Combining the above principles is difficult because of the complexity of multicriteria problems on the one hand and the use of criteria from different origins and of conflicting nature on the other hand. MCDM can facilitate and favor the analysis of compromise between the criteria. It equally permits us to manage the heterogeneity of the criteria scale and the fuzzy and imprecise nature of the evaluation that it helps clarify. Linking the multicriteria evaluation of an asset portfolio and the research of a satisfactory solution to the investor's preferences, the MCDM methods allow us to take into account the investors' specific objectives. Also, these methods do not impose any normative scheme on the comportment of the investors. The use of MCDM methods allows synthesizing in a single procedure the theoretical and practical aspects of PM and then allows a nonnormative use of theory.

2.3 MCDM Methodologies

All of the articles ($n = 147$) that have been compiled are classified by the methodology employed in Tables 2.1, 2.2, and 2.3. Most (39 studies) are in the category of multiobjective mathematical programming followed (25 studies) by goal programming. Some of the most popular MCDM methodologies are described in the following sections. For detailed descriptions of many of the MCDM methodologies, see Zopounidis and Doumpos (2002).

2.3.1 Multiobjective Mathematical Programming

Multiobjective mathematical programming (MMP) (see Steuer 1986) is an extension of the traditional mathematical programming theory in the case where multiple objective functions need to be optimized. The general formulation of a MMP problem is as follows:

$$\begin{aligned} &\text{Max or Min } \{f_1(x), f_2(x), \dots, f_n(x)\} \\ &\text{Subject to: } x \in S \end{aligned}$$

where x is the vector of the decision variables; f_1, f_2, \dots, f_n are the objective functions (linear or nonlinear) to be optimized; and S is the set of feasible solutions.

In contrast to the traditional mathematical programming theory, within the MMP framework the usual concept of an optimal solution is no longer applicable. This is because the objective functions are of conflicting nature (the opposite is rarely the case). Therefore, it is not possible to find a solution that optimizes simultaneously all of the objective functions. In this regard, within the MMP framework, the major

Table 2.1 MCDM and portfolio management: general framework and reviews

MCDM and PM	No. of articles	Studies
General framework	34	Steuer et al. (2005, 2006a, b, 2007a, b), Polyashuk (2005), Ahmed and El-Alem (2005), Spronk et al. (2005), Zopounidis and Doumpos (2002), Bana and Soares (2001), Zopounidis and Hurson (2001), Hallerbach (1994), Hallerbach and Spronk (2000), Ogryczak (2000), Schwehm (2000), Zopounidis (1999), Scarelli (1998), Hurson and Zopounidis (1993, 1995, 1997), Spronk and Hallerbach (1997), Yu (1997), Tibiletti (1994), Chevalier and Gupta (1993), Ekeland (1993), Khoury et al. (1993), Manas (1993), Zeleny (1977, 1981, 1982), Colson and Zeleny (1979, 1980), Ross (1976), Jacquillat (1972)
Reviews	4	Spronk et al. (2005), Steuer and Na (2003), Zopounidis and Doumpos (2002), Zopounidis (1999)

Table 2.2 Classification of MCDM portfolio management studies by methodology

Methodology	No. of articles	Studies
MMP	39	Steuer et al. (2005, 2006a, b, 2007a, b), Ahmed and El-Alem (2005), Prakash et al. (2003), Leung et al. (2001), Ogryczak (2000), Schniederjans and Schniederjans (2000), Bertsimas et al. (1999), Mansini and Speranza (1999), Shing and Nagasawa (1999), Zopounidis et al. (1998), Rustem (1998), Chunnachinda et al. (1997), Coffin and Taylor (1996), Skulimowski (1996), Speranza (1993, 1994, 1996), Chen (1995), Konno and Suzuki (1995), L'Hoir and Teghem (1995), Konno et al. (1993), Weber and Current (1993), Rys and Ziemba (1991), Skocz et al. (1989), Kobayashi et al. (1986), Nakayama et al. (1983), Muhlemann and Lockett (1980), Wilhelm (1980), Muhlemann et al. (1978), Sealey (1977), Shapiro (1976), Caplin and Kornbluth (1975), Stoner and Reback (1975), Steuer (1974), Stone (1973)
Goal programming	25	Perez Gladish et al. (2007), Arenas Parra et al. (2001), Doumpos et al. (1999), Powell and Premachandra (1998), Cooper et al. (1997), Dominiak (1997a), Tamiz et al. (1996, 1997), Khorramshahgol and Okoruwa (1994), Schniederjans et al. (1993), Vermeulen et al. (1993), Colson and Bruyn (1989), Spronk and Zambruno (1985), Schniederjans (1984), Spronk and Veeneklaas (1983), Spronk and Zambruno (1981), Harrington and Fischer (1980), Lee and Chesser (1980), Kumar and Philippatos (1979), Kumar et al. (1978), Taylor and Keown (1978), Booth and Dash (1977), El Sheshai et al. (1977), Orne et al. (1975), Lee and Lerro (1973)
Compromise programming	4	Ballestero and Pla-Santamaria (2003, 2004), Ballestero (1998), Ballestero and Romero (1996)
Evolutionary programming	7	Anagnostopoulos and Mamanis (2010, 2011), Beasley et al. (2003), Branke et al. (2009), De Giorgi (2008), Hens and Schenk-Hoppe (2005), Kremmel et al. (2011)
MAUT	9	Ballestero et al. (2007), Ehrgott et al. (2004), Jog et al. (1999a), Dominiak (1997b), Chuvej and Mount-Campbell (1989), Bodily and White (1983), Evrard and Zisswiller (1982), Bassler et al. (1978), Schwartz and Vertinsky (1977)
AHP	5	Rashid and Tabucanon (1991), Meziani and Rezvani (1990), Jensen (1987), Lockett et al. (1986), Saaty et al. (1980)
MACBETH	2	Bana and Soares (2004, 2001)
ELECTRE	5	Martel et al. (1991, 1988), Szala (1990), Khoury et al. (1993), Hurson and Ricci (1998)
PROMETHEE	5	Albadvi et al. (2007), Bouri et al. (2002), Khoury and Martel (1990), Martel et al. (1991), Hababou and Martel (1998)
UTA	1	Zopounidis (1993)
UTASTAR	2	Samaras et al. (2008, 2003a)
UTADIS	2	Zopounidis et al. (1999), Doumpos (2000)

(continued)

Table 2.2 (continued)

Methodology	No. of articles	Studies
MHDIS		Doumpos et al. (2000)
Rough sets theory	2	Jog et al. (1999b), Jog and Michalowski (1994)
Combinations of MCDM methods	9	Xidonas et al. (2008b, 2007a, b), Pendaraki et al. (2005), Zopounidis and Doumpos (2000b), Hurson and Zopounidis (1995, 1997), Zopounidis et al. (1995b), Rios-Garcia and Rios-Insua (1983)

Abbreviations: MMP for Multiobjective Mathematical Programming; MAUT for Multi Attribute Utility Theory; AHP for Analytical Hierarchy Process; MACBETH for Measuring Attractiveness by a Categorical Based Evaluation Technique; ELECTRE for ELimination Et Choix Traduisant la REalite; PROMETHEE for Preference Ranking Organization Method for Enrichment Evaluations; UTA for UTILites Additives; UTADIS for UTILites Additives DIScriminantes; MHDIS for Multi-group Hierarchical Discrimination Method

Table 2.3 MCDM portfolio management and decision support systems

Methodology	No. of articles	Studies
Reviews	4	Matsatsinis et al. (2002), Zopounidis and Doumpos (2000b), Siskos and Spiridakos (1999), Zopounidis et al. (1997)
MMP	3	Zopounidis et al. (1998), Colson and Bruyn (1989), Siskos and Despotis (1989)
MAUT	1	Dong et al. (2005)
MCBETH	1	Bana and Soares (2004)
UTA	2	Siskos et al. (1993), Zopounidis (1993)
UTASTAR	2	Samaras et al. (2003a, 2003b, 2008)
Combinations of MCDM methods	2	Zopounidis and Doumpos (2000b), Zopounidis et al. (1995b)
Intelligent DSS	5	Poh (2000), Liu and Lee (1997), Tam et al. (1991), Lee et al. (1989), Shane et al. (1987)
Intelligent MCDDS	2	Samaras and Matsatsinis (2003), Vranes et al. (1996)

point of interest is to search for an appropriate “compromise” solution. When searching for such a solution, only the efficient set is considered. The efficient set consists of solutions, which are not dominated by any other solution on the prespecified objectives. Such solutions are referred to as efficient solutions, non-dominated solutions, or Pareto optimal solutions.

Several appropriate procedures have been developed to solve MMP problems. These procedures are interactive and iterative. The general framework within which these procedures operate is a two-stage process. In the first stage, an initial efficient solution or group of solutions is presented to the decision-maker (DM). If this solution is acceptable to the DM (i.e., if it satisfies expectations on the given objectives), the solution procedure stops. If it is not acceptable, the DM is asked to provide information regarding his preferences on the prespecified objectives. This information involves

the objectives that need to be improved and the tradeoffs that he is willing to undertake to achieve these improvements. The purpose of defining such information is to specify a new search direction for the development of new, improved solutions. This process is repeated until a solution is obtained that is in accordance with the DM's preferences or until no further improvement of the current solution is possible.

2.3.2 Goal Programming

An alternative approach to addressing constrained optimization problems in the presence of multiple objectives is the goal programming (GP) approach, established by Charnes and Cooper (1961). The concept of "goal" is different from that of "objective." An objective simply defines a search direction (e.g., profit maximization). In contrast, a goal defines a target against which the attained solutions are compared. In this regard, GP optimizes the deviations from the prespecified targets, rather than performance of the solutions. The general form of a GP model is the following:

$$\begin{aligned} & \text{Max or Min } h(d_i^+, d_i^-) \\ & \text{Subject to:} \\ & g_i(x) - d_i^+ + d_i^- = t_i \\ & x \in S \\ & d_i^+, d_i^- \geq 0 \end{aligned}$$

where g_i is goal i defined as a function (linear or nonlinear) of the decision variables x ; t_i is the target value for goal g_i ; d_i^+ and d_i^- are the deviations from the target value t_i ($d_i^+ \cdot d_i^- = 0$), representing the underachievement and overachievement of the goal, respectively; and h is a function (usually linear) of the deviational variables.

The above general formulation shows that an objective function of an MMP formulation is transformed into a constraint within the context of a GP formulation. The right-hand side of these constraints includes the target values of the goals, which can be defined as either some satisfactory values of the goals or their optimal values.

2.3.3 Outranking Relations

The foundations of the outranking relation theory were established by Bernard Roy (Roy 1968) during the late 1960s through the development of the ELECTRE (ELimination Et Choix Traduisant la REalite) family of methods. Since then, it has been widely used by MCDM researchers, mainly in Europe. The outranking relation

is a binary one that enables the DM to assess the strength of the outranking character of alternative a_j over alternative a_k . The strength increases if there are enough arguments (coalition of criteria) to confirm that a_j is at least as good as a_k , and there is no strong evidence to refute this statement.

Outranking relations techniques operate in two stages. The first stage involves the development of an outranking relation among the considered alternatives, and the second stage involves exploitation of the developed outranking relation to choose the best alternatives (problematic α), sort them into homogeneous groups (problematic β) or rank them from the most to the least preferred ones (problematic γ). A detailed presentation of all outranking methods can be found in the books of Belton and Stewart (2002) and Vincke (1992).

2.3.4 Utility Functions-Based Approaches

The multiattribute utility theory (Keeney and Raiffa 1993) extends the traditional utility theory to the multidimensional case. Even from the early stages of the MCDM field, the strong theoretical foundations of the multiattribute utility theory (MAUT) framework have been among the cornerstones of the development of MCDM and its practical implementation. The objective of MAUT is to model and represent the DM's preferential system into a utility/value function U . The utility function is a nonlinear function defined on the criteria space, such that:

$$U(a_j) > U(a_k) \Leftrightarrow a_j \succ a_k \text{ (} a_j \text{ is preferred to } a_k \text{)}$$

$$U(a_j) = U(a_k) \Leftrightarrow a_j \sim a_k \text{ (} a_j \text{ is indifferent to } a_k \text{)}$$

The most commonly used form of utility function is the additive one:

$$U(a_j) = p_1 u_1(g_{j1}) + \dots + p_n u_n(g_{jn})$$

where u_1, u_2, \dots, u_n are the marginal utility functions corresponding to the evaluation criteria. Each marginal utility function $u_i(g_i)$ defines the utility/value of the alternatives for each individual criterion g_i , p_1, p_2, \dots, p_n are constants representing the trade-off that the DM is willing to take on a criterion to gain one unit on criterion g_i . These constants are often considered to represent the weights of the criteria and they are defined such that they add up to one.

Generally, the process for developing an additive utility function is based on cooperation between the decision analyst and the DM. This process involves specification of the criteria trade-offs and the form of the marginal utility functions. The specification of these parameters is performed through interactive procedures, such as the mid-point value technique proposed by Keeney and Raiffa (1993). The realization of such interactive procedures is often facilitated by the

use of multicriteria decision support systems, such as the MACBETH system developed by Bana and Vansnick (1994).

2.3.5 Disaggregation Analysis: UTA Method

The UTA (UTilités Additives) method (Jacquet-Lagrange and Siskos 1982) is an ordinal regression method developed to address ranking problems. The objective of the method is to develop an additive utility function that is as consistent as possible with the DM's judgment policy. The input to the method involves a set of reference alternatives $A' = \{a_1, a_2, \dots, a_m\}$. For each reference alternative the DM is asked to provide his global evaluation so as to form a total preorder of the alternatives in A' : $a_1 \succ a_2 \succ \dots \succ a_m$ (the indifference relation \sim can also be used in the preorder). The developed utility model is assumed to be consistent with the DM's judgment policy if it is able to reproduce the given preorder of the reference alternatives as consistently as possible. In that regard, the utility model should be developed so $U(a_1) > U(a_2) > \dots > U(a_m)$.

In developing the utility model to meet this requirement, there are two possible errors that may occur (Siskos and Yannacopoulos 1985): (1) the underestimation error σ_j^- , when the developed model assigns an alternative $a_j \in A'$ to a higher (better) rank than the one specified in the given preorder (the alternative is underestimated by the DM); and (2) the overestimation error σ_j^+ , when the developed model assigns an alternative $a_j \in A'$ to a lower (worse) rank than the one specified in the given preorder (the alternative is overestimated by the DM). The objective of the model development process is to minimize the sum of these errors.

A popular variant of the UTA method is the UTADIS (UTilités Additives DIScriminantes) method (Jacquet-Lagrange 1995; Doumpos and Zopounidis 2002), developed for sorting/classification problems. Similar to the UTA method, the DM is asked to provide a global evaluation on a set of reference alternatives $A' = \{a_1, a_2, \dots, a_m\}$. In this case, however, the DM is not asked to rank the alternatives in A' . Instead, he classifies the reference alternatives into homogeneous groups C_1, C_2, \dots, C_q defined in an ordinal way, such that $C_1 \succ C_2 \succ \dots \succ C_q$ (i.e., group C_1 includes the most preferred alternatives, whereas group C_q includes the least preferred ones). Within this context, the developed additive utility model is consistent with the DM's global judgment if the following conditions are satisfied:

$$\begin{aligned}
 U(a_j) &\geq t_1, & \forall a_j \in C_1 \\
 t_1 &> U(a_j) \geq t_2, & \forall a_j \in C_2 \\
 &\dots\dots\dots & \dots\dots\dots \\
 U(a_j) &< t_{q-1}, & \forall a_j \in C_q
 \end{aligned}$$

where $t_1 > t_2 > \dots > t_{q-1}$ are thresholds defined in the global utility scale [0,1] to discriminate the groups (each t_k is the lower bound of group C_k). Similar to the

UTA method, the underestimation and overestimation errors are used to measure the differences between the model's results and the predefined classification of the reference alternatives. In this case, the two types of error are defined as follows: (1) the overestimation error is $\sigma_j^+ = \max \{0, t_k - U(a_j)\}$, $\forall a_j \in C_k, k = 1, 2, \dots, q-1$; and (2) the underestimation error is $\sigma_j^- = \max \{0, U(a_j) - t_{k-1}\}$, $\forall a_j \in C_k, k = 2, 3, \dots, q$. The additive utility model is developed to minimize these errors using a linear programming formulation (see Doumpos and Zopounidis 2002).

2.4 Review of Existing Studies

In this section emphasis is laid on presentation of the existing research activity in the field of PM and MCDM through an elaborate bibliographic review of the coherent studies. Since the pioneering work of Markowitz (1952, 1959) on the theory of portfolio analysis based on the mean-variance formulation, several portfolio selection models have been proposed. According to this formulation, an investor regards expected return as desirable and variation of return (variance) as undesirable. On the basis of the Markowitz mean-variance formulation, many researchers developed miscellaneous new methodologies. Elton et al. (2007) provided an overview of these methodologies. Apart from the mean-variance model, they cited the single index models, multiindex models, average correlation models, mixed models, utility models in which the preference function of the investor plays a key role in the construction of an optimum risky portfolio, and models that employ different criteria such as the geometric mean return, safety first, stochastic dominance, and skewness. Pardalos et al. (1994) also provided a review and some computational results of the use of optimization models for portfolio selection.

The portfolio construction problem can be realized in two phases (Hurson and Zopounidis 1995, 1997): The first phase is an evaluation of the available securities to select those that best meet the investor's preferences. The second phase is specification of the amount of capital to be invested in each of the securities selected during the first phase. Implementation of these two stages in the traditional portfolio theory is based on the mean-variance approach. Within this multidimensional context, the MCDM paradigm provides a plethora of appropriate methodologies to support evaluation of the available securities as well as portfolio synthesis/optimization. The former (evaluation of securities) has been studied by MCDM researchers using discrete evaluation methods (outranking relations, MAUT, preference disaggregation analysis, rough sets). Studies conducted on this topic have focused on the modeling and representation of the investor's policy, goals, and objectives in a mathematical model. The model aggregates all of the pertinent factors describing the performance of the securities and provides their overall evaluation. The securities with the higher overall evaluation are selected for portfolio synthesis purposes in a later stage of the analysis. This stage is realized within the MCDM framework as a multiple-objective mathematical programming/goal programming problem.

The DM specifies the portfolio synthesis criteria (the objectives/goals), and an iterative and interactive process is invoked to identify a portfolio that best meets his investment policy.

Zopounidis et al. (1998) classified the studies concerning the use of multicriteria analysis in portfolio selection according to their special methodological background (Pardalos et al. 1995; Siskos and Zopounidis 1993) as follows: (a) multiobjective mathematical programming; (b) multiattribute utility theory; (c) outranking relations; and (d) preference disaggregation approach. Doumpos (2000) categorized the research studies in portfolio management into four basic classes: (a) models focusing on the analysis and perception of securities' behavior; (b) forecasting models focusing on rapid spotting of security trends; (c) security evaluation methodologies focusing on modeling of the investor's preferences; (d) portfolio synthesis and optimization methodologies. Hurson and Zopounidis (1995), Zopounidis and Doumpos (2002), and Steuer and Na (2003) provided elaborate, detailed reviews concerning the field of multiple criteria portfolio selection.

A representative sample of some significant studies in the field follows. Saaty et al. (1980) proposed constructing a portfolio using analytical hierarchy process methodology. Lee and Chesser (1980) presented a goal programming model to construct a portfolio. Rios-Garcia and Rios-Insua (1983) constructed a portfolio using the MAUT and multiobjective linear programming. Evrard and Zisswiller (1983) used the MAUT to perform a valuation of some stocks. Nakayama et al. (1983) propose a graphics interactive methodology to construct a portfolio using multiple criteria. Martel et al. (1988) performed a portfolio selection using the outranking methods ELECTRE (ELimination and Choice Expressing REALity) I and ELECTRE II. Colson and De Bruyn (1989) proposed a system that performs a stock valuation and allows construction of a portfolio. Szala (1990) performed stock evaluation in collaboration with a French investment company. Khoury et al. (1993) used the outranking methods ELECTRE IS and ELECTRE III to select international index portfolios. The purpose of Colson and Zeleny (1979) was to construct an efficient frontier in concordance with the principles of stochastic dominance. Hurson and Zopounidis (1993) proposed managing portfolio selection using the MINORA system (a preference disaggregation approach), which is presented in the following section. Zopounidis et al. (1998) proposed the use of the ADELAIS (Aide à la DÉcision pour systèmes Linéaires multicritères par Aide à la Structuration des préférences) system to construct a portfolio using some diversification constraints that represented the investor's personal preferences and multiple stock-market criteria. Tamiz et al. (1996) proposed the use of goal programming for portfolio evaluation and selection. Dominiak (1997) presented a procedure for security selection that uses a multicriteria discrete analysis method based on the idea of reference solution. Hurson and Ricci (1998) proposed combining the Arbitrage Pricing Theory (APT) and MCDM to model the portfolio management process.

Steuer et al. (2007b) employed six categories to put multiple criteria oriented portfolio analysis research into perspective: (a) overall framework; (b) portfolio ranking; (c) skewness inclusion; (d) use of alternative measures of risk; (e) decision support systems; and (f) the modeling of individual investor preferences. The first

category included articles that are overview pieces, such as those of Hallerbach and Spronk (2002a, b) and Bana and Soares (2001), in which the benefits of embracing multiple criteria concepts in financial decision-making are outlined. Employing tools from multiple criteria decision analysis for portfolio ranking, articles by Yu (1997), Jog et al. (1999) and Bouri et al. (2002) are included. The category of skewness inclusion is represented by contributions from Konno and Suzuki (1995) and Chunhachinda et al. (1997). In the alternative measures of risk category are the efforts of Zeleny (1977), Konno and Yamazaki (1991), and Doumpos et al. (1999). In the category of decision support systems employing mathematical programming techniques are the approaches of Ogryczak (2000), Ehrgott et al. (2004), and Zopounidis and Doumpos (2000b). In the sixth category, recognizing that some criteria may come from financial-economic theory and others may come from the individual investor, we have Spronk and Hallerbach (1997), Ballestero (1998), and Bana and Soares (2004).

The above-mentioned studies and a compilation of several more relative articles are summarized in Tables 2.1, 2.2, and 2.3. These tables constitute an updated composition of the review studies by Zopounidis (1999), Zopounidis and Doumpos (2002), Steuer and Na (2003), and Spronk et al. (2005). Needless to say, it is possible that an article can be classified in more than one category.

The categorization we adopt here contains the following.

- (a) Articles ($n=38$) that emphasize the general framework for MCDM and PM or are reviews of the field (see Table 2.1).
- (b) Articles ($n=110$) that are classified according their specific methodological approach. The methodological approaches we include here are multiobjective mathematical programming, goal programming, compromise programming, the MAUT, the analytical hierarchy process, MACBETH, ELECTRE, PROMETHEE, UTA, UTASTAR, UTADIS, MHDIS, the rough sets theory, and combinations of MCDM methods (see Table 2.2).
- (c) Articles ($n=22$) that constitute combinations of the decision support systems (DSS) field with the MCDM portfolio management framework (see Table 2.3).

2.5 Conclusions

This chapter discussed the contribution of MCDM to the management of problems associated with the portfolio, focusing on the justification of its multidimensional character and on the use of various MCDM methodologies to support them. In the past, the financial theory addressing PM/selection problems was in the very narrow framework of optimization. MCDM broadens this framework and successfully combines sophistication, realism, and rapid computation.

Zopounidis (1999) and Zopounidis and Doumpos (2002) underscored the main advantages that the MCDM paradigm provides not only in PM but in other financial decision-making as well: (a) the possibility of structuring complex evaluation

problems; (b) introduction of quantitative and qualitative criteria in the evaluation process; (c) transparency during the evaluation, allowing good argumentation regarding financial decisions; and (d) introduction of sophisticated, flexible, realistic scientific methods in the financial decision-making process.

The most important aspect is that MCDM enables the decision-maker to participate actively in the financial decision-making process and helps him understand the peculiarities and the special features of the real-world problems he must face. In conclusion, MCDM methods seem to have a promising future in the field of PM because they offer a highly methodological and realistic framework regarding decision-making problems.

Chapter 3

Stock Selection

3.1 Introduction

This chapter primarily addresses security analysis and evaluation. We develop a multicriteria methodology for equity selection, exploiting the valuable tool of financial analysis (FA), which is the most appropriate evaluation approach regarding investment decisions within a long-term horizon. FA involves identifying the strengths and weaknesses of firms, mainly through judgmental procedures. The latter address the qualitative evaluation and interpretation of financial ratios as they arise from accounting statements. FA can also be viewed as the activity of providing input during the portfolio construction phase because it entails the process of analyzing the special characteristics of securities and corresponding firms, leading to final selection recommendations.

As has already been mentioned, the portfolio selection problem can be realized as a two-stage process (Hurson and Zopounidis 1995, 1997): (a) evaluation of the available securities to select the ones that best meet the investor's preferences, and (b) specification of the amount of capital to be invested in each of the securities selected during the first stage. As far as the first stage of this multidimensional context is concerned, the multiple criteria decision-making MCDM paradigm provides a plethora of appropriate methodologies to support evaluation of the available securities. The issue of security evaluation has been studied by MCDM researchers using discrete evaluation methods, including outranking relations, the multiattribute utility theory (MAUT), preference disaggregation analysis, and rough sets, among others. Studies conducted on this topic have focused on the modeling and representation of the investor's policy, goals, and objectives in a mathematical model. The model aggregates all of the pertinent factors describing the performance of the securities and provides their overall evaluation. The securities with the highest overall evaluations are selected for participating in the next phase of the process (portfolio construction).

Within this frame, FA can be utilized for selecting attractive equities by means of evaluating the overall corporate performance of the corresponding firms

(see Edirisinghe and Zhang 2007; Samaras et al. 2008). Evaluating the performance of corporate entities and organizations is an important activity for their management personnel and shareholders as well as for investors and policymakers. Such an evaluation provides the management and shareholders with a tool with which to assess the strengths and weaknesses of the firm as well as its competitive advantages over its competitors. It thus provides guidance regarding the choice of the measures that need to be taken to overcome existing problems. Investors (institutional and individual) are interested in the assessment of corporate performance for guidance to their investment decisions, and policymakers may use such an assessment to identify the existing problems in the business environment and take measures that ensure sustainable economic growth and social stability. The performance of a firm or an organization is clearly multidimensional as it is affected by a variety of factors of different nature, such as: (a) financial factors indicating the financial position of the firm/organization; (b) strategic factors of a qualitative nature that define the internal operation of the firm and its relation to the market (e.g., organization, management, market trend); (c) economic factors that define the economic and business environment.

3.2 Review

The aggregation of all the above factors into a global evaluation index is a subjective process that depends on the decision-maker's (DM's) values and judgment policy. These findings are in full accordance with the MCDM paradigm, thus leading several operational researchers to investigate the capabilities that MCDM methods provide regarding the problems of corporate performance evaluation and equity selection. We review some of the most important studies in the field, as follows.

Srinivasan and Ruparel (1990) proposed the CGX multicriteria intelligent decision support system (DSS) for dealing with credit-granting problems. The credit-granting decision process, which is modeled through the analytical hierarchy process (AHP) (Saaty et al. 1980) multicriteria method, aims at deriving the perceived probabilities of default and payment of the loan. The evaluation criteria include both financial ratios (e.g., debt capacity ratios, profitability ratios, liquidity ratios) and qualitative criteria (e.g., customer background, pay record, geographical location, business potential).

Diakoulaki et al. (1992) utilized the results of the analysis of a MAUT model (Keeney and Raiffa 1993) applied to a large sample of Greek pharmaceutical companies to indicate how suitable some common financial ratios are as indices of a firm's overall performance. The results showed that profitability constitutes the most representative measure for the differentiation and ranking of companies. Also, a sound capital structure is a necessary, but not sufficient, condition to ensure the profitability and effective operation of the firm.

Mareschal and Brans (1991) presented the BANKADVISER, a multicriteria industrial evaluation system that provides an evaluation of individual items, such as firms, industries, companies, and industrial clients. The evaluation procedure employs the PROMETHEE (Brans et al. 1986) method and is based on financial

data from each firm's financial statements. The system's aim is to allow the user to explore managing data about the clients, analyzing their economic profile, detecting their strong and weak features, and evaluating any risk associated with them.

Siskos et al. (1994) presented an integrated DSS for the analysis and financing of firms by an industrial development bank in Greece. First, the system evaluates the financial performance of firms (financial ratios of profitability, managerial performance, solvency) during a 5-year period, which provides inferences about their development tendencies. Multivariate statistical techniques are also available to help identify the most significant financial ratios and to group firms into coherent categories. Finally, the UTA (Jacquet-Lagrange and Siskos 1982) multicriteria method ranks the firms from the most solvent to the bankrupt, thereby helping the bank select the less risky firms for financing.

Zopounidis et al. (1996) presented the FINEVA multicriteria knowledge-based DSS for assessing corporate performance and viability. The FINEVA expert system offers (a) an expert initial financial and qualitative evaluation of firms; (b) principal components analysis to identify the most significant financial ratios; and (c) the multicriteria method UTASTAR (Siskos and Yannacopoulos 1985), which combines the results of the expert system and the principal components analysis, providing a final evaluation of firms.

Babic and Plazibat (1998) dealt with the ranking of enterprises according to the achieved level of business efficiency using the PROMETHEE and AHP methods. The PROMETHEE method is used for final ranking, and the AHP determines the importance of the criteria. The main purpose of this work was to present methodology that can answer the question about financial standing of a particular enterprise at any given moment.

Zopounidis and Doumpos (2001) proposed an alternative approach to classic statistical methodologies that have been used extensively to study financial classification problems. More specifically, these authors presented the FINCLAS (FINancial CLASsification) multicriteria DSS, which utilizes the UTADIS (Devaud et al. 1980) method for assessing corporate performance and the viability of firms. The system incorporates a plethora of financial modeling tools along with powerful preference disaggregation methods that lead to the development of additive utility models for classifying the considered alternatives into predefined classes.

Samaras and Matsatsinis (2003) proposed the Intelligent INVESTOR, an intelligent multicriteria DSS which aims at offering an overall consideration of the portfolio management problem. The system incorporates all the advanced portfolio management tools, such as fundamental analysis, technical analysis, market psychology, and uses both multicriteria analysis methods and rule-based expert systems technology.

Samaras et al. (2003a) presented a multicriteria methodology and the corresponding DSS for evaluating stocks from the American Stock Exchange. The methodology is based on fundamental analysis ratios and utilizes the UTASTAR method to rank the stocks from best to worst, taking into account the potential investor's attitude toward risk. The system, which is intended for both institutional and private investors, incorporates a large volume of relevant information and operates in real-world conditions because its data are constantly updated.

Table 3.1 Applications of MCDM approaches in the assessment of corporate performance

Methods	Studies	Type of organization
Reviews	Spronk et al. (2005)	
	Steuer and Na (2003)	
	Zopounidis and Doumpos (2002)	
	Zopounidis (1999)	
AHP	Lee et al. (1995)	Firms
	Jablonski (1993)	Firms
MAUT	Yeh et al. (2000)	Firms
	Baourakis et al. (2002)	Firms
PROMETHEE	Diakoulaki et al. (1992)	Firms
	Zmitri et al. (1998)	Banks
	Pardalos et al. (1997)	Insurances
UTA	Mareschal and Mertens (1993, 1990)	Insurances/Banks
	Zopounidis et al. (1995a)	Banks
UTASTAR	Siskos and Zopounidis (1987)	Firms
	Zopounidis et al. (1996)	Firms
UTADIS	Kosmidou et al. (2004)	Banks
	Spathis et al. (2002)	Banks
	Zopounidis and Doumpos (2001, 1998)	Firms
	Voulgaris et al. (2000)	Firms
Combinations of MCDA methods	Michalopoulos et al. (1998)	Banks
	Babic and Plazibat (1998)	Firms
	Colson and Mbangala (1998)	Firms

Table 3.2 MCDSS in the assessment of corporate performance

Methods	Studies	Type of organization
Reviews	Zopounidis and Doumpos (2000a)	
	Siskos and Spiridakos (1999)	
	Zopounidis et al. (1997)	
ELECTRE/PROMETHEE	Caloghirou et al. (1999)	Firms
	Mareschal and Mertens (1992)	Banks
	Mareschal and Brans (1991)	Firms
UTA	Siskos et al. (1994)	Firms
	Zopounidis et al. (1992)	Firms
	Siskos and Zopounidis (1987)	Firms
	Siskos (1986)	Firms
UTASTAR	Zopounidis et al. (1996)	Firms
UTADIS	Zopounidis and Doumpos (1998, 2000b, 2001)	Firms
Intelligent MCDDS	Matsatsinis et al. (1997)	Firms
	Zopounidis et al. (1996)	Firms
	Hartvigsen (1990)	Firms

An indicative list of articles on the topic is given in Tables 3.1 and 3.2. The categorization we adopt here contains the following.

- (a) Articles that are classified according their specific methodological approach and the organizational type that is evaluated (this category includes review pieces).

The methodological approaches we include here are AHP, MAUT, PROMETHEE, UTA, UTASTAR, UTADIS, and combinations of MCDM methods (i.e., methodologies in which more than one multicriteria technique is used).

- (b) Articles that present multicriteria decision support systems (MCDSS) within the field of corporate performance evaluation.

3.3 Proposed Methodology

3.3.1 *General Description*

The aim of the proposed methodology (Xidonas et al. 2009a) is selection of equities that reflect firms characterized by significant financial strength. For this purpose the approach developed utilizes the valuable tool of FA. Within this framework, FA is employed to select competitive equities by appraising the overall corporate performance of the corresponding firms.

One of the methodology's main features is that the firms participating in the evaluation process are categorized in classes (eight classes in total are defined), with respect to their corresponding industry. The ELECTRE Tri multicriteria method is then applied separately in each of these classes. Finally, the partial results are integrated, considering also the major issue of time trends. The crucially important issue of the industry/sectoral's accounting peculiarities is taken into account. Each sorting result the methodology provides has a special structure and is based on a specific criteria set (a total of four sets of criteria were constructed). It is related to the specific business activity of the firm and corresponds to the specific accounting plan in which each company belongs. This means that there is no uniform sorting of stocks but specialized sorting per industry. With this method, the huge issue of competition between rival firms is fully taken into consideration, and unreasonable comparisons are excluded.

According to Mousseau et al. (2000), the ELECTRE Tri method can be used in ordered multiple criteria sorting problems for assigning alternatives to predefined categories. It is done by comparing each alternative with the profiles, defining the limits of the categories, and by exploiting a preference model of the DM, informing on weights and thresholds of the criteria. The three categories that are predefined in the current study—acceptable stocks, stocks to be studied further, unacceptable stocks—allow for rather satisfactory modeling of the equity selection problem. An extended analysis regarding the rationale for choosing the ELECTRE Tri method is outlined in Sect. 3.3.3.

Finally, it must be noted that the proposed methodology was applied in strong cooperation with a panel of experts, financial analysts, and portfolio managers. Their contribution was of catalytic impact at all stages of the collaboration: (a) classification of alternatives; (b) construction of criteria sets; (c) application of the “resistance to change grid” weighting method; (d) determination of categories profiles and thresholds; and (e) validation of results. During all phases of the study,

the experts were fully assisted by the authors regarding the intuitive explanation of the selected multicriteria method's technical aspects and details. As noted in Sect. 3.3.4, the authors in the current case carried out the role of the “analyst” or “facilitator” in the decision-aiding process (Roy 1996).

The proposed methodology is graphically depicted in Fig. 3.1.

A short, step-by-step description of how the proposed methodology can be applied to the problem of equity selection is as follows.

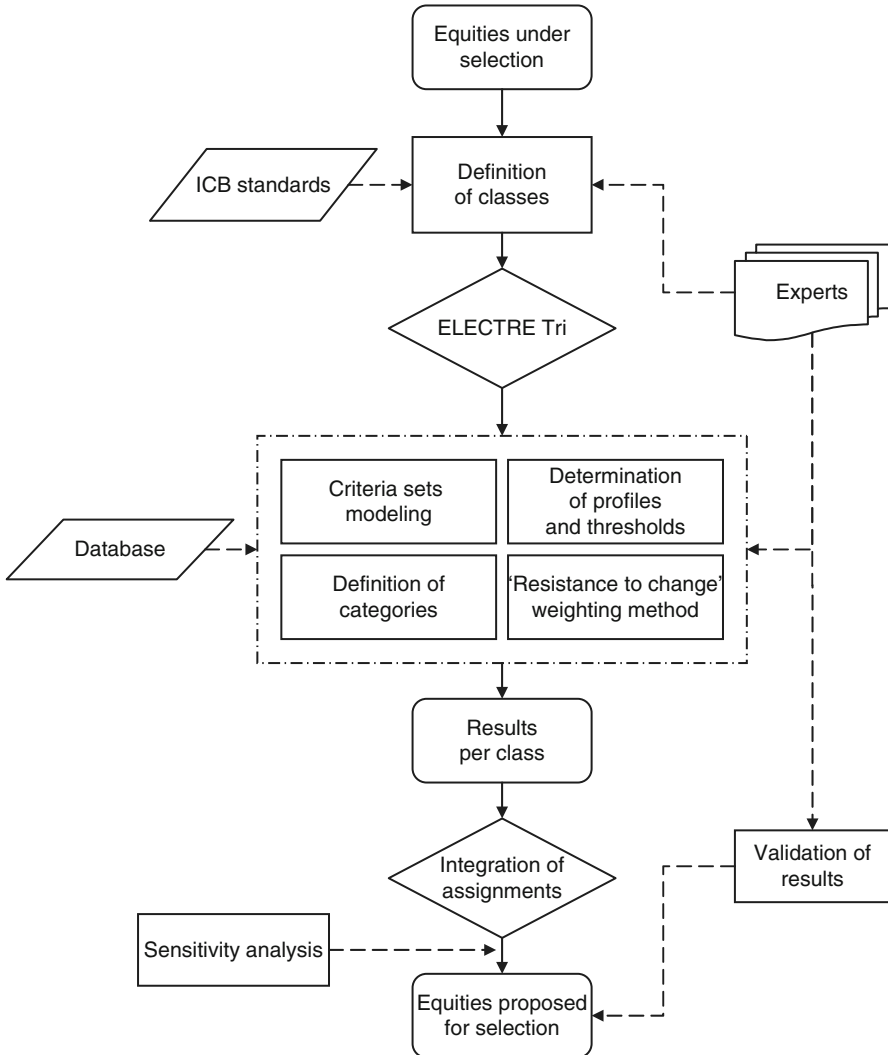


Fig. 3.1 Proposed methodology

The key characteristics of the proposed methodology are analyzed in detail in the following sections.

- Step 1:* Apply the ELECTRE Tri method to each of the eight defined classes of firms
- Step 2:* For each one of the eight sortings, take the overlap of assignment procedures for each category
- Step 3a:* Equities of firms that have been classified in category C_2 in both the optimistic and pessimistic assignment procedures are not proposed for selection. (C_2 consists of equities that reflect firms with medium financial performance; see Sect. 3.3.8 for details.)
- Step 3b:* Equities of firms that have been classified in category C_1 in both the optimistic and pessimistic assignment are not proposed for selection. (C_1 consists of equities that reflect firms with poor financial performance; see Sect. 3.3.8 for details.)
- Step 3c:* Equities of firms that have been classified in different categories under the two types of assignment are not proposed for selection
- Step 4:* Equities of firms that have been classified in category C_3 in both the optimistic and pessimistic assignment are eligible for selection. (C_3 consists of equities that reflect firms with excellent financial performance; see Sect. 3.3.8 for details.)
- Step 5:* Apply *Steps 1–4* for all years
- Step 6:* For each class, take the overlap of those equities of firms that have been classified in category C_3 (in both the optimistic and pessimistic assignment) in at least 2 out of the 3 years of the study period. The financial aspect behind this allegation has to do with the fact that we allow a firm to have unsatisfactory financial results only once during the study period (3 consecutive years)
- Step 7:* The final set of equities resulting after applying *Steps 1–6* contains securities that are proposed to the DM for selection

3.3.2 *ELECTRE Tri Method*

The family of ELECTRE methods were initially introduced by Roy (1968) through the development of the ELECTRE I method, the first to employ the outranking relation concept. Since then, several extensions have been proposed, including ELECTRE II, III, IV, IS, and Tri (Roy 1996). These methods address different types of problem, including choice (ELECTRE I, IS), ranking (ELECTRE II, III, IV), and sorting/classification (ELECTRE Tri). For an excellent and elaborate presentation of the ELECTRE family methods, see Rogers et al. (2000).

ELECTRE Tri (Yu 1992) is a multiple criteria assignment method that assigns project options to predefined categories. The assignment of option α results from a

comparison of α with the profiles defining the limits of the categories. Assume F denotes the set of indices of the profiles of the criteria g_1, g_2, \dots, g_m , ($F = \{1, 2, \dots, m\}$), and B denotes the set of indices of the profiles defining $p+1$ categories, ($B = \{1, 2, \dots, p\}$), with b_h being the upper limit of category C_h and the lower limit of the category C_{h+1} , $h = 1, 2, \dots, p$. It is assumed that criteria are monotonically increasing, with preference increasing with increasing criterion value.

3.3.2.1 Building the Outranking Relation

ELECTRE Tri builds an outranking relation S , which confirms or rejects the assertion aSb_h , which implies “ a is at least as good as the reference option b_h .” As with ELECTRE III and IV, preferences are defined through pseudo-criteria. The indifference and preference thresholds ($q_j(b_h)$ and $p_j(b_h)$) constitute the intracriterion preferential information and reflect the imprecise nature of the valuations $g_j(a)$. The expression $q_j(b_h)$ specifies the largest difference $g_j(a) - g_j(b_h)$ that preserves indifference between α and b_h on the criterion g_j ; $p_j(b_h)$ represents the smallest difference $g_j(a) - g_j(b_h)$ compatible with a preference in favor of α on criterion g_j .

To confirm the statement aSb_h , one must comply with two conditions.

- Concordance: For the outranking of b_h by α to be accepted, a sufficient majority of criteria should be in favor of this assertion.
- Nondiscordance: When the concordance condition holds, none of the criteria in the minority should oppose the assertion aSb_h in too strong a manner.

The following two intercriterion parameters are utilized in the construction of the outranking relation S .

- The set of the criterion weighting (k_1, k_2, \dots, k_m) is used as part of the calculation of concordance through computation of the relative importance of the coalition of criteria supporting the assertion that α outranks b_h .
- The set of veto thresholds ($v_1(b_h), v_2(b_h), \dots, v_m(b_h)$) is used in the discordance test, representing the smallest difference, which will veto or counteract the outranking of α by b_h .

ELECTRE-Tri builds an index $\sigma(a, b_h) \in [0, 1]$ that represents the degree of credibility of the assertion that α outranks b_h , $\forall a \in A, \forall h \in B$. The assertion aSb_h is considered to be valid if $\sigma(a, b_h) \geq \lambda$, where λ is a “cutoff threshold,” such that $\lambda \in [0.5, 1]$.

$\sigma(a, b_h)$ is estimated as follows.

- (a) Compute the partial concordance index $c_j(a, b_h)$, $\forall j \in F$:

$$c_j(a, b_h) = 0, \text{ if } g_j(b_h) - g_j(a) \geq p_j(b_h)$$

$$c_j(a, b_h) = 1, \text{ if } g_j(b_h) - g_j(a) \leq q_j(b_h)$$

$$c_j(a, b_h) = (p_j(b_h) + g_j(a) - g_j(b_h)) / (p_j(b_h) - q_j(b_h))$$

Otherwise:

(b) Compute the overall concordance index:

$$c(a, b_h) = \frac{\sum_{j \in F} k_j c_j(a, b_h)}{\sum_{j \in F} k_j}$$

(c) Compute the discordance indices:

$$d_j(a, b_h) = 0, \text{ if } g_j(a) \leq g_j(b_h) + p_j(b_h)$$

$$d_j(a, b_h) = 1, \text{ if } g_j(a) > g_j(b_h) + v_j(b_h) \text{ Otherwise:}$$

$$d_j(a, b_h) \in [0, 1]$$

(d) Compute the credibility index:

$$\sigma(a, b_h) = c(a, b_h) \prod_{j \in \bar{F}} \frac{1 - d_j(a, b_h)}{1 - c(a, b_h)} \text{ where}$$

$$\bar{F} = \{j \in F : d_j(a, b_h) > c(a, b_h)\}$$

3.3.2.2 Exploiting the Outranking Relation

The values of $\sigma(a, b_h)$, $\sigma(b_h, a)$, and λ determine the preference situation between α and b_h :

- $\sigma(a, b_h) \geq \lambda$ and $\sigma(b_h, a) \geq \lambda$
 $\Rightarrow aSb_h$ and $b_hSa \Rightarrow alb_h$, i.e. a is indifferent to b_h
- $\sigma(a, b_h) \geq \lambda$ and $\sigma(b_h, a) < \lambda$
 $\Rightarrow aSb_h$ and not $b_hSa \Rightarrow alb_h \Rightarrow a > b_h$, i.e. a is preferred to b_h (weakly or strongly)
- $\sigma(a, b_h) < \lambda$ and $\sigma(b_h, a) \geq \lambda$
 \Rightarrow not aSb_h and $b_hSa \Rightarrow b_h > a$, i.e. b_h is preferred to a (weakly or strongly)
- $\sigma(a, b_h) < \lambda$ and $\sigma(b_h, a) < \lambda$
 \Rightarrow not aSb_h and not $b_hSa \Rightarrow alb_h \Rightarrow aRb_h$, i.e. a is incomparable to b_h

Two assignment procedures are then available.

Pessimistic procedure:

- (a) Compare α successfully to b_i , for $i = p, p-1, \dots, 0$,
- (b) b_h being the first profile such that aSb_h
- (c) Assign α to category C_{h+1} ($a \rightarrow C_{h+1}$)

The direction of the ranking obtained from the pessimistic procedure is from best to worst.

Optimistic procedure:

- (d) Compare α successfully to b_i , for $i = 1, 2, \dots, p$,
- (e) b_h being the first profile such that $b_h > a$,
- (f) Assign α to category C_h ($a \rightarrow C_h$)

In this case, the direction of the ranking obtained goes from worst to best.

To summarize the results from the two procedures, a table can be constructed in which the options are referred to in terms of the categories to which they are assigned by the two procedures.

Whatever assignment procedure is utilized, the following seven requirements must be met.

- No option can be indifferent to more than one reference option.
- Each option must be assigned to one reference category only (uniqueness/unicity).
- The assignment of any one option to its allotted category is not dependent on the assignment of any of the other options (independence).
- The procedure for assigning options to categories must be entirely consistent with the design of the reference options themselves (conformity).
- When two options have the same outranking relation with a given reference option, they must be assigned to the same category (homogeneity).
- If option α' outranks α , then α' must be assigned to a category at least as good as the one to which α is assigned (monotonicity).
- The grouping together of two neighboring categories must not cause the alteration of options to categories not affected by the alteration (stability).

3.3.3 *Reasons for Employing the ELECTRE Tri Method*

The ELECTRE Tri method incorporates two interesting modeling capabilities: the notion of incomparability and the potential of obtaining two assignment procedures, one optimistic and one pessimistic.

In the classic preference structures, such as the utility functions approach, it is supposed that one can obtain pairwise comparisons between all the alternatives. However, certain situations such as multidimensional and conflicting preferences of the DM, uncertainty, and ambiguity or cases where alternatives have highly satisfactory values for some criteria and simultaneously extremely poor values for others, can create incomparabilities (Figueira et al. 2005). In the case of the ELECTRE Tri method, the notion of incomparability refers to cases where some alternatives belong to different categories within the two assignment procedures; that is, they are incomparable with one or more reference profiles (Roy 1996; Rogers et al. 2000). In other words, the incomparability prevents unrealistic and mandatory comparisons between alternatives.

The ELECTRE Tri method manages incomparability between alternatives in such a way that it identifies those having particularities in their evaluation and for this reason must be given further attention. This is a matter of crucial importance within the problem of equity selection (Hurson and Zopounidis 1995) and is resolved through the exploitation of the two assignment procedures: Its results are compared, and important information is elicited for the decision-maker (DM). A better view of the exploitation of the incomparability notion in the current study is given in Sect. 3.3.8, where interpretation of the results is introduced. According to the analysis provided, the corresponding equities of firms that have been classified in different categories under the two types of assignment procedures are not selected for proposal to the DM.

The choice of the ELECTRE Tri method is also based on its quite extensive applicability regarding problems of modern financial decision-making. A large number of financial applications within the framework of the outranking relations theory have been recorded in the studies of Zopounidis (1999), Zopounidis and Doumpos (2002), Spronk et al. (2005), and Xidonas and Psarras (2009).

The final reason for utilizing a member of the ELECTRE family methods has to do with the fact that these methods are easy to perceive by the DM. When an intuitive explanation of the method's technical aspects and details was provided to the experts participating in the study, they expressed their satisfaction regarding its effectiveness and characterized it as an interesting support tool for decision-making.

It must be stressed at this point that the ELECTRE family methods pose certain difficulties in their use and require careful manipulations by all the people involved in the decision-making process. As with all the outranking methods, a phase of critical significance is the one related to the proper assignment of parameters (e.g., indifference, preference, and veto thresholds) to reflect the real preferences of the DM. Improper determination of these parameters may lead to inconsistent results that do not reflect the DM's preference system. Regarding the proposed methodology, as is pointed out in Sect. 3.3.8, this predicament is addressed by exploiting the experts' valuable experience in security analysis, along with a plethora of statistical data concerning the alternative securities provided by a leading provider of financial and business information in Greece.

3.3.4 Actors Involved in the Decision-Making Process

Decisions are rarely made by a single individual. Even if responsibility for the decision ultimately rests with a well-identified individual, the decision is generally the product of an interaction between this individual's preferences and those of others. Indeed, in many cases the final decision might not be the responsibility of or influenced by single individuals. It could involve entities (e.g., an elected or appointed body or a board of directors). It could also involve a group (community) with less than well-defined boundaries (e.g., a professional lobby). These actors (individuals, entities, communities) are what we call stakeholders, in that they have an important interest in the decision and can intervene to affect it directly through

the value systems they possess. Additionally, there are those who do not actively participate in shaping the decision but who are affected by its consequences and whose preferences must be considered when arriving at a decision (third parties).

The various stakeholders in a decision process might be relatively diverse, having different objectives and conflicting value systems. Therefore, a specific application of decision aid is rarely comprehensive enough to benefit all of them. For this reason, decision-aiding almost always requires that a particular stakeholder is identified (the DM). Identifying a DM entails specifying the objectives under which he operates. Often, the DM does not have the background to perform the decision aid. In this case, the one performing the aid (analyst or facilitator) is generally different from the DM (Roy 1996).

In the application that is presented and illustrates the proposed methodology, no real DM (private or an institutional investor) is involved. The role of the DM was assumed by the experts who effectively cooperated during the development and validation of the proposed methodology.

3.3.5 Alternatives

A critical issue that the proposed methodology resolves has to do with providing the flexibility of simultaneously evaluating a significantly large number of firms (alternatives) from a wide range of business activities.

The methodology's key characteristic that allows for this convenience is that the firms that participate in the evaluation process are categorized into classes with respect to their corresponding industry. The American Stock Exchange (ASE) follows the

Table 3.3 Definition of classes

Class	Industry	Supersector
<i>a</i>	Consumer goods	Food and beverage
		Personal and household goods
<i>b</i>	Industrials	Construction and materials
		Industrial goods and services
<i>c</i>	Technology	Technology
	Telecommunications	Telecommunications
<i>d</i>	Basic materials	Chemicals
		Basic resources
		Oil and gas
<i>e</i>	Consumer services	Oil and gas
		Retail
		Media
		Travel and leisure
<i>f</i>	Utilities	Utilities
	Health care	Health care
<i>g</i>	Financials	Financial services
<i>g</i>	Financials	Banks
<i>h</i>	Financials	Insurance

Industry Classification Benchmark (ICB) standards (www.icbenchmark.com). In general, this was the pattern adopted for definition of the classes. As shown in Table 3.3, the proposed methodology categorizes the firms of the ASE into eight classes. This means that the ELECTRE Tri method is applied, separately, in each of these classes.

The only deviation from the ICB standards, regarding the definition of the classes, was that the number of firms in some industries was fairly low. The rationale adopted in this point suggested integration and merger of coherent and contextual industries. For example (see also Table 3.15), the industry of Telecommunications' (3 firms) was embodied in the highly related industry of Technology (22 firms) to constitute the unified class *c*. Under the same rationale, class *d* consists of firms that belong to industries of Basic materials (25 firms) and Oil and gas (3 firms).

The reason for defining different classes of firms is related to the need to acquire fair, objective, representative evaluation results within the framework of comparing alternatives with similar characteristics (i.e., firms with business activities that relate to each other). Thus, the crucial issue of competition between rival firms is taken into account and unrealistic and inconsistent comparisons are avoided (e.g., comparing a bank institution to a consumer goods company).

3.3.6 *Criteria Modeling*

The proposed methodology was developed in cooperation with a panel of experts. Their contribution to identifying the criteria (financial ratios) that were most appropriate to use for evaluating corporate performance was valuable. After a detailed review of the international literature (Courtis 1978; Greig 1992; Holthausen and Larcker 1992; Ou and Penman 1992; Penman 1992; Lewellen 2003; Bernstein and Wild 1999; Stickney et al. 2006; Edirisinghe and Zhang 2007; Fridson et al. 2008), an initial set of financial ratios was chosen on the basis of their popularity and relevance to the assessment of corporate performance and viability within the framework of equity portfolio selection. At a series of meetings with experts, additional financial ratios were proposed and others were considered not necessary.

With the agreement of the experts, four sets of financial ratios were constructed to assess corporate performance (see Tables 3.4–3.7). Each criterion set is related to a different type of generic firm activity. On this basis, the four criteria sets focused on the evaluation of: (a) industry/commerce firms; (b) financial services firms; (c) banking institutions; and (d) insurance firms. The need to obtain objective, representative evaluation results was the reason for employing different criteria sets, as not all firms follow the same accounting plan (Samaras et al. 2008). Utilizing this approach, the crucial issue of sectoral accounting particularities was taken into account. The choice of specialized criteria sets was the next safety valve for fair and balanced results after the initial classification was adopted for evaluating firms within the same industry. Finally, the financial ratios used were categorized into four major groups: profitability ratios, activity ratios, liquidity ratios, and solvency/structure ratios.

Table 3.4 Criteria set for the evaluation of industry/commerce firms

	Criterion	Definition	Criterion direction	Perspective	Measuring unit
$g_{1,1}$	Return on assets	Earnings before interest and taxes divided by total assets	Max	Profitability	Percentage
$g_{1,2}$	Return on equity	Net income divided by shareholders equity	Max	Profitability	Percentage
$g_{1,3}$	Net profit margin	Net income divided by sales	Max	Profitability	Percentage
$g_{1,4}$	Deadline of receivables	(Customers plus accounts receivable) * 365 divided by sales	Min	Activity	No. of days
$g_{1,5}$	Deadline of payables	(Suppliers plus accounts payable) * 365 divided by sales	Min	Activity	No. of days
$g_{1,6}$	Assets turnover	Sales divided by total assets	Max	Activity	Fraction
$g_{1,7}$	Acid liquidity	Current assets minus inventories divided by current liabilities	Max	Liquidity	Fraction
$g_{1,8}$	Cash liquidity	Cash plus cash equivalents divided by current liabilities	Max	Liquidity	Fraction
$g_{1,9}$	Current liabilities to working capital	Current liabilities divided by current assets minus current liabilities	Min	Liquidity	Fraction
$g_{1,10}$	Solvency ratio	Total liabilities divided by shareholder's equity	Min	Solvency/structure	Fraction
$g_{1,11}$	Leverage ratio	Total assets divided by shareholder's equity	Max	Solvency/structure	Fraction
$g_{1,12}$	Financial expenses coverage	Earnings before interest and taxes divided by interest expenses	Max	Solvency/structure	Fraction

Table 3.5 Criteria set for the evaluation of financial services firms

	Criterion	Definition	Criterion direction	Perspective	Measuring unit
$g_{2,1}$	Return on assets	Earnings before interest and taxes divided by total assets	Max	Profitability	Percentage
$g_{2,2}$	Return on equity	Net income divided by shareholders equity	Max	Profitability	Percentage
$g_{2,3}$	Net profit margin	Net income divided by sales	Max	Profitability	Percentage
$g_{2,4}$	Personnel's performance	Earnings before interest and taxes divided by numbers of employees	Max	Profitability	Euros
$g_{2,5}$	Assets turnover	Sales divided by total assets	Max	Activity/liquidity	Fraction
$g_{2,6}$	Acid liquidity	Current assets minus inventory divided by current liabilities	Max	Activity/liquidity	Fraction
$g_{2,7}$	Solvency ratio	Total liabilities divided by shareholder's equity	Min	Solvency/structure	Fraction
$g_{2,8}$	Leverage ratio	Total assets divided by shareholder's equity	Max	Solvency/structure	Fraction

Table 3.6 Criteria set for the evaluation of banking institutions

	Criterion	Definition	Criterion direction	Perspective	Measuring unit
$g_{3,1}$	Return on assets	Earnings before interest and taxes divided by total assets	Max	Profitability	Percentage
$g_{3,2}$	Return on equity	Net income divided by shareholders equity	Max	Profitability	Percentage
$g_{3,3}$	Interest-bearing assets/liabilities spread	Average interest bearing assets return minus average liabilities interest cost	Max	Profitability	Fraction
$g_{3,4}$	Net interest margin	Net interest income divided by average total assets	Max	Profitability	Percentage
$g_{3,5}$	Efficiency	Total operating expenses divided by operating income	Max	Profitability	Percentage
$g_{3,6}$	Personnel's performance	Earnings before interest and taxes divided by numbers of employees	Max	Profitability	Euros
$g_{3,7}$	Equity to total assets	Shareholder's equity divided by total assets	Max	Structure	Percentage
$g_{3,8}$	Interest-bearing assets to total assets	Interest-bearing assets divided by total assets	Max	Structure	Percentage
$g_{3,9}$	Total loans to deposits	Total loans divided by total deposits	Min	Structure	Percentage
$g_{3,10}$	Provisions to total loans	Loan provisions plus other receivable provisions divided by total loans	Min	Structure	Percentage

Table 3.7 Criteria set for the evaluation of insurance firms

	Criterion	Definition	Criterion direction	Perspective	Measuring unit
$g_{4,1}$	Return on assets	Earnings before interest and taxes divided by total assets	Max	Profitability	Percentage
$g_{4,2}$	Return on equity	Net income divided by shareholders equity	Max	Profitability	Percentage
$g_{4,3}$	Net profit margin	Net income divided by sales	Max	Profitability	Percentage
$g_{4,4}$	Personnel's performance	Earnings before interest and taxes divided by numbers of employees	Max	Profitability	Euros
$g_{4,5}$	Deadline of receivables	(Customers plus accounts receivable) * 365 divided by sales	Min	Activity/liquidity	No. of days
$g_{4,6}$	Acid liquidity	Current assets minus inventory divided by current liabilities	Max	Activity/liquidity	Fraction
$g_{4,7}$	Solvency ratio	Total liabilities divided by shareholder's equity	Min	Solvency/structure	Fraction
$g_{4,8}$	Insurance provisions to liabilities	Total insurance provisions divided by total liabilities	Min	Solvency/structure	Percentage

According to the proposed methodology and with respect to Table 3.3, the connection between the different classes of firms and the criteria sets was as follows.

- Firms that belong to classes a, b, c, d, and e (consumer goods, industrials, technology, telecommunications, oil/gas, basic materials, consumer services, utilities, health care) are evaluated through the industry/commerce criteria set.
- Firms that belong to class f (financial services) are evaluated through the financial services criteria set.
- Firms that belong to class g (banks) are evaluated through the banking institutions criteria set.
- Firms that belong to class h (insurances) are evaluated through the insurance criteria set.

3.3.7 *Weighting Method*

The assignment of importance weightings to each criterion is a crucial issue in the application of all versions of the ELECTRE model (with the exception of ELECTRE IV). Because it is a noncompensatory decision aid model, the interpretation of weights is different than for a compensatory system such as MAUT (Keeney and Raiffa 1993). Within ELECTRE, the weights used are not of constant scale. They are simply a measure of the relative importance of the criteria involved. Rogers et al. (2000) distinguish four methods that can be employed to weight criteria for use within ELECTRE: (a) the direct weighting system (Hokkanen and Salminen 1997); (b) the Mousseau system (Mousseau 1995); (c) the “pack of cards” technique (Simos 1990); and (d) the “resistance-to-change grid” weighting method (Rogers and Bruen 1998).

The method chosen for the determination of weights was the resistance-to-change grid. This method represents an improvement in comparison to the other approaches. (a) It is relatively simple and straightforward. (b) It has a theoretical basis within the psychology of human preference relationships. (c) The weights obtained can be directly connected, in theoretical terms, to the DM’s concept of personal importance. (d) The method has been widely used in a large number of real-world applications.

The resistance-to-change grid is based on a theory from the area of psychology, the “personal construct theory” (Kelly 1955). It is part of an effort to explain how DMs automatically place decision criteria into a hierarchy of relative importance. According to Rogers and Bruen (1998), the resistance-to-change grid is shown to be a simple, comprehensible, legitimate weighting system. These three qualities are, according to Simos (1990), essential for a weighting technique to be usable in practice within the frame of the ELECTRE family methods. The weights finally obtained from the method are based on, and can be related directly back to, the concept of relative importance.

The main feature of the resistance-to-change grid weighting method is that pairwise comparisons between all the criteria are made within a matrix format. In a

given cell within the resistance-to change-grid, the following notation is used to signify the result obtained: (a) An “X” indicates that the column criterion is more important than the row criterion. (b) A “blank” indicates that the row criterion is more important than the column criterion. (c) An “I” indicates that the two criteria are of equal importance.

The scoring mechanism for the matrix involves counting, for each criterion, all the “blanks” in the rows and all the “X’s” in the column where the row criterion meets itself. An analytical representation of the resistance-to-change grid for the criteria set of industry/commerce firms may be seen in Table 3.8 (the weights for the rest of the criteria sets are summarized in Tables 3.9–3.11). The following examples illustrate the scoring process: (a) considering criterion $g_{1,1}$ (return on assets), there are 8 row “blanks”; thus, the resistance score (sum) is 8. (b) Considering criterion $g_{1,2}$ (return on equity), there are 9 row “blanks” and 1 “X” in the column where the $g_{1,2}$ row criterion meets itself; thus, the resistance score is 10. (c) Considering criterion $g_{1,8}$ (cash liquidity), there are 3 row “blanks” and 2 “X’s” in the column where the $g_{1,8}$ row criterion meets itself; thus, the resistance score is 5. Once the resistance scores for each criterion are obtained, a simple normalization process can be applied to obtain the final weightings, as shown in Table 3.8.

The description of the scoring process provided here reflects a more intuitive and practical explanation approach. The interested reader can find all the theoretical details in Rogers and Bruen (1998) and Rogers et al. (2000). The experts involved in the application found the resistance-to-change grid weighting method user-friendly and perceivable, and they expressed their satisfaction as far the obtained weighting results is concerned.

3.3.8 *Definition of Categories and Determination of Thresholds*

According to the proposed methodology, three categories were determined for the sorting of alternatives. The defined categories are shown in Table 3.12.

Table 3.13 presents four ways for interpreting the sorting results. The key idea behind the above issue was exploitation of the modeling capabilities that the ELECTRE Tri method incorporates (see Sect. 3.2).

Table 3.14 presents the profiles and thresholds for the firms of class *a* (year 2004). Similar matrices were constructed and used to evaluate all of the other classes of firms. One of the experts’ major contribution was the determination of all these parameters. Indeed, the methodology’s critical success factors were related to their valuable experience in security analysis, along with the plethora of statistical data (such as financial ratios of each firm for three consecutive years and the corresponding industry/sectoral average values) provided by the ICAP databank [ICAP S.A. (www.icap.gr) is the leading provider of financial and business information in Greece]. The availability of such detailed and elaborate information gave the experts assistance that was of crucial importance in their difficult task of making all the necessary assessments and finally obtaining the profile and threshold vectors.

Table 3.9 Criteria weights for the financial services firms criteria set

$g_{2,1}$	$g_{2,2}$	$g_{2,3}$	$g_{2,4}$	$g_{2,5}$	$g_{2,6}$	$g_{2,7}$	$g_{2,8}$
Return on assets	Return on equity	Net profit margin	Personnel's performance	Assets turnover	Acid liquidity	Solvency ratio	Leverage ratio
17.86	17.86	21.43	10.71	14.29	7.14	3.57	7.14

Table 3.10 Criteria weights for the banking institutions criteria set

$g_{3,1}$	$g_{3,2}$	$g_{3,3}$	$g_{3,4}$	$g_{3,5}$	$g_{3,6}$	$g_{3,7}$	$g_{3,8}$	$g_{3,9}$	$g_{3,10}$
Return on assets	Return on equity	Interest-bearing assets/liabilities spread	Net interest margin	Efficiency	Personnel's performance	Equity to total assets	Interest-bearing assets to total assets	Total loans to deposits	Provisions to total loans
7.32	19.51	19.51	14.63	17.07	7.32	2.44	2.44	7.32	2.44

Table 3.11 Criteria weights for the insurance firms criteria set

	$g_{4.1}$	$g_{4.2}$	$g_{4.3}$	$g_{4.4}$	$g_{4.5}$	$g_{4.6}$	$g_{4.7}$	$g_{4.8}$
	Return on assets	Return on equity	Net profit margin	Personnel's performance	Deadline of receivables	Acid liquidity	Solvency ratio	Insurance provisions to liabilities
Weight (%)	14.81	7.41	25.93	11.11	18.52	14.81	3.70	3.70

Table 3.12 Definition of categories

Category	Description
C_3	Firms involved in this category are characterized by excellent financial strength according to their performances for the criteria of all the examined perspectives (profitability, activity, liquidity, solvency, structure). With respect to their rivals in the corresponding industry, they are placed at the top of the ranking for all the ratios employed. These firms are considered to enjoy the best future prospects and constitute the most powerful and reliable investment opportunities during the specific period of analysis. Equities of these firms can be considered for participation in investment portfolios in a medium- to long-term horizon
C_2	This category contains firms that are characterized by medium financial strength. The performance of these firms in the examined criteria is moderate. In relation to their competitors, they are placed around the industry average values. The firms are not considered investment opportunities, at least for the specific period of analysis
C_1	The firms of this category are characterized by extremely poor financial strength within all the examined perspectives (profitability, activity, liquidity, solvency, structure). Relatively to their rivals, they are placed fairly well below the industry's average values. Equities of these firms do not constitute a rational investment choice for the specific period examined, at least for the medium to long term. Selection of these equities for participation in portfolios can only be considered within the frame of an aggressive/risky investment policy and only for obtaining short-term profits

Table 3.13 Interpretation of results

Case	Description
1st	The corresponding equities of firms that have been classified in category C_3 in both the optimistic and pessimistic assignment are proposed for selection without hesitation. These firms had satisfactory values for all the criteria set
2nd	The corresponding equities of firms that have been classified in category C_2 in both the optimistic and pessimistic assignment are currently not proposed for selection. This is because these firms had moderate values for all the criteria set. These firms have characteristics that must be studied further
3rd	The corresponding equities of firms that have been classified in category C_1 in both the optimistic and pessimistic assignment are irrevocably not proposed for selection. These firms had unsatisfactory values for all the criteria set
4th	The corresponding equities of firms that have been classified in different categories under the two types of assignment procedures are currently not proposed for selection. These firms have to be studied further because the notion of incomparability underlies their particularities

Table 3.14 Profiles and thresholds for the firms of class *a* (year 2004)

	$g_{1,1}$	$g_{1,2}$	$g_{1,3}$	$g_{1,4}$	$g_{1,5}$	$g_{1,6}$	$g_{1,7}$	$g_{1,8}$	$g_{1,9}$	$g_{1,10}$	$g_{1,11}$	$g_{1,12}$
b_2	6.27	9.17	7.30	122	58	0.66	1.33	0.13	0.97	0.51	2.10	4.09
$q_i(b_2)$	1.1	4.55	3.31	22	12	0.12	0.29	0.08	0.27	0.15	0.32	0.67
$p_i(b_2)$	3.72	11.16	11.97	42	34	0.29	1.13	0.34	0.52	0.23	1.24	3.34
b_1	3.44	3.95	3.92	135	96	0.47	0.87	0.03	1.35	1.22	1.74	3.515
$q_i(b_1)$	0.74	1.2	1.14	3	19	0.08	0.16	0.05	0.16	0.34	0.11	0.22
$p_i(b_1)$	1.86	2.99	1.54	10	25	0.13	0.32	0.1	0.25	0.49	0.19	0.95

3.4 Application and Results

3.4.1 Field of Application

The proposed methodology described in the previous section has been applied to data concerning firms whose equities are traded in the ASE. However, it is important to note that the usefulness of the proposed methodology is not affected by the fact that it is applied only to the ASE. The data employed in this application are available to analysts and investors in other countries. Furthermore, no assumptions are made concerning the special characteristics of the stock exchange.

A total of 259 firms (90 firms of high capitalization and 169 firms of medium to low capitalization) were considered for application of the proposed methodology. They covered a broad spectrum of business activities. In all, 62 firms were excluded from the study [owing to securities of special stock exchange characteristics ($n=14$), securities under supervision ($n=21$), securities under suspension ($n=17$), and preferred securities ($n=10$)]. The time period of the study was 3 consecutive years (2004–2006). Table 3.15 summarizes the distribution of the 259 firms in the corresponding industries and supersectors.

Table 3.16 provides information relative to the correspondence of each firm with its industry and supersector, as well as the capitalization category of each firm (bold-type characters indicate high capitalization securities and non-bold-type characters indicate medium and low capitalizations stocks). Finally, Table 3.17 suggestively presents the performance evaluation matrix for alternatives (firms) of class *a*. Similar performance matrices were available and were utilized to evaluate all of the other classes of firms.

3.4.2 Results

With respect to the implementation steps of the proposed methodology described in Sect. 3.3.1 and suggestively for the equities of firms of class *a* (consumer goods), we present in Tables 3.18–3.21 the corresponding partial results. More precisely, in Table 3.18 are presented the sorting results (both the pessimistic and optimistic

Table 3.15 Distribution of firms per industry/supersector

Class	Industry	Supersector	No. of companies per supersector	No. of companies per class
<i>a</i>	Consumer goods	Food and beverage	28	64
		Personal and household goods	36	
<i>b</i>	Industrials	Construction and materials	29	54
		Industrial goods and services	25	
<i>c</i>	Technology	Technology	22	25
	Telecommunications	Telecommunications	3	
<i>d</i>	Basic materials	Chemicals	9	28
		Basic resources	16	
		Oil and gas	3	
<i>e</i>	Consumer services	Retail	12	49
		Media	11	
		Travel and leisure	14	
		Utilities	4	
		Health care	8	
<i>f</i>	Financials	Financial services	20	20
<i>g</i>	Financials	Banks	14	14
<i>h</i>	Financials	Insurances	5	5

assignments) for the year 2004 (*Step 1*). Table 3.19 shows, for the same year, the overlap of assignment procedures for category C_3 (*Step 4*). The overlap of assignment procedures for category C_3 (for all years) is presented in Table 20 (*Step 5*). In Table 3.21 is presented the overlap of these equities of firms of class *a* that have been classified in category C_3 (both optimistic and pessimistic assignment) for at least 2 out of the 3 years of the period studied (*Step 6*).

Table 3.22 presents the final set of equities that are proposed to the DM for selection (*Step 7*). This set consists of 100 securities (out of the 259 initially considered), of which 49 are high capitalization equities. Table 3.22 reveals an important feature of the proposed methodology: There is no uniform sorting of stocks, but there is specialized sorting per industry. In this way, the huge issue of competition between rival firms is fully taken into consideration while unreasonable comparisons between them are excluded.

The securities proposed for selection represent firms characterized by excellent financial strength according to their performance in the criteria of all the examined perspectives (profitability, activity, liquidity, solvency, structure). With respect to their rivals in the corresponding industry, they are placed at the top of the ranking for all the ratios employed. These firms are believed to enjoy the best future prospects and constitute the most powerful and reliable investment opportunities during the specific period of analysis. Equities of these firms can be considered by the

Table 3.16 Firms and the corresponding industry/supersector

OASIS				
No.	code	Name of firm	Industry	Supersector
1	AAAK	Tria Alpha (CR)	Consumer goods	Personal and household goods
2	ALLK	Allatini (CB)	Consumer goods	Food and beverage
3	ALSIN	Alsenco (CR)	Consumer goods	Personal and household goods
4	VARG	Varagis (CR)	Consumer goods	Personal and household goods
5	VARNI	Varvaresos (CB)	Consumer goods	Personal and household goods
6	VELL	Vell Group (CR)	Consumer goods	Personal and household goods
7	VIVART	Vivartia (CR)	Consumer goods	Food and beverage
8	VIOKA	Viocarpet (CR)	Consumer goods	Personal and household goods
9	VOX	Fashion Box (CR)	Consumer goods	Personal and household goods
10	GALAX	Galaxidi (CR)	Consumer goods	Food and beverage
11	GRIGO	Grigoris Mikrogeumata (CR)	Consumer goods	Food and beverage
12	DIXTH	Dias Ithiokalieryies (CR)	Consumer goods	Food and beverage
13	DOURO	Douros (CR)	Consumer goods	Personal and household goods
14	DROME	Dromeas (CR)	Consumer goods	Personal and household goods
15	EVZ	Elliniki Viomihania Zaharis (CB)	Consumer goods	Food and beverage
16	EVROF	Evrofarma (CR)	Consumer goods	Food and beverage
17	EEEK	Coca Cola Tria Epsilon (CB)	Consumer goods	Food and beverage
18	ELVE	Elve Endimaton (CB)	Consumer goods	Personal and household goods
19	ELGEK	Elgeka (CR)	Consumer goods	Food and beverage
20	ELIXTH	Ellinikes Ithiokalieryies (CR)	Consumer goods	Food and beverage
21	ELMEK	Elmec Sport (CR)	Consumer goods	Personal and household goods
22	ELYF	Elliniki Ifadourgia (CR)	Consumer goods	Personal and household goods
23	ELFK	Elfico (CR)	Consumer goods	Personal and household goods
24	EPILK	Epilektos (CB)	Consumer goods	Personal and household goods
25	EFTZI	FG Europe (CR)	Consumer goods	Personal and household goods
...
243	ATE	Agrotiki Bank (CR)	Financials	Banks
244	ATT	Attica Bank (CR)	Financials	Banks
245	GTE	Geniki Bank (CR)	Financials	Banks
246	EGNAC	Egnatia Bank (CR)	Financials	Banks
247	EMP	Emporiki Bank (CR)	Financials	Banks
248	ETE	Ethniki Bank (CR)	Financials	Banks
249	EUROV	Eurobank (CR)	Financials	Banks
250	KYPR	Kiprou Bank (CR)	Financials	Banks
251	MARFV	Marfin Bank (CR)	Financials	Banks
252	PEIR	Pireaus Bank (CR)	Financials	Banks
253	PRO	Proton Bank (CR)	Financials	Banks
254	TT	Tahidromiko Tamieutirio (CR)	Financials	Banks
255	AGRAS	Agortiki Asfalistikiki (CR)	Financials	Insurances
256	ASASK	Aspis Pronia (CR)	Financials	Insurances
257	EEGA	Ethniki Asfalion (CR)	Financials	Insurances
258	EUVRK	Eurobrokers (CR)	Financials	Insurances
259	EUPIK	Europaiki Pisti (CR)	Financials	Insurances

Table 3.17 Performance matrix for alternatives of class *a* (all years)

No	Alternatives	Profitability						Activity															
		$g_{1,1}$			$g_{1,2}$			$g_{1,3}$			$g_{1,4}$			$g_{1,12}$									
		2004	2005	2006	2004	2005	2006	2004	2005	2006	2004	2005	2006	2004	2005	2006	2004	2005	2006				
		Return on assets						Return on equity						Net profit margin									
		2004	2005	2006	2004	2005	2006	2004	2005	2006	2004	2005	2006	2004	2005	2006	2004	2005	2006	2004	2005	2006	
1	AAAK	2.32	-6.32	-0.31	1.42	-13.07	-3.76	1.36	-23.09	-3.48	135	372	219	...	1.92	1.92	1.61	3.43	3.10	3.10	3.43	3.10	
2	ALLK	3.44	-0.53	2.09	4.28	-2.96	1.56	4.45	-3.17	2.08	121	136	145	...	1.92	1.56	4.34	3.43	1.92	1.92	3.43	1.92	
3	ALSIN	6.79	3.83	1.95	9.72	2.46	-8.10	3.20	0.83	-2.73	233	244	258	...	3.49	1.93	1.75	1.23	0.48	1.93	1.75	1.23	
4	VARG	-0.83	0.64	-1.23	-1.65	0.62	-2.99	-2.09	0.78	-3.74	82	116	188	...	1.50	1.94	3.515	2.78	3.20	1.94	3.515	2.78	
5	VARNI	4.24	-2.63	-2.81	4.31	-9.45	-12.1	4.74	-10.92	-12.5	96	103	87	...	1.92	1.90	2.04	3.43	3.00	1.92	2.04	3.43	
6	VELL	4.18	-7.51	1.52	7.94	-23.12	-0.62	6.17	-20.82	-0.38	300	368	263	...	1.92	1.95	4.09	3.43	0.86	1.92	4.09	3.43	
7	VIVART	5.95	4.63	6.21	7.35	1.78	4.43	106.1	24.90	5.23	132	145	88	...	2.62	2.18	2.45	1.17	1.49	2.62	2.18	2.45	
8	VIOKA	1.46	3.88	3.69	1.32	4.56	4.34	5.08	18.08	13.92	132	354	466	...	1.30	1.43	6.06	10.51	5.70	1.30	6.06	10.51	
9	VOX	7.04	8.32	11.36	13.72	17.24	24.46	5.06	5.33	6.81	135	121	119	...	2.41	2.52	5.53	7.22	6.84	2.41	5.53	7.22	
10	GALAX	0.54	7.08	7.42	-2.63	14.43	15.39	-1.61	8.54	8.49	74	84	91	...	2.50	2.66	0.33	5.39	4.51	2.50	2.66	0.33	
11	GRIGO	9.90	5.10	14.59	39.36	4.10	54.54	5.99	0.59	9.89	132	145	143	...	7.30	5.16	2.35	1.12	3.63	7.30	5.16	2.35	
12	DIXTH	3.76	7.91	21.73	11.70	26.15	23.25	8.55	14.12	76.50	135	85	146	...	3.31	1.07	3.515	3.43	3.00	3.31	1.07	3.515	
13	DOURO	2.82	0.44	0.64	2.38	-0.77	-0.77	3.46	-1.23	-1.22	92	101	88	...	1.92	1.96	2.80	0.43	0.53	1.92	1.96	2.80	0.43
...
52	SAR	5.30	6.23	6.63	25.85	23.75	24.16	7.30	8.49	10.71	159	156	146	...	4.47	3.65	7.56	6.83	3.10	4.47	3.65	7.56	6.83
53	SARAN	7.28	-0.74	10.52	15.60	-11.75	26.02	9.79	-7.60	17.58	132	81	175	...	1.92	3.62	3.20	3.43	3.15	1.92	3.62	3.20	3.43
54	SATOK	6.24	8.89	10.86	10.30	15.36	19.10	6.29	9.82	13.51	131	110	115	...	2.46	2.26	2.73	3.36	4.54	2.46	2.26	2.73	3.36
55	SELO	-0.51	10.27	6.60	-3.33	16.36	9.46	-4.93	26.37	11.82	119	155	133	...	1.81	1.90	3.515	8.34	4.07	1.81	1.90	3.515	8.34
56	SENTR	-1.90	6.34	7.02	-7.37	11.39	14.01	-2.36	3.34	4.47	144	147	191	...	2.51	2.78	3.515	3.52	3.55	2.51	2.78	3.515	3.52
57	TEXT	1.04	-9.92	-3.80	0.11	-16.65	-7.34	0.12	-27.34	-9.01	197	182	131	...	1.92	1.90	1.08	3.43	3.20	1.92	1.90	1.08	3.43
58	YALKO	6.43	4.26	6.24	10.47	6.41	10.14	6.26	3.76	5.48	183	203	208	...	2.22	2.23	4.09	3.10	3.69	2.22	2.23	4.09	3.10
59	FIER	1.92	3.07	4.77	1.85	4.45	7.41	1.64	4.12	6.59	118	119	113	...	1.89	1.78	1.97	4.28	7.80	1.89	1.78	1.97	4.28
60	FINTO	2.71	2.30	1.32	1.74	1.17	-0.90	3.03	1.76	-1.27	122	123	125	...	1.72	1.91	1.65	1.42	0.73	1.72	1.91	1.65	1.42
61	FOLI	8.06	9.36	7.81	13.77	17.84	13.98	39.00	50.81	44.70	131	157	181	...	2.28	3.23	3.83	6.12	2.25	2.28	3.23	3.83	6.12
62	FRUK	17.34	8.09	19.32	19.60	9.04	21.05	5.08	4.17	5.20	132	145	145	...	1.12	1.11	3.515	3.43	59.05	1.12	1.11	3.515	3.43
63	HATZK	6.48	2.16	13.72	6.77	2.26	28.51	320.7	62.03	43.86	132	145	144	...	1.05	2.08	3.515	280.9	3.00	1.05	2.08	3.515	280.9
64	HKRAN	3.78	0.63	0.54	5.15	0.45	0.07	6.60	0.76	0.11	213	283	286	...	1.35	1.37	3.515	2.12	1.10	1.35	1.37	3.515	2.12

Table 3.18 Class α results (year 2004)

Category	Pessimistic assignment						Optimistic assignment								
C_3	2 ALLK	5 VARNI	7 VIVART	9 VOX	11 GRIGO	2 ALLK	5 VARNI	7 VIVART	9 VOX	11 GRIGO	2 ALLK	5 VARNI	7 VIVART	9 VOX	11 GRIGO
	12 DICHT	14 DROME	15 EBZ	16 EVROF	17 EEEK	12 DICHT	14 DROME	15 EBZ	16 EVROF	17 EEEK	12 DICHT	14 DROME	15 EBZ	16 EVROF	17 EEEK
	18 ELVE	19 ELGEEK	21 ELM EK	22 ELYF	25 EFTZI	18 ELVE	19 ELGEEK	21 ELM EK	22 ELYF	25 EFTZI	18 ELVE	19 ELGEEK	21 ELM EK	22 ELYF	25 EFTZI
	26 INFIS	27 KANAK	28 KARD	29 KATSK	30 KEGO	26 INFIS	27 KANAK	28 KARD	29 KATSK	30 KEGO	26 INFIS	27 KANAK	28 KARD	29 KATSK	30 KEGO
	31 KEPEN	33 KORRES	35 KRETA	36 KRI	40 MIN	31 KEPEN	33 KORRES	35 KRETA	36 KRI	40 MIN	31 KEPEN	33 KORRES	35 KRETA	36 KRI	40 MIN
	42 MPELA	43 MPENK	46 NHR	52 SAR	53 SARAN	42 MPELA	43 MPENK	46 NHR	52 SAR	53 SARAN	42 MPELA	43 MPENK	46 NHR	52 SAR	53 SARAN
	54 SATOK	58 YAL KO	61 FOLI	62 FRLK	63 HATZK	54 SATOK	58 YAL KO	61 FOLI	62 FRLK	63 HATZK	54 SATOK	58 YAL KO	61 FOLI	62 FRLK	63 HATZK
C_2	3 ALSIN	6 VELL	13 DOURO	32 KMOL	34 KREKA	3 ALSIN	4 VARG	6 BELL	10 GALAX	13 DOURO	3 ALSIN	4 VARG	6 BELL	10 GALAX	13 DOURO
	45 NAUP	64 HKARN				24 EPILK	32 KMOL	34 KREKA	37 KTLA	45 NAUP	24 EPILK	32 KMOL	34 KREKA	37 KTLA	45 NAUP
						48 PERS	50 RINTE	55 SELO	59 FIER	64 HKRAN	48 PERS	50 RINTE	55 SELO	59 FIER	64 HKRAN
C_1	1 AAAK	4 VARG	8 VIOKA	10 GALAX	20 ELICHTH	1 AAAK	8 VIOKA	20 ELICHTH	23 ELFK	38 LOULI	1 AAAK	8 VIOKA	20 ELICHTH	23 ELFK	38 LOULI
	23 ELFK	24 EPILK	37 KTLA	38 LOULI	39 MAXIM	23 ELFK	39 MAXIM	41 MOUZK	44 MPOKA	47 OLYMP	23 ELFK	39 MAXIM	41 MOUZK	44 MPOKA	47 OLYMP
	41 MOUZK	44 MPOKA	47 KTLA	48 PERS	49 RILKE	41 MOUZK	49 RILKE	51 SANYO	56 SENTR	60 FINTO	41 MOUZK	49 RILKE	51 SANYO	56 SENTR	60 FINTO
	50 RINTE	51 SANYO	55 SELO	56 SENTR	57 TEXT	50 RINTE	57 TEXT				50 RINTE	57 TEXT			
	59 FIER	60 SANYO				59 FIER					59 FIER				

Table 3.19 Overlap of assignment procedures for category C_3 of class a (year 2004)

Category					
C_3	2 ALLK	5 VARNI	7 VIVART	9 VOX	11 GRIGO
	12 DICHT	14 DROME	15 EBZ	16 EVROF	17 EEEK
	18 ELVE	19 ELGEK	21 ELMEK	22 ELYF	25 EFTZI
	26 INFIS	27 KANAK	28 KARD	29 KATSK	30 KEGO
	31 KEPEN	33 KORRES	35 KRETA	36 KRI	40 MIN
	42 MPELA	43 MPENK	46 NHR	52 SAR	53 SARAN
	54 SATOK	58 YALKO	61 FOLI	62 FRLK	63 HATZK

Table 3.20 Overlap of assignment procedures for category C_3 of class a (all years)

2004	2 ALLK	5 VARNI	7 VIVART	9 VOX	11 GRIGO	
	12 DICHT	14 DROME	15 EBZ	16 EVROF	17 EEEK	
	18 ELVE	19 ELGEK	21 ELMEK	22 ELYF	25 EFTZI	
	26 INFIS	27 KANAK	28 KARD	29 KATSK	30 KEGO	
	31 KEPEN	33 KORRES	35 KRETA	36 KRI	40 MIN	
	42 MPELA	43 MPENK	46 NHR	52 SAR	53 SARAN	
	54 SATOK	58 YALKO	61 FOLI	62 FRLK	63 HATZK	
	2005	7 VIVART	9 VOX	10 GALAX	12 DICHT	15 EBZ
		16 EVROF	17 EEEK	19 ELGEK	20 ELICHT	21 ELMEK
		22 ELYF	25 EFTZI	26 INFIS	27 KANAK	28 KARD
29 KATSK		30 KEGO	32 MOL	33 KORRES	35 KRETA	
36 KRI		40 MIN	42 MPELA	43 MPENK	46 NHR	
49 RILKE		52 SAR	54 SATOK	56 SENTER	58 YALKO	
59 FIER		60 FINTO	62 FRLK			
2006	7 VIVART	9 VOX	10 GALAX	11 GRIGO	14 DROME	
	17 EEEK	21 ELMEK	25 EFTZI	26 INFIS	27 KANAK	
	28 KARD	29 KATSK	30 KEGO	33 KORRES	36 KRI	
	40 MIN	42 MPELA	46 NHR	48 PERS	51 SANYO	
	52 SAR	54 SATOK	55 SELO	56 SENTER	58 YALKO	
	59 FIER	62 FRLK	63 HATZK			

Table 3.21 Overlap of those equities of firms of class a , that have been classified in category C_3 (both optimistic and pessimistic assignment) in at least 2 out of the 3 years of the study period

Class a	7 VIVART	9 VOX	10 GALAX	11 GRIGO	14 DROME
	17 EEEK	21 ELMEK	25 EFTZI	26 INFIS	27 KANAK
	28 KARD	29 KATSK	30 KEGO	33 KORRES	36 KRI
	40 MIN	42 MPELA	46 NHR	52 SAR	54 SATOK
	56 SENTER	58 YALKO	59 FIER	62 FRLK	63 HATZK

Table 3.22 Final results

Class <i>a</i>	7 VIVART	9 VOX	10 GALAX	11 GRIGO	14 DROME
	17 EEEK	21 ELMEK	25 EFTZI	26 INFIS	27 KANAK
	28 KARD	29 KATSK	30 KEGO	33 KORRES	36 KRI
	40 MIN	42 MPELA	46 NHR	52 SAR	54 SATOK
	56 SENTR	58 YALKO	59 FIER	62 FRLK	63 HATZK
Class <i>b</i>	74 VOSYS	75 GEVKA	80 EKTER	83 ELTK	86 HERAC
	91 KLEM	92 KLM	94 LYK	97 MEVA	99 METK
	104 NIOUS	106 OLTH	107 OLP	109 PETRO	114 TERNA
	115 TITK	116 FLEXO	117 FRIGO		
Class <i>c</i>	119 AGRI	123 BYTE	129 KOSMO	131 KOUES	138 PLAIS
	140 REIN				
Class <i>d</i>	145 ALMY	148 DROUK	152 ELPE	158 MERKO	159 MOH
	161 MYTIL	162 NEOXH	166 SIDE	167 SIDMA	171 HAKOR
Class <i>e</i>	173 AVK	176 ANEK	177 ARAIG	178 ASKO	183 VSTAR
	186 EYAPS	189 HLEAT	190 HYATT	191 IASO	194 INLOT
	195 KAE	199 LAMPASA	205 MOTO	211 OPAP	212 OTOEL
	214 REV	216 SPRI	217 SFA		
Class <i>f</i>	221 AIOLK	222 ALTI	223 ANDRO	224 ASTAK	226 GEK
	227 GNEF	228 DIAS	230 EUPRO	231 EHAE	232 INTER
	235 KOUM	238 PEA	240 SIENS		
Class <i>g</i>	241 ALFA	243 ATE	248 ETE	249 EUROB	250 KYPR
	252 PEIR	254 TT			
Class <i>h</i>	255 AGRAS	258 EURBK	259 EUPIK		

rational investor to be prudent options for participation in portfolios, within a medium- to long-term horizon.

3.4.3 Validation of Results

The proposed methodology includes a final validation stage, where the results are tested at both a qualitative and a quantitative level.

Experts performed qualitative validation of the results, and their contribution was of crucial importance. They expressed their satisfaction with the final results and confirmed that the obtained results were in categorical concurrence with the set of high-performance securities that they heuristically manage in their everyday practice. Indeed, among the securities of the final proposed set, they identified almost all the “winning” equities of the ASE with respect to the particular time period of the application. Moreover, there were even equities in the final proposed set that had not been recognized by the experts but, as confirmed by the market, were appropriate for direct investment opportunities. Our method suggested that they be further studied for potential detection of mispriced securities.

In addition to the qualitative assessment, a quantitative testing of the final results was carried out. Our aim was to show that the stocks we propose for selection on the basis of a 3-year financial analysis are securities with satisfactory stock market behavior (i.e., satisfactory subsequent stock performance) (see Greig 1992; Holthausen and Larcker 1992; Ou and Penman 1992; Rapach and Wohar 2005). The criteria used to capture each security's stock market behavior were the two fundamental risk–return measures of financial theory: the average capital return per share and the standard deviation of return. More specifically:

- The average capital return per share is given by the formula:

$$\bar{r} = \sum_{t=1}^n \frac{r_t}{n}$$

where r_t is the capital return per share in period t . The capital return per share in period t is given by the formula:

$$r_t = \frac{p_t - p_{t-1} + d_t}{p_{t-1}}$$

where p_t is the stock price at the end of period t ; p_{t-1} is the stock price at the end of period $t-1$; and d_t is the dividend that the stock gives to the investor during period t .

- The standard deviation of capital return per share is given by the formula:

$$\sigma = \sqrt{\sum_{t=1}^n \frac{[r_t - \bar{r}]^2}{n}}$$

where r_t is the capital return per share in period t ; and \bar{r} is the average capital return per share.

Within the framework of the validation process, the time period for calculation of the above measures included the record of each security's weekly based closing prices, between April 1, 2007 and March 31, 2008. (There was a 3-month time lag between December 31, 2006 and March 31, 2007, when the two measures were calculated so all the companies' financial statements of year 2006 could be published.) This specific 1-year horizon follows the time period of the proposed methodology's application (3 consecutive years from 2004 to 2006) and sufficiently captures each security's future stock market performance.

For each one of the eight classes, Tables 3.23 and 3.24 summarize the minimum, maximum, and mean values of the average capital return and the standard deviation of capital return for: (a) the whole sample of the 259 stocks; and (b) the 100 stocks proposed for selection according to the methodology.

The first noticeable findings have to do with the fact that, in comparison to the whole sample of the 259 stocks, the set of 100 stocks proposed for selection performed

Table 3.23 Minimum, maximum, and mean values of the average capital return and the standard deviation of capital return for the whole sample of 259 stocks (per class)

Class	No. of securities	Average capital return			Standard deviation of capital return		
		Min	Mean	Max	Min	Mean	Max
<i>a</i>	64	-3.41	0.155	12.819	3.088	7.572	47.978
<i>b</i>	54	-2.318	-0.46	1.004	1.946	5.987	13.042
<i>c</i>	25	-1.5	1.191	35.502	2.222	8.223	52.123
<i>d</i>	28	-1.84	-0.631	0.278	2.491	5.246	8.877
<i>e</i>	49	-1.692	0.171	1.831	2.428	6.031	12.051
<i>f</i>	20	-1.038	-0.128	2.32	2.041	6.221	34.33
<i>g</i>	14	-0.778	-0.497	-0.14	1.758	4.034	5.519
<i>h</i>	5	-0.847	-0.486	-0.169	4.074	6.187	10.799

Table 3.24 Minimum, maximum, and mean values of the average capital return and the standard deviation of capital return for the whole sample of the 100 stocks proposed for selection (per class)

Class	No. of securities	Average capital return			Standard deviation of capital return		
		Min	Mean	Max	Min	Mean	Max
<i>a</i>	25	-1.777	0.171	1.348	3.088	5.858	10.381
<i>b</i>	18	-1.132	-0.1	1.004	1.946	5.144	9.217
<i>c</i>	6	-0.989	0.113	1.199	2.222	6.357	10.514
<i>d</i>	10	-1.84	-0.75	-0.057	3.619	4.85	7.348
<i>e</i>	18	-1.692	0.216	1.831	2.428	5.398	8.484
<i>f</i>	13	-1.038	-0.363	0.064	2.041	4.109	7.772
<i>g</i>	7	-0.762	-0.464	-0.14	3.196	4.095	5.112
<i>h</i>	3	-0.685	-0.366	-0.169	4.074	6.372	10.799

as follows: (a) higher class means in five of the eight classes regarding the average capital return (classes *a*, *b*, *e*, *g*, *h*); (b) lower class means in six of the eight classes (classes *a*, *b*, *c*, *d*, *e*, *f*) regarding the standard deviation of capital return. The whole picture becomes clearer when the validation statistics of Table 3.25 are taken into consideration.

The analysis showed that 59 of the 100 stocks proposed for selection had a higher average capital return than the corresponding class mean values of the whole sample of 259 stocks. The highest percentage (72.2%) was observed for class *b* (industrials), where 13 of the 18 stocks proposed for selection had a better average capital return than the corresponding class mean of the whole sample. The lowest percentage (52%) was observed for class *a* (consumer goods), where 13 of the 25 stocks proposed for selection had a worse average capital return than the corresponding class mean of the whole sample.

As far as the risk dimension is concerned, the analysis showed that 74 of the 100 stocks proposed for selection had a lower standard deviation of capital return than the corresponding class mean values for the whole sample of 259 stocks.

Table 3.25 Validation statistics

Class	No. of securities with average capital return above the class mean	Percentage (%)	No. of securities with standard deviation of return below the class mean	Percentage (%)
<i>a</i>	13	52.0	22	88.0
<i>b</i>	13	72.2	12	66.7
<i>c</i>	4	66.7	5	83.3
<i>d</i>	6	60.0	7	70.0
<i>e</i>	10	55.6	12	66.7
<i>f</i>	7	53.8	11	84.6
<i>g</i>	4	57.1	3	42.9
<i>h</i>	2	66.7	2	66.7
Total	59	59.0	74	74.0

The highest percentage (88%) was observed for class *a* (consumer goods), where 22 of the 25 stocks proposed for selection had a better standard deviation of capital return than the corresponding class mean of the whole sample. The lowest percentage (42.9%) was observed for class *g* (banks), where three of the seven stocks proposed for selection had a worse standard deviation of return than the corresponding class mean of the whole sample.

The above findings are encouraging as the problem of correlating the actual returns of stocks with corporate performance of the corresponding firms, as captured in financial ratios, is one of the most challenging in modern financial decision-making (see Greig 1992; Ou and Penman 1992). It should also be noted that there were interesting percentages regarding the risk dimension, indicating stock market stability for firms enjoying corporate health and financial strength.

3.4.4 Sensitivity Analysis

The sorting of alternatives in the ELECTRE Tri method remains dependent on the values of various thresholds and indices of importance. Therefore, in most cases, sensitivity analysis is recommended. For the application that has been presented, the sensitivity analysis was conducted with respect to the criteria weights. A large number of weighting scenarios were examined (the generation rationale had to do with low, random, and simultaneous fluctuations on the weights of the baseline scenarios), and the obtained sorting results had no or extremely slight variation compared to the results of the baseline scenarios. It has to be stressed that the ELECTRE Tri method is not a direct pairwise methodology. For each option, the outranking relations derived are with categories, not with the other options under consideration. It thus tends to be less sensitive than pairwise-based ELECTRE methods to the presence of “clones” (i.e. options lying very close to each other on their criterion valuations).

3.5 Conclusions

A multicriteria approach for equity selection was presented. The methodology exploits for this purpose the valuable tool of FA. Within this framework, the underlying rationale adopted was that FA can be utilized for selecting attractive equities by means of evaluating the overall corporate performance of the corresponding firms.

The special features and contribution of the approach presented are outlined as follows.

- Several criteria are incorporated into the decision process that represent the way real decisions are supported and strategies are implemented. Also, the proposed methodology takes into consideration both the DM's preference system and the analyst's professional experience.
- A significantly large number of firms (alternatives) from a wide range of business sectors can be evaluated simultaneously. The methodology's key characteristic that allows this convenience is that the firms participating in the evaluation process are categorized into classes with respect to their industry. The ELECTRE Tri multicriteria method is then applied separately in each one of these classes. Finally, the results are integrated, considering also the major issue of the time trend.
- The crucial issue of industry/sectoral accounting particularities was taken into account. The sorting provided by the methodology is highly reliable and representative as every sorting has a different structure and is based on a specific criteria set that corresponds to the specific accounting plan in which each company belongs.
- There is no uniform sorting of stocks. There is specialized sorting per industry. In this way, the huge issue of competition between rival firms is fully taken into consideration, and unreasonable comparisons between them are excluded.

As testified in the bibliographic review part of the article, the MCDM paradigm provides a broad spectrum of methodological approaches for effectively addressing the problem of portfolio selection. It seems that the outranking relations theory framework might also provide a rather interesting alternative methodological basis for modeling the initial phase of the portfolio selection problem (i.e. the one that refers to the selection of the most attractive securities) despite its difficulties regarding the assignment of the required technical parameters.

At this point, it must be stressed that the current study constitutes the first stage of an integrated multiple criteria methodological framework developed by the authors for supporting decisions that concern the construction and selection of equity portfolios. At the second stage of this framework, a mixed-integer multiobjective mathematical programming model is developed to generate the Pareto optimal portfolios consisting of the dynamic set of securities obtained at the first stage. Because at the first stage the efforts were focused on detecting the most attractive stocks on the basis of corporate performance and viability of the corresponding

firms, the aim at the second stage is to synthesize portfolios by taking into consideration all of the critical aspects of the portfolio selection problem. To this end, issues such as the diversification effect between securities or the inclusion of certain risk measures (i.e., the standard deviation of stock returns or the beta coefficient) are fully incorporated in the decision process during the second stage of the framework.

Finally, further work that may be considered for broadening and enhancing the methodology proposed in this chapter should focus on the following three points: (a) embodiment of the methodology in a web-based decision information system so real-time investment decisions can be supported; (b) expansion of the criteria set toward a qualitative direction by considering a broader grid of decision parameters, such as the quality of management and the firm's market position; (c) expansion of the methodology's focus to include additional asset classes.

Chapter 4

Portfolio Optimization

4.1 Introduction

In this chapter, we strongly advocate a multicriteria approach to address the problem of portfolio construction and selection, taking into account: (a) the limits related to the Markowitz conventional theory, the results from the estimation of the models, and the philosophy of the single-objective optimization approach; and (b) the behavior of investors, who, in addition to the above-mentioned anomalies, could have additional criteria in mind, beyond risk and return. To address these issues effectively, we present an integrated and innovative methodological approach, within the frame of multiobjective mathematical programming (MMP), for constructing and selecting equity portfolios.

4.2 Methodological Framework

4.2.1 *Proposed Approach*

The existing research activity in the conjoint field of portfolio management (PM) and multiple criteria decision-making (MCDM) is quite extended, with many valuable suggestions for improving the effectiveness of people involved in investment activities, directly or indirectly. However, few propositions, if any, are concerned with an integrated methodological framework, fully implemented in a decision support system, for modeling the complex and ill-structured problem of portfolio generation and selection. The portfolio generation problem responds to the need of creating a number of candidate portfolios, whereas the portfolio selection problem aims at selecting one of them.

The contribution of the proposed approach (Mavrotas et al. 2008; Xidonas et al. 2008b; Xidonas et al. 2011) is that it takes into consideration and resolves the inherent multidimensional nature of the problem while allowing the decision-maker

(DM) to express his preferences during all the phases of the decision process. The portfolios are created and evaluated based on a multicriteria process. The methodology has been developed in close cooperation with a panel of experienced equity portfolio managers, whose contribution was of catalytic impact at all the stages of the collaboration.

The special characteristics and contribution of the proposed approach are summarized as follows:

1. The proposed approach aims to broaden the classic theory and successfully combine sophistication, realism, and fast computation. Beyond the classic biobjective (maximize expected return/minimize risk) formulation of Markowitz, four objective functions are simultaneously optimized to provide efficient solutions. An additional measure of return (the portfolio's relative dividend yield) along with a measure of risk, the portfolio's beta coefficient (representing market risk), are incorporated in the optimization process and expand the conventional framework. With the proposed approach, the conventional framework is represented by the portfolio's average historical return and mean absolute deviation (representing nonsystematic risk), instead of variance, to relax the computational burden (Konno and Yamazaki 1991).
2. One of the most critical phases of the PM process is the phase during which the DM formulates his investment policy statement (IPS) and expresses his investment objectives and constraints. The proposed approach helps the DM model his preferences explicitly and accurately.
3. The heart of the proposed approach is the innovative multiobjective optimization method utilized for solving mixed-integer linear programming models generated during modeling of the decision process. The method used is the augmented ϵ -constrained method (Mavrotas 2009), the so-called AUGMECON, which is classified in the category of generation or a posteriori MMP methods. It generates Pareto optimal portfolios, among which the DM is going to choose the most preferred one.
4. After the Pareto set of portfolios is obtained (portfolios generation) and because of the usually large number of solutions produced in a multiobjective optimization problem, the DM needs assistance when making his final choice. The proposed approach is equipped with a highly effective interactive filtering technique (Steuer 1989), appropriate in gradually focusing on the most preferred solution.
5. The proposed approach gives the DM the potential to incorporate in his models not only continuous but also binary decision variables, which in the theory of finance is called "cardinality constraints." The incorporation of binary variables offers even more realistic modeling options to the DM. He can then easily formulate logical conditions dealing with the interdependence of the incorporated securities or set lower bounds on the incorporated securities. This modeling choice also allows the DM to have complete control of the number of securities that are incorporated in the portfolio. The AUGMECON method is particularly suitable for dealing with multiobjective problems that have binary variables, as it deals effectively with nonconvex feasible regions.

6. The PM process involves processing a large volume of financial data. For this reason, the contribution of specialized information systems in the field is imperative. The proposed approach is implemented in the Integrated Portfolio Synthesis and Selection Information System (IPSSIS) decision support system (DSS). The IPSSIS system, being fully parameterized and having flexible architecture, provides the user with remarkable computational power.

The process flowchart of the proposed approach is graphically depicted in Fig. 4.1.

At the first stage of the methodology, the DM denotes the IPS he adopts and defines his investment objectives and constraints. He has the potential to choose whether to optimize all or some of the model's four objectives and to express specific preferences related to particular business sectors and securities. He also has the option to make precise adjustments in regard to other specialized issues, such as the degree of market risk he accepts, the extent to which he wants to diversify his portfolio, and the capitalization synthesis he desires. Then, the multiobjective mixed-integer linear programming model is formulated in the well-known General Algebraic Modeling System (GAMS) platform and solved exploiting the augmented ε -constrained method, producing the Pareto optimal (efficient) portfolios. In the next phase, the DM participates in the interactive filtering process of the Pareto optimal portfolios that have resulted to choose the most preferred. All the phases of the proposed methodological approach are analyzed in detail in the following sections.

4.2.2 *Generation of the Pareto Optimal Solutions with the ε -Constraint Method*

The general MMP model is defined as follows (Steuer 1989):

$$\max (f_1(x), f_2(x), \dots, f_p(x)) \text{ s.t. } x \in S \quad (4.1)$$

where x is the vector of decision variables; $f_1(x), \dots, f_p(x)$ are the p objective functions; and S is the feasible region. In MMP, the concept of optimality is replaced with that of efficiency or Pareto optimality. The Pareto optimal or efficient or non-dominated solutions (portfolios in the current case) are those solutions that cannot be improved in one objective function without harming their performance in at least one of the others.

According to Hwang and Masud (1979), the methods for solving MMP problems can be classified into three categories according to the phase in which the DM is involved in the decision-making process, expressing his preferences: a priori methods, interactive methods, and generation, or a posteriori, methods.

In a priori methods, the DM expresses his/her preferences before the solution process (e.g., setting goals or weights for the objective functions). The criticism

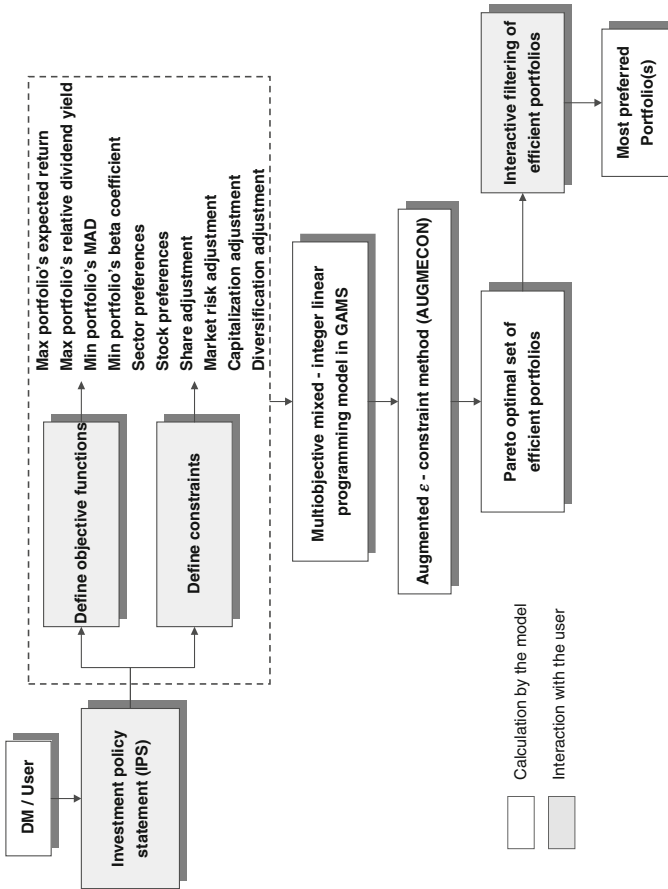


Fig. 4.1 Process flowchart of the proposed methodological approach. *DM* decision-maker, *Max* maximum, *Min* minimum, *MAD* mean absolute deviation, *GAMS* General Algebraic Modeling System

about the a priori methods is that it is difficult for the DM to know beforehand and to be able to quantify accurately (either by means of goals or weights) his/her preferences. In the interactive methods, phases of dialogue with the DM are interchanged with phases of calculation, and the process usually converges after several iterations to the most preferred solution. The DM progressively drives the search with his answers. The drawback is that (s)he never sees the whole picture (the set of Pareto optimal solutions) or an approximation of it. Hence, the most preferred solution is “most preferred” in relation to what he/she has seen and compared so far. In a posteriori (generation) methods, the Pareto optimal solutions of the problem (all of them or a sufficient representation) are generated, after which the DM gets involved in selecting the most preferred one. In the current study, we use a generation method (ε -constraint method) accompanied by a decision aid tool for selecting the most preferred among the Pareto optimal solutions.

The generation methods are less popular because of their computational effort (calculation of the Pareto set is usually a time-consuming process) and the lack of widely available software. However, they have some significant advantages (e.g., representation of the Pareto set, demonstration of the full picture to the DM). The most widely used generation methods are the weighting and the ε -constraint methods. In the weighting method, a weighted sum of the objective functions is optimized. By varying the weights of the objective functions, we obtain different efficient solutions. In the ε -constraint method, we optimize one of the objective functions using the other objective functions as constraints, incorporating them in the constraint part of the model, as shown below (Cohon 1978; Chankong and Haimes 1983).

$$\max \{f_1(x) \mid f_j(x) \geq e_j, j = 2 \dots p, \wedge x \in S\} \quad (4.2)$$

Efficient solutions of the problem are obtained by parametric variation in the right-hand side (RHS) of the constrained objective functions (e_j). The ε -constraint method has several advantages over the weighting method.

1. For linear problems, the weighting method is applied to the original feasible region and results in a corner solution (extreme solution), thus generating only efficient extreme solutions. On the contrary, the ε -constraint method alters the original feasible region and can produce nonextreme efficient solutions. As a consequence, with the weighting method we may conduct a lot of runs that are redundant in the sense that there can be numerous combinations of weights that result in the same efficient extreme solution. On the other hand, with the ε -constraint we can exploit almost every run to produce a different efficient solution, thus obtaining a richer representation of the efficient set.
2. The weighting method cannot produce unsupported efficient solutions in multiobjective integer and mixed integer programming problems. The ε -constraint method does not suffer from this pitfall (Steuer 1989; Miettinen 1998).

3. In the weighting method the scaling of the objective functions has a strong influence on the obtained results. Therefore, we need to scale the objective functions to a common scale before forming the weighted sum. This is not necessary with the ε -constraint method.
4. An additional advantage of the ε -constraint method is that we can control the number of efficient solutions generated by properly adjusting the number of grid points in each of the objective function ranges. This is not easy with the weighting method (see point 1 above).

Several versions of the ε -constraint method have been developed in attempts to improve its performance or adapt it to a specific problem (see Ehrgott and Ryan 2002; Laumanns et al. 2006; Hamacher et al. 2007). Despite its advantages over the weighting method, the ε -constraint method has three points that need attention in its implementation: (a) calculation of the range of the objective functions over the efficient set; (b) guarantee of efficiency of the obtained solution; (c) increased solution time for problems with several (more than two) objective functions. We address these three issues with a novel version of the ε -constraint method the augmented ε -constraint method (AUGMECON).

A detailed description of the AUGMECON method is beyond the scope of this book, but the interested reader can find it in Mavrotas (2009). We point out briefly its innovations related to the above three issues.

1. First, we use lexicographic optimization to construct the payoff table. In this way we guarantee the efficiency of the obtained solution and more reliable calculation of the objective functions' ranges.
2. Second, we modify the objective function of the single-objective problem adding a second priority term to guarantee that the obtained optimal solution is Pareto optimal for the original multiobjective problem (thereby avoiding weak Pareto optimal solutions).
3. Third, we accelerate the whole process by introducing an "early exit from the loops" option when the intermediate problems become infeasible. This capability saves much computational time for problems with more than two or three objective functions.

The augmented ε -constraint method is especially beneficial when there are several objective functions in the problem (e.g., Mavrotas et al. 2007).

Practically, the augmented ε -constraint method is applied as follows: From the payoff table we obtain the range of each of the $p-1$ objective functions that are going to be used as constraints. Then, we divide the range of the i -th objective function to q_i equal intervals using $(q_i - 1)$ intermediate equidistant grid points. Thus, we have in total $(q_i + 1)$ grid points that are used to vary parametrically the RHS (e_i) of the i -th objective function. The total number of runs becomes $(q_2 + 1) \times (q_3 + 1) \times \dots \times (q_p + 1)$. A desirable characteristic of the ε -constraint method is that we can control the density of the efficient set representation by properly assigning values to the q_i . The higher the number of grid points, the more dense is the representation of the efficient set but at the cost of greater computation time. A trade-off between

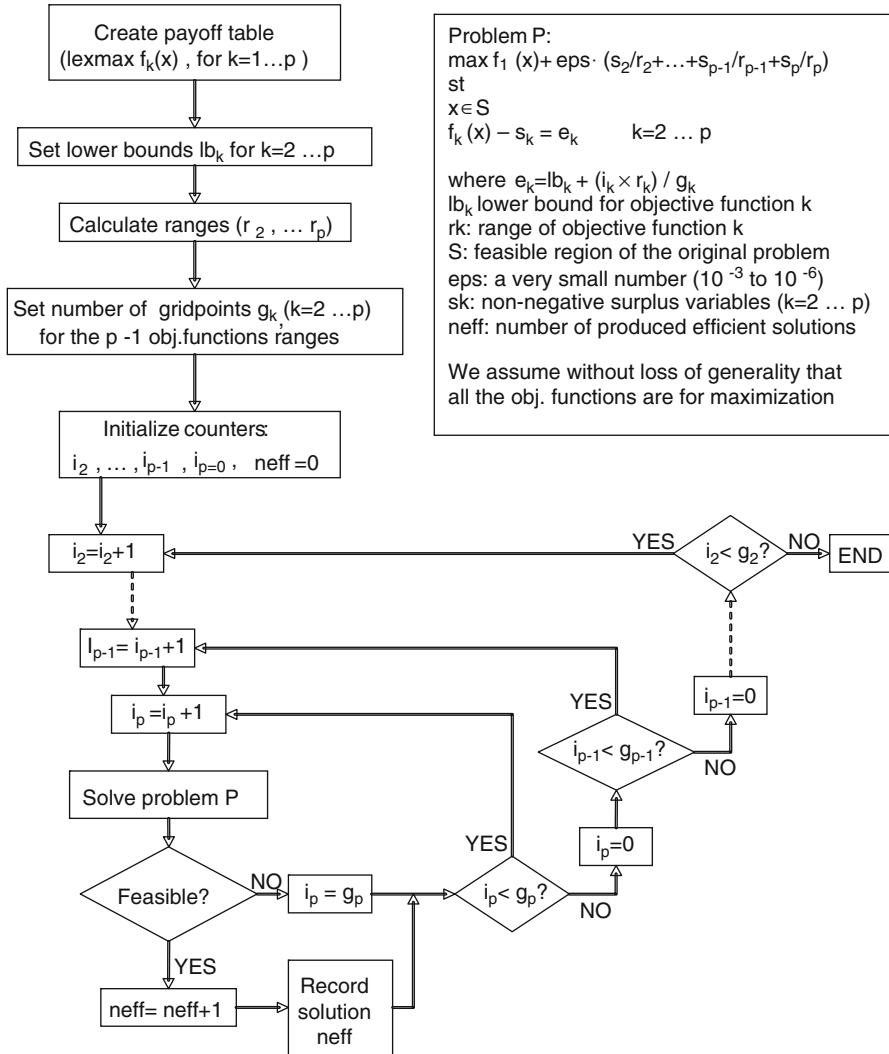


Fig. 4.2 Flowchart of the AUGMECON method

the density of the efficient set and the computation time is always advisable. A flowchart of the algorithm is shown in Fig. 4.2. The augmented ϵ -constraint method has been coded in the GAMS, a widely used modeling language (Brooke et al. 1998). It is an effort to provide the multicriteria community with access to powerful optimization tools and, vice versa, to provide the many GAMS users with tools for effectively dealing with multiobjective optimization. The code is available in the GAMS library with an educational example (<http://www.gams.com/modlib/libhtml/epshtm.htm>) and supporting documentation (Mavrotas 2007). The interested reader can use AUGMECON for his or her own problems by modifying only

the part of the code that has to do with the example (the specific objective functions and constraints), as well as the parameters of AUGMECON (number of grid points per objective function). The GAMS version of AUGMECON can be used in multi-objective linear programming, mixed-integer programming, or even nonlinear programming problems (given that the necessary solvers are installed).

4.2.3 Selection of the Most Preferred Among the Pareto Optimal Solutions

Once the Pareto optimal set of solutions is obtained, the subsequent task is to assist the DM in making his final choice among these solutions (decision support). One option is to use one of the discrete MCDM methods (see Belton and Stewart 2002) regarding the obtained Pareto optimal solutions as the decision alternatives and the objective functions as the performance criteria. However, in the present case we incorporated a simple, straightforward selection mechanism to assist the DM in his final selection with little computational effort. That is, we used the technique of interactive filtering of the solutions (Steuer 1989) which is appropriate in gradually focusing on the most preferred solution, reducing the “information overload” caused by the usually large number of Pareto optimal solutions evaluated in a number of objective functions. With this technique, a representative, small subset of the Pareto optimal solutions is automatically calculated using the “first point outside the neighborhood” algorithm. The DM selects his most preferred, efficient solution from a small sample of representative Pareto optimal solutions that is automatically produced by the method. For the DM, it is easier to compare along a number of criteria (usually more than two, perhaps three to seven) alternatives instead of hundreds. This selection drives the search to a reduced area, and the procedure (selection among representative samples) is repeated for a predetermined number of iterations. The reduction factor of the searching space is automatically adjusted according to the number of initial solutions, the number of iterations, and the number of solutions in the representative set. For illustrative purposes, a small example of the interactive filtering process is shown in Fig. 4.3.

The aim of the interactive filtering process is to select the most preferred among the 20 Pareto optimal solutions that are depicted graphically in two dimensions (Fig. 4.3a). The representative set of the five solutions is first calculated (solutions 1, 4, 7, 9, and 13 in the dark circles) using the algorithm of the first point outside the neighborhood, and these five solutions are shown to the DM. Assume that the DM selects solution 9. The search space then contracts around solution 9 (dashed line in Fig. 4.3b). The corresponding representative set now consists of solutions 2, 6, 9, 13, and 17 as it is calculated from the method. Assume that the DM selects solution 17. In the final (third) iteration (Fig. 4.3c), the search space is contracted around solution 17 (dashed line). The five solutions (7, 8, 10, 14, 17) are shown to the DM.

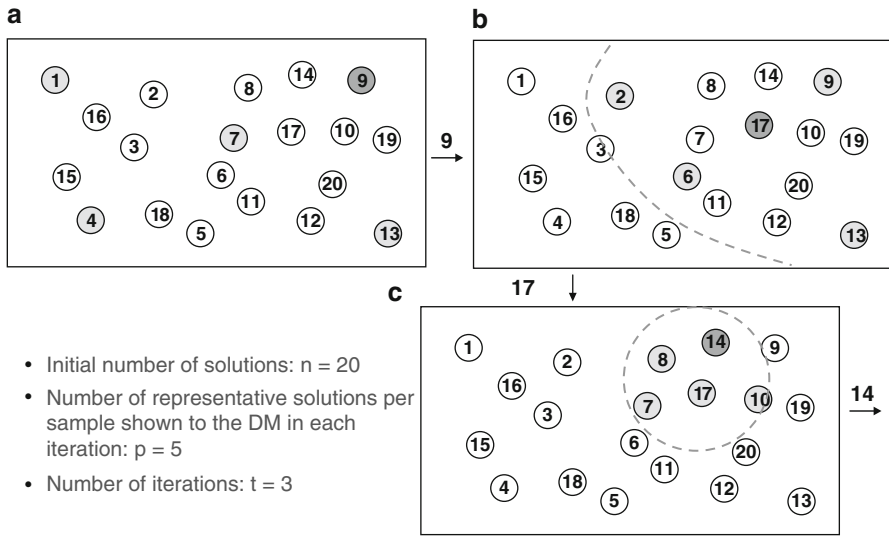


Fig. 4.3 Graphical representation of the interactive filtering process

Let us assume that he selects solution 14, which is the final output of the interactive filtering technique (the most preferred Pareto optimal solution). More details about the interactive filtering can be found in Steuer (1989).

4.3 Model Building Process and Application

4.3.1 Field of Application

The proposed methodological approach presented has been applied to data concerning equities traded in the ASE. The sample considered in the study consists of 60 securities covering a broad spectrum of business activities, taking into account the major issue of the diversification effect (see Statman 1987; Brennan 1975; Evans and Archer 1968). The study period includes the record of the weekly based closing prices between January 1, 2004 and June 31, 2007. Table 4.1 provides information relative to the correspondence of each security with its industry and supersector, as well as the capitalization category of each security (bold-type entries for high capitalization stocks and non-bold-type entries for medium and low capitalizations stocks).

It is important to note that the usefulness of the proposed approach is not affected by the fact that it is applied only to the ASE. The types of data employed in the application are also available to analysts and investors in other countries. Furthermore, no assumptions were made concerning the special characteristics of the stock exchange. It also must be stressed that the role of the DM in the current application was undertaken by equity portfolio managers who effectively cooperated during the development and validation of the proposed methodology.

Table 4.1 Securities and the corresponding industry/supersector

OASIS				
Variables	code	Name of company	Industry	Supersector
X_1	VIVART	VIVARTIA (CR)	Consumer goods	Food and beverage
X_2	BOX	FASHION BOX (CR)	Consumer goods	Personal and household goods
X_3	EEEEK	COCA COLA 3E (CB)	Consumer goods	Food and beverage
X_4	INFIS	INTERFISH (CR)	Consumer goods	Food and beverage
X_5	KANAK	KANAKIS (CR)	Consumer goods	Food and beverage
X_6	KARD	KARDASILARIS (CR)	Consumer goods	Food and beverage
X_7	KATSK	KATSELI YIOI (CR)	Consumer goods	Food and beverage
X_8	MPELA	JUMBO (CR)	Consumer goods	Personal and household goods
X_9	SATOK	SATO (CR)	Consumer goods	Personal and household goods
X_{10}	YALKO	YALCO (CB)	Consumer goods	Personal and household goods
X_{11}	FOLI	FOLLI FOLLIE (CR)	Consumer goods	Personal and household goods
X_{12}	FRLK	FOURLIS (CR)	Consumer goods	Personal and household goods
X_{13}	AVAX	JP AVAX (CR)	Industrials	Construction and materials
X_{14}	VOSYS	VOGIATZOGLOU (CR)	Industrials	Industrial goods and services
...
X_{46}	SFA	SFAKIANAKIS (CR)	Consumer services	Retail
X_{47}	ANDRO	ANDROMEDA AEEX (CR)	Financials	Financial services
X_{48}	ASTAK	ALPHA AKINITA (CR)	Financials	Financial services
X_{49}	VOVOS	VOVOS BABIS (CR)	Financials	Financial services
X_{50}	GNEF	GLOBAL AEEX (CR)	Financials	Financial services
X_{51}	DIAS	DIAS AEEX (CR)	Financials	Financial services
X_{52}	KOUM	KOUMPAS (CR)	Financials	Financial services
X_{53}	ALFA	ALPHA BANK (CR)	Financials	Banks
X_{54}	ATE	AGROTIKI TRAPEZA (CR)	Financials	Banks
X_{55}	ETE	ETHNIKI TRAPEZA (CR)	Financials	Banks
X_{56}	EUROB	EUROBANK EFG (CR)	Financials	Banks
X_{57}	KYPR	KYPROU TRAPEZA (CR)	Financials	Banks
X_{58}	PEIR	PIREUS TRAPEZA (CR)	Financials	Banks
X_{59}	EEGA	ETHNIKI ASFALION (CR)	Financials	Insurances
X_{60}	EUPIK	EUROPAIKI PISTI (CR)	Financials	Insurances

4.3.2 Model Building

According to Maginn et al. (2007) the PM process is an integrated set of steps undertaken in a consistent manner to create and maintain an appropriate portfolio to meet the investor's stated goals. The cornerstone of the PM process and an issue of

fundamental importance is the IPS, which clearly sets out the investor's objective and constraints. The investment objectives are defined as the desired investment outcomes and, in general, mainly pertain to return and risk issues. The investment constraints are defined as the limitations on the investor's ability to take full or partial advantage of particular investments. In the conventional approach, the investment objectives are restrictively modeled by maximizing the portfolio's expected return and minimizing its variance. Other specific preferences—such as the desired dividend yield, exposure tolerance to the underlying market risk, or particular diversification preferences—that the investor might consider can be embodied in the model as constraints. One of the fundamental aims of the developed model is to incorporate effectively in a (as much as possible) realistic way all the investor's (i.e., the DM's) investment objectives and constraints under the holistic prism of the MMP optimization rationale. The model's special characteristics—decision variables, objective functions, constraints—are analyzed in detail in the following sections.

4.3.2.1 Decision Variables

The decision variables of the model are both continuous and binary. The continuous variables X_i (where $i=1, \dots, n$ and $n=60$) represent the percentage of capital to be invested in the i -th security in the portfolio (see the first column of Table 4.1). The binary variables B_i represent the existence of the i -th security in the portfolio ($B_i=1$) or not ($B_i=0$).

Incorporation of these binary variables offers flexibility and more realistic modeling of the decision situation for three main reasons.

1. Logical conditions dealing with the interdependence of the incorporated securities can be easily formulated (i.e., a logical condition may be “if security a is incorporated in the model, security b must be also present”).
2. Lower bounds can be set to the incorporated securities. Hence, if security a is incorporated in the portfolio, its weight must be at least a minimum value.
3. With the binary variables we have complete control of the number of securities that are incorporated in the portfolio (e.g., the number of securities must be between 10 and 20).

All three conditions cannot be modeled with conventional linear programming, which handles only continuous variables. The incorporation of binary variables gives rise to a mixed-integer programming model. These models are more difficult to solve, but they provide a more realistic representation of the real decision situation, allowing the DM to establish more complex conditions. Nowadays, related hardware and software can provide the solution of difficult mixed-integer programming problems in a few minutes, so the solution time is no longer a serious problem.

4.3.2.2 Objective Functions

The model's four objective functions (descriptions and mathematical formulations) are presented here in detail. The first two objectives (portfolio's return and relative dividend yield) reflect the dimension of performance and yield, whereas the other two objectives (portfolio's mean absolute deviation and beta coefficient) reflect the dimension of risk. (The portfolio's mean absolute deviation is employed as a measure for the nonsystematic risk, and the portfolio's beta coefficient is employed as a measure of the market risk.) It must be emphasized that, in practice, the DM can select any combination of the four objective functions to produce efficient portfolios. Therefore, the case of the Markowitz model is a subcase that can be easily formulated in the DSS.

a) *Maximize portfolio's return*

$$\text{maximize } Z_1 = \sum_{i=1}^n \bar{r}_i X_i \quad (4.3)$$

where n is the number of securities, and \bar{r}_i is the average capital return of the i -th security. As far as the definition and formula of the average capital return for the i -th security is concerned:

$$\bar{r}_i = E(r_i) = \sum_{t=1}^T \frac{r_t}{T} \quad (4.4)$$

where r_t is the capital return per share during period t . The capital return per share during period t is given by the formula:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \quad (4.5)$$

where p_t is the stock price during period t , and p_{t-1} is the stock price during period $t-1$.

b) *Maximize portfolio's relative dividend yield*

$$\text{maximize } Z_2 = \sum_{i=1}^n \text{RelDY}_i X_i \quad (4.6)$$

where RelDY_i is the relative dividend's yield of the i -th security. As far as the definition and formula of the relative dividend yield for the i -th security is concerned:

$$\text{RelDY}_i = \frac{d_i}{d_{\text{sub}}} \quad (4.7)$$

where d_i is the dividend yield of security I , and d_{sub} is the dividend yield of the subsector to which the security belongs. to. The dividend yield of a security during period t is given by the formula:

$$DY_t = \frac{d_t}{p_t} \quad (4.8)$$

where d_t is the dividend the stock gives to the investor during period t , and p_t is the stock price during period t .

The relative dividend yield is a criterion that was proposed by the experts, instead of the conventional dividend yield ratio, as a more realistic measure of comparison (see also Martel et al. 1988; Ehr Gott et al. 2004; Xidonas et al. 2008a).

c) Minimize portfolio's mean absolute deviation

$$\text{minimize } Z_3 = \frac{1}{T} \sum_{t=1}^T \left| \sum_{i=1}^n X_i (r_{it} - E(r_i)) \right| \quad (4.9)$$

where T is the number of periods across which the portfolio's variation is calculated. Note that the absolute value of the expression destroys the linearity of the model. To preserve the linearity of the model, we apply the Konno and Yamazaki (1991) transformation. According to this transformation we use T additional positive continuous variables (Y_t), which represent the absolute deviation during each period, and $2 \times T$ constraints as follows.

$$\sum_{i=1}^n X_i (r_{it} - E(r_i)) + Y_t \geq 0 \quad \forall t = 1 \dots T \quad (4.10)$$

$$\sum_{i=1}^n X_i (r_{it} - E(r_i)) - Y_t \leq 0 \quad \forall t = 1 \dots T \quad (4.11)$$

Accordingly, the objective function is transformed to:

$$\text{minimize } Z_3 = \frac{1}{T} \sum_{t=1}^T Y_t \quad (4.12)$$

In the current case study, we used weekly data from January 2004 to June 2007, which means $T=183$. Thus, the cost of the linearization in the mixed-integer programming model is the addition of 183 continuous variables and 366 constraints.

Regarding the MAD criterion, the interested reader might also see Angelelli et al. (2008), Feinstein and Thapa (1993) and Michalowski and Ogryczak (2001).

d) Minimize portfolio's beta coefficient

$$\text{minimize } Z_4 = \sum_{i=1}^n b_i X_i \quad (4.13)$$

Table 4.2 Evaluation of each security to the selected criteria and the weekly deviations from the 3-year mean

Variables	OASIS code	Average capital return	Relative dividend yield	Beta coefficient	Deviation from 3-year mean			
					Week 1	Week 2	...	Week 183
X_1	VIVART	0.0075	0.6385	1.0420	0.079	-0.043	...	0.016
X_2	BOX	0.0033	0.5625	0.7293	0.047	-0.021	...	-0.022
X_3	EEEE	0.0045	1.0444	0.6641	0.042	0.059	...	0.027
X_4	INFIS	0.0035	0.2308	0.0789	0.006	-0.124	...	0.216
X_5	KANAK	0.0020	1.6615	0.7296	0.053	-0.004	...	-0.018
X_6	KARD	0.0015	2.0077	1.1769	0.040	-0.013	...	-0.007
X_7	KATSK	0.0013	0.9615	0.3040	-0.010	-0.040	...	-0.036
X_8	MPELA	0.0111	1.0000	0.7505	0.037	-0.015	...	0.026
X_9	SATOK	0.0092	0.6231	1.6403	0.118	0.012	...	-0.020
X_{10}	YALKO	0.0005	5.5000	1.2448	0.052	0.000	...	-0.006
X_{11}	FOLI	0.0024	0.3625	0.7785	0.053	0.022	...	-0.046
X_{12}	FRLK	0.0122	0.2250	1.2573	0.111	0.125	...	0.021
X_{13}	AVAX	0.0036	0.7789	1.2201	0.064	-0.015	...	0.007
X_{14}	VOSYS	0.0047	1.1333	0.5374	0.081	-0.025	...	0.086
..
X_{46}	SFA	0.0133	0.5684	0.7357	0.060	-0.013	...	-0.126
X_{47}	ANDRO	0.0014	1.0763	0.4279	0.036	0.020	...	0.013
X_{48}	ASTAK	0.0018	1.9118	0.6719	0.041	-0.007	...	-0.013
X_{49}	VOVOS	0.0025	0.9824	0.1620	-0.006	-0.002	...	0.004
X_{50}	GNEF	0.0027	0.9974	0.5323	-0.019	-0.059	...	-0.005
X_{51}	DIAS	0.0028	0.9197	0.6945	0.042	0.080	...	0.067
X_{52}	KOUM	0.0084	0.1868	1.9452	0.208	0.026	...	0.010
X_{53}	ALFA	0.0046	0.8474	1.1067	0.068	0.033	...	-0.017
X_{54}	ATE	0.0012	0.6132	1.2438	0.010	0.019	...	0.011
X_{55}	ETE	0.0068	0.6211	1.5259	0.074	0.053	...	0.018
X_{56}	EUROB	0.0052	0.8342	1.2146	0.052	0.024	...	-0.050
X_{57}	KYPR	0.0109	0.6158	1.0903	0.081	0.047	...	-0.019
X_{58}	PEIR	0.0078	0.6237	1.1750	0.067	0.057	...	-0.009
X_{59}	EEGA	0.0041	1.0000	1.8186	0.068	0.012	...	0.015
X_{60}	EUPIK	0.0065	0.9500	0.9924	0.067	-0.049	...	0.051

where b_i is the beta coefficient of the i -th security. This criterion reflects the DM's attitude toward systematic risk. A DM adopting a conservative investment profile, for example, asks for minimization of the beta coefficient.

Practical illustrations regarding the use of this measure can be found in Xidonas et al. (2010a) and Zopounidis et al. (1998).

Table 4.2 summarizes the evaluation of each security for the model's four objective functions. Note that all the necessary data utilized in the application are provided in the *Statistical Bulletins* of the ASE (www.ase.gr).

4.3.2.3 Constraints

The model incorporates two kinds of constraint: mandatory constraints and policy constraints. The mandatory constraints are necessary for proper formulation of the model with the minimum requirements. The policy constraints depend on the DM and his policy regarding the portfolio design.

a) Completeness constraint

The completeness constraint is mandatory and requires that all of the available capital be invested.

$$\sum_{i=1}^n X_i = 1 \quad (4.14)$$

b) Auxiliary constraints

The $2 \times T$ constraints mentioned in (4.10) and (4.11) are needed for linearization of the expression for the MAD (third objective function). In the specific model they are mandatory constraints.

c) Diversification adjustment

The diversification adjustment is a constraint that allows direct determination of the number of securities in the portfolio, addressing in this way the diversification issue. In the current application the number of securities in the portfolio must vary between 7 and 14 (see Brennan 1975; Statman 1987).

$$7 \leq \sum_{i=1}^n B_i \leq 14 \quad (4.15)$$

d) Lower and upper bounds in share adjustment

The lower and upper bounds in the share adjustment constraint allows exact calibration of the lower and upper share bounds of a stock in a portfolio. This particular constraint gives additional potential to the DM to diversify his portfolios in an indirect way. The maximum share of each security in the portfolio cannot exceed 18%, and if a security is incorporated into the portfolio its share must be at least 2% (minimum share).

$$X_i - 0.18B_i \leq 0 \quad \forall i = 1, \dots, n \quad (4.16)$$

$$X_i - 0.02B_i \geq 0 \quad \forall i = 1, \dots, n \quad (4.17)$$

e) Specific sector preferences

The specific sector preferences constraint allows determination of upper investment bounds in specific supersectors. This particular adjustment is of great significance in the case of supersectors (i.e., corresponding sectoral stock market indexes) showing negative returns for a particular period. In the current application,

upper bounds were set in the travel and leisure (S_{11}), health care (S_{13}), financial services (S_{14}), and insurance (S_{16}) supersectors.

$$\sum_{i \in S_{11} \cup S_{13}} X_i \leq 0.06 \text{ and } \sum_{i \in S_{14} \cup S_{16}} X_i \leq 0.08 \quad (4.18)$$

f) Specific stock preferences

The specific stock preferences constraint allows determination of lower investment bounds for specific stocks. The adjustment has a serious meaning when the DM has a categorical preference in particular securities. In the current application, lower bounds were set in the following stocks: X_8 (MPELA), X_{28} (OTE), X_{55} (ETE), and X_{57} (KYPR).

$$X_8 \geq 0.04, X_{28} \geq 0.07, X_{55} \geq 0.07 \text{ and } X_{57} \geq 0.04 \quad (4.19)$$

g) Beta or market risk adjustment

The market risk adjustment allows direct tuning of the portfolio's beta coefficient. In the current application, a lower bound has been set for the investment amount in securities with beta less than one [$BLT1$ is the set of stocks (32 securities) with beta less than one]. The DM sets the lower bound of the total weight of these securities in the portfolio at 0.6. In this regard, the DM can set his preferences reflecting his attitude toward systematic risk. Low values for the RHS indicate aggressive (risk-prone) behavior, whereas high values indicate conservative (risk-averse) behavior. In the specific case, a rather conservative attitude was expressed.

$$\sum_{i \in BLT1} X_i \geq 0.6 \quad (4.20)$$

h) Capitalization adjustment

The capitalization adjustment allows precise calibration of the portfolio's capitalization synthesis. In the current application, a lower bound has been set for the investment amount in securities of high capitalization [BC is the set of stocks (38 securities) of high capitalization]. In this regard, the DM can set his preferences relative to his capitalization mix preference. In the specific case, a rather high capitalization mix preference was expressed.

$$\sum_{i \in BC} X_i \geq 0.6 \quad (4.21)$$

The final model consists of four objective functions, 243 continuous variables (60 continuous variables representing the percentage of capital to be invested in stock and 183 continuous variables representing the weekly deviations from the 3-year mean), 60 binary variables, and 509 constraints.

4.4 Decision Support System Implementation

4.4.1 IPSSIS Decision Support System

The PM process involves the analysis of a vast volume of financial information and data. Analyzing a continuous flow of such an amount of information for every available security to support real-time investment decisions is clearly impossible without the support of a computer system designed to facilitate both the data management process and analysis of the available information. Thus, the contribution of specialized information systems in portfolio management becomes apparent.

The mixed-integer multiobjective linear programming model just presented has been created and solved using the IPSSIS DSS. The IPSSIS system has been developed in the Management and Decision Support Systems Laboratory (MDSSL) and the Laboratory of Industrial & Energy Economics (LIEE) of the National Technical University of Athens (NTUA). Figure 4.4 presents the structure of the main options available in the software. The IPSSIS system, which implements the augmented ε -constraint MMP method, is the outcome of an attempt to integrate a powerful multiobjective optimization technique with DSS technology to provide equity portfolio managers with a highly effective and up-to-date tool to support decisions that concern the portfolio engineering process.

The three fundamental characteristics of IPSSIS portfolio construction and selection system are the following.

1. It fully supports the DM in making investment decisions regarding tportfolio construction and selection operations, two of the most significant phases of the PM process. The system is equipped with highly sophisticated scientific models and algorithms and offers satisfactory computational capabilities.

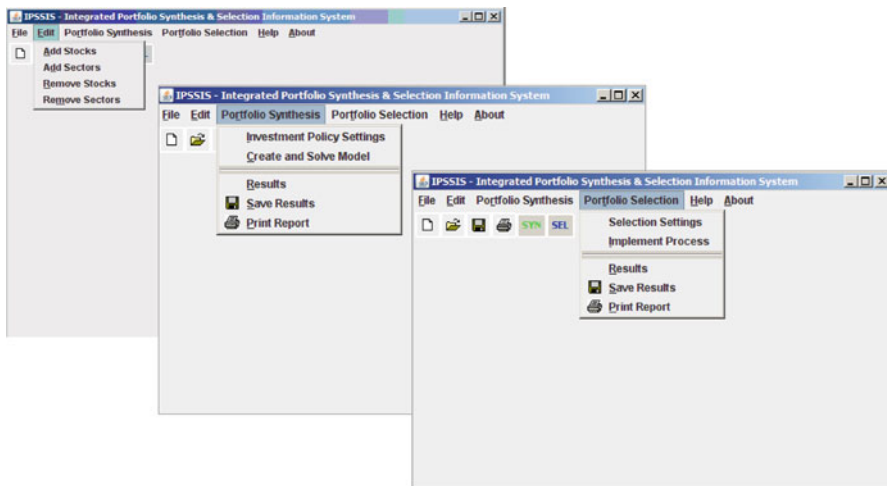


Fig. 4.4 Structure of the main options available in the software

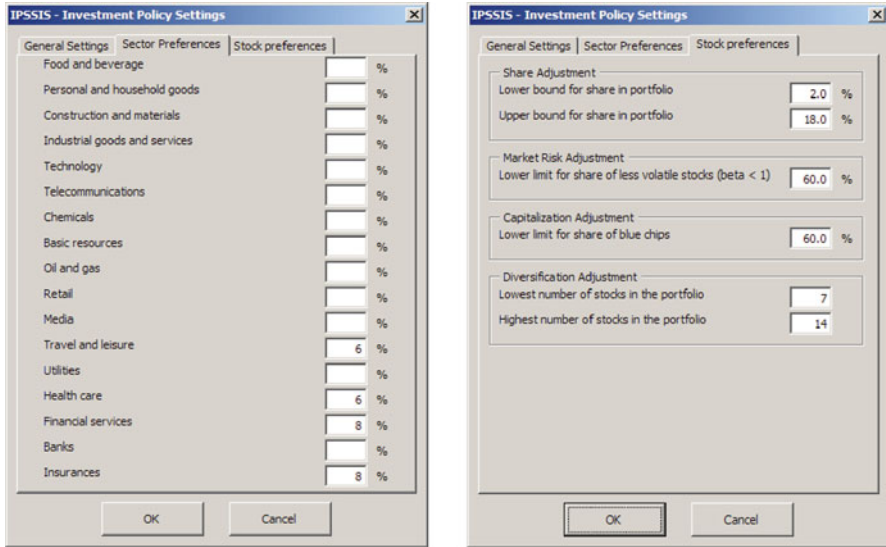


Fig. 4.5 Adjusting the investment policy settings in the IPSSIS system

2. It incorporates a high level of interaction each time it generates specialized investment proposals to satisfy the user's investment policy profile. Thus, the system increases and improves his role during the decision-making process, while allowing overall formulation and specialized modeling of his preferences.
3. It is fully parameterized. It can be installed and operate under real-world conditions and can be used in any stock exchange, provided it is equipped with the respective databases. Also, its architecture provides the flexibility of incorporating it into any work and development environment.

The system has been developed using the Java SE Runtime Environment 6. It operates on any IBM-compatible personal computer that has the Microsoft Windows XP operating system, Microsoft Office Excel 2003, and the GAMS modeling system installed (version 22.2 or higher). The system does not have any special hardware requirements other than those necessary to use Microsoft Windows XP. Nevertheless, to ensure smooth operation of the system, the use of a Pentium Core 2 Duo PC and 10 Mb of free hard disk space is recommended.

The structure of the IPSSIS system is similar to the general structure of the decision support system proposed by Sprague and Carlson (1982). The basic modules of the system include the database, the model base, and the user interface, and there is complete interaction and integration of these modules. The database and model base management are closely related to the user-friendly Windows-based user interface of the system. The user interface enables the portfolio manager to handle the system's database easily (through the *Edit* menu) and exploit the optimization and interactive filtering toolboxes (through the *Portfolio Synthesis* and the *Portfolio Selection* menus, respectively). Figures 4.5 and 4.6 present the dialogue boxes that refer to the

No	Name of company	Symbol	Superaector	Blue chip	Lowest bound	Portfolio	RelativeVol	BetaC_coef			
						Max	Max	Min			
1	VIVARTA (CR)	VIVART	Food and beverage	Yes		0.0075	0.6395	1.0420	0.079	-0.043	0.01
2	FASHION BOX (CR)	BOX	Food and beverage	Yes		0.0033	0.9625	0.7293	0.047	-0.021	0.03
3	COCA COLA TRIA EPELON (CB)	EEKK	Personal and household goods	Yes		0.0045	1.0441	0.8641	0.042	0.059	0.00
4	INTERFISH KTHYOKALLERGIES (CR)	IFFS	Construction and materials	Yes		0.0035	0.2308	0.0789	0.006	-0.124	0.01
5	KANAKIS (CR)	KANAK	Industrial goods and services	Yes		0.0020	1.6615	0.7296	0.053	-0.004	0.04
6	KARADOLARIS (CR)	KARD	Technology	Yes		0.0015	2.0077	1.1709	0.140	-0.113	0.05
7	KATSILI YIOTI (CR)	KATSK	Telecommunications	Yes		0.0013	0.9615	0.3040	-0.010	-0.040	-0.01
8	JUMBO (CR)	IMPLA	Basic resources	Yes	4%	0.0111	1.0000	0.7505	0.037	-0.015	0.05
9	SATO (CR)	SATOK	Personal and household goods	Yes		0.0092	0.6231	1.6403	0.116	0.012	0.10
10	YALCO KONSTANTINOI (CB)	YALCK	Personal and household goods	Yes		0.0095	0.5000	1.2448	0.052	0.006	0.00
11	FOLLI FOLLE (CR)	FOLI	Personal and household goods	Yes		0.0024	0.3625	0.7785	0.053	0.022	-0.01
12	FOURUS SYMMETONON (CR)	FRUK	Personal and household goods	Yes		0.0122	0.2250	1.2573	0.111	0.125	0.05
13	AVAX (CR)	AVAK	Construction and materials	Yes		0.0038	0.7169	1.2201	0.064	-0.015	-0.01
14	VOGATZOGLOU SYSTEMS (CR)	VOGYS	Industrial goods and services	Yes		0.0047	1.1333	0.5374	0.001	-0.025	-0.03
15	GENIKO (CB)	GENKA	Industrial goods and services	Yes		0.0057	1.0133	1.3323	0.100	-0.030	0.04
16	EXTER (CR)	EXTER	Construction and materials	Yes		0.0009	0.9737	0.9993	0.099	-0.094	0.10
17	ELTRAC (CB)	ELTK	Industrial goods and services	Yes		0.0078	0.8152	0.8022	0.055	-0.007	0.09
18	RIAKUS AGETI (CR)	HERAK	Construction and materials	Yes		0.0052	0.2390	0.9667	0.031	-0.003	0.06
19	KLEEMAN HELLAS (CR)	KLEM	Industrial goods and services	Yes		0.0054	1.1200	1.1480	0.047	0.020	0.04
20	KLOVONIKS LARFAS (CR)	KLRF	Construction and materials	Yes		0.0111	0.8165	1.3550	-0.157	0.035	-0.10
21	IMETCA (CR)	IMETK	Industrial goods and services	Yes		0.0058	1.3750	1.3570	0.048	0.048	0.18
22	TERMA (CR)	TERMA	Construction and materials	Yes		0.0041	0.8895	1.6912	0.041	-0.017	0.01
23	TTAKI (CR)	TTIK	Construction and materials	Yes		0.0050	0.8250	0.8005	0.027	-0.018	0.01
24	FRIGOLASS (CR)	FRIGO	Industrial goods and services	Yes		0.0108	0.8950	0.7599	0.066	0.043	0.00
25	BYTE COMPUTE (CR)	BYTE	Technology	Yes		0.0021	0.6844	0.7790	0.053	-0.019	0.12
26	OSMOTE (CR)	KOSHO	Telecommunications	Yes		0.0048	0.9999	0.4699	0.025	0.083	-0.23
27	INFOQUEST (CR)	KOVES	Technology	Yes		0.0009	0.3719	2.4350	0.147	0.015	0.01
28	OTE (CR)	OTE	Telecommunications	Yes	7%	0.0051	0.9600	0.9235	0.073	0.101	0.02
29	RAINBOW (CR)	REH	Technology	Yes		0.0090	0.2444	1.7540	0.077	-0.008	0.09
30	ALOUFIS KYLIONAS (CR)	ALKEY	Basic resources	Yes		0.0023	0.3844	1.0249	0.029	-0.031	0.06
31	ELIPIKA PETRELAJA (CR)	ELPE	Oil and gas	Yes		0.0038	1.0028	0.7647	0.003	0.089	0.05
32	MOTOR OIL (CR)	MOH	Oil and gas	Yes		0.0094	1.0034	0.5420	-0.009	0.041	0.05
33	INTILIAIOS (CR)	INTIL	Basic resources	Yes		0.0122	1.0053	1.6008	0.073	0.057	0.06
34	NEOHMIKI (CR)	NEOCH	Chemicals	Yes		0.0103	0.7000	1.1979	0.094	0.000	-0.00
35	SEENOR (CB)	SEDE	Basic resources	Yes		0.0113	1.2231	0.8683	0.003	-0.017	0.03
36	HALKOR (CB)	HAKOR	Basic resources	Yes		0.0081	1.0000	1.9020	0.024	0.012	0.09
37	VASILPOPOLOS (CR)	AVBK	Retail	Yes		0.0042	0.9737	0.3720	0.007	0.011	0.10
38	BLUE STAR (CB)	VSTAR	Travel and leisure	Yes		0.0075	1.1263	1.2809	0.092	0.084	0.01
39	DEI (CR)	DEH	Utilities	Yes		0.0009	0.9625	0.5525	0.017	0.002	0.03
40	IASO (CR)	IASO	Health care	Yes		0.0061	1.0033	0.8039	0.007	0.009	0.04

Fig. 4.6 Adjusting the investment policy settings in the IPSSIS system (the corresponding MS Excel file)

adjustment of the investment policy settings (objectives and constraints), as determined in the previous section.

4.4.2 Generation of Pareto Optimal Portfolios

The IPSSIS system utilizes the GAMS/CPLEX solver (as mentioned, the augmented ϵ -constraint has been formulated for GAMS and is available in the GAMS model's library). In the specific case, we used five grid points for each one of the four objective functions, which means that $125 (= 5^3)$ solutions of a mixed-integer programming problem are normally needed. However, because of the "early exit from the loops" feature of the augmented ϵ -constraint method, which is activated when infeasibilities occur, only 86 of the nominal number of 125 runs were performed with a solution time of 196 s in a Pentium Core Duo PC at 1.83 GHz. With this grid, the number of the obtained Pareto portfolios was 53. Using a denser grid, we can obtain a richer representation of the Pareto set, but the solution time is expected to increase significantly. For example, we also solved the same problem increasing the number of grid points to 11 (10 equidistant intervals for each objective function). In this case, the nominal number of runs was $1,331 (= 11^3)$. Because of the "early exit from the loops," 860 runs were performed, producing 440 Pareto portfolios after 1,020 s. Thus, a denser representation of the Pareto set is obtained at the cost of more (although not prohibitive) computational time. The output of the GAMS model is

Table 4.3 Evaluation of each Pareto portfolio in regard to the four objective functions

Pareto portfolios	No. of stocks	Portfolio return	Relative dividend yield	Beta coefficient	Mean absolute deviation
1	9	0.0108	0.8073	0.9511	0.0210
2	10	0.0101	1.1742	0.9893	0.0211
3	9	0.0093	1.5412	1.0167	0.0211
4	8	0.0079	1.9081	0.9716	0.0212
5	11	0.0037	2.2750	0.9990	0.0180
6	9	0.0108	0.8073	0.9433	0.0211
7	9	0.0100	1.1742	0.9433	0.0208
8	9	0.0092	1.5412	0.9433	0.0216
9	9	0.0075	1.9081	0.9433	0.0204
10	9	0.0100	0.8073	0.7927	0.0214
11	11	0.0087	1.1742	0.7927	0.0188
12	11	0.0074	1.5412	0.7927	0.0190
13	11	0.0047	1.9081	0.7927	0.0164
...
41	13	0.0076	1.5412	0.9936	0.0143
42	14	0.0060	1.9081	1.0032	0.0143
43	14	0.0091	0.8472	0.9433	0.0143
44	13	0.0084	1.1742	0.9433	0.0143
45	14	0.0073	1.5412	0.9433	0.0143
46	14	0.0056	1.9081	0.9433	0.0143
47	13	0.0084	0.8121	0.7927	0.0143
48	13	0.0075	1.1742	0.7927	0.0143
49	14	0.0059	1.5412	0.7927	0.0143
50	13	0.0068	0.8242	0.6422	0.0143
51	14	0.0053	1.1742	0.6422	0.0143
52	14	0.0060	0.8265	0.8735	0.0111
53	14	0.0058	0.8358	0.7927	0.0111

the evaluation of each Pareto portfolio in regard to the four objective functions along with the number of securities in each portfolio (Table 4.3) and the weight of each security in the Pareto portfolio (Table 4.4).

It is observed that 31 from the 60 securities are involved in the 53 Pareto portfolios. This means that about 50% of the total securities are not eligible in none of the Pareto portfolios according to the four objective functions. The number of securities in each Pareto portfolio varies from 8 to 14. As it was expected, the portfolios with the greater number of securities occur when the minimum MAD is pursued (the diversification effect). In this stage, fruitful information might be extracted for the individual characteristics and statistics of each one security regarding its participation in the Pareto portfolios (see Table 4.5). For example, we can calculate the number of appearances of each security in the Pareto portfolios as well as the minimum, average and maximum weight of the security across all the Pareto portfolios. In this way the DM gets a very clear view of which securities are more often present and which are not. Conclusively, the actual contribution of the proposed approach in the

Table 4.4 Synthesis of the Pareto optimal portfolios

	X_1	X_2	X_3	X_4	...	X_{57}	X_{58}	X_{59}	X_{60}
Pareto portfolios	VIVART (%)	BOX (%)	EEEEK (%)	INFIS (%)		KYPR (%)	PEIR (%)	EEGA (%)	EUPIK (%)
1	0.00	0.00	0.00	0.00	...	5.60	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	...	4.70	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
10	0.00	0.00	0.00	7.00	...	4.00	0.00	0.00	0.00
...
44	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
45	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
46	0.00	0.00	7.20	0.00	...	4.00	0.00	0.00	0.00
47	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
48	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
49	0.00	0.00	0.00	0.00	...	4.00	0.00	0.00	0.00
50	0.00	0.00	0.00	5.00	...	4.00	0.00	0.00	0.00
51	0.00	0.00	0.00	4.30	...	4.00	0.00	0.00	0.00
52	0.00	11.30	7.50	0.00	...	5.30	0.00	0.00	0.00
53	0.00	11.30	6.90	0.00	...	4.00	0.00	0.00	0.00

portfolio construction process is to aid the DM to express his preferences regarding the basic characteristics of the desired portfolios and then to reduce the search space only to the relevant Pareto optimal choices.

4.4.3 Implementing the Interactive Filtering Process

In the next phase, the DM proceeds to implementation of the interactive filtering process, which is used to select the portfolio he most prefers among a number of Pareto optimal portfolios. The number of iterations is set at three, and the number of representative solutions that are shown to the DM at each iteration is set at five. These are indicative values, as the interactive filtering process can be fully parameterized on the number of iterations and the sample size that is presented to the DM.

4.4.3.1 First Iteration

After the first iteration, five representative portfolios from the complete set of 53 Pareto solutions are proposed to the DM. The absolute (attained objective values)

Table 4.5 Individual security characteristics and statistics

Variables	OASIS code	Appear	Minimum (%)	Average (%)	Maximum (%)
X_1	VIVART	0	0.00	0.00	0.00
X_2	BOX	2	0.00	0.43	11.30
X_3	EEEE	4	0.00	0.49	7.50
X_4	INFIS	11	0.00	2.00	18.00
X_5	KANAK	4	0.00	0.44	14.00
X_6	KARD	2	0.00	0.25	11.00
X_7	KATSK	7	0.00	0.91	18.00
X_8	MPELA	53	4.00	15.87	18.00
X_9	SATOK	0	0.00	0.00	0.00
X_{10}	YALKO	37	0.00	8.47	18.00
X_{11}	FOLI	0	0.00	0.00	0.00
X_{12}	FRLK	8	0.00	0.85	9.00
X_{13}	AVAX	0	0.00	0.00	0.00
X_{14}	VOSYS	3	0.00	0.20	4.70
...
X_{46}	SFA	45	0.00	11.81	18.00
X_{47}	ANDRO	0	0.00	0.00	0.00
X_{48}	ASTAK	6	0.00	0.74	8.00
X_{49}	VOVOS	20	0.00	2.66	8.00
X_{50}	GNEF	8	0.00	0.84	8.00
X_{51}	DIAS	0	0.00	0.00	0.00
X_{52}	KOUM	0	0.00	0.00	0.00
X_{53}	ALFA	0	0.00	0.00	0.00
X_{54}	ATE	0	0.00	0.00	0.00
X_{55}	ETE	53	7.00	7.00	7.00
X_{56}	EUROB	0	0.00	0.00	0.00
X_{57}	KYPR	53	4.00	4.29	9.50
X_{58}	PEIR	0	0.00	0.00	0.00
X_{59}	EEGA	0	0.00	0.00	0.00
X_{60}	EUPIK	0	0.00	0.00	0.00

and relative (accomplishment percentages with respect to optimal values) performance of the five portfolios is shown in Table 4.6. The IPSSIS system provides the user with the potential of each of five portfolios based on what it achieves regarding the four objective functions. This is done in an illustrative graphical representation of the percent accomplishment of optimal performance (see Fig. 4.7). This type of representation gives the user the chance to obtain an, as much as possible, visual notion of the results. The choice of the experts after the first iteration was Portfolio 4 because it expressed a categorical preference of simultaneous high performance in regard to portfolio return and relative dividend yield. Also, the 50.597% of relative performance of Portfolio 4 reflected an absolute beta value of 0.9716, which is an affordable value. The low performance in the MAD objective was expected to be counterbalanced in the following iterations. Portfolios 1, 14, and 40 were instantly rejected because of their extremely poor performance in the relative dividend yield

Table 4.6 Absolute and relative performance of the Pareto portfolios for each iteration

<i>First iteration</i>					
Pareto portfolios	No. of stocks	Portfolio return	Relative dividend yield	Beta coefficient	Mean absolute deviation
1	9	0.0108	0.8073	0.9511	0.0210
4	8	0.0079	1.9081	0.9716	0.0212
13	11	0.0047	1.9081	0.7927	0.0164
14	10	0.0079	0.8073	0.6422	0.0183
40	12	0.0085	1.1742	0.9744	0.0143
Pareto portfolios	No. of stocks	Portfolio return (%)	Relative dividend yield (%)	Beta coefficient (%)	Mean absolute deviation (%)
1	9	100.000	35.486	51.688	52.857
4	8	73.148	83.873	50.597	52.358
13	11	43.519	83.873	62.016	67.683
14	10	73.148	35.486	76.549	60.656
40	12	78.704	51.613	50.452	77.622
<i>Second iteration</i>					
Pareto portfolios	No. of stocks	Portfolio return	Relative dividend yield	Beta coefficient	Mean absolute deviation
4	8	0.0079	1.9081	0.9716	0.0212
24	9	0.0091	1.5412	0.9433	0.0206
29	12	0.0074	1.9081	1.0185	0.0174
32	11	0.0084	1.5412	0.9433	0.0174
12	11	0.0074	1.5412	0.7927	0.0190
Pareto portfolios	No. of stocks	Portfolio return (%)	Relative dividend yield (%)	Beta coefficient (%)	Mean absolute deviation (%)
4	8	73.148	83.873	50.597	52.358
24	9	84.259	67.745	52.115	53.883
29	12	68.519	83.873	48.267	63.793
32	11	77.778	67.745	52.115	63.793
12	11	68.519	67.745	62.016	58.421
<i>Third iteration</i>					
Pareto portfolios	No. of stocks	Portfolio return	Relative dividend yield	Beta coefficient	Mean absolute deviation
32	11	0.0084	1.5412	0.9433	0.0174
28	11	0.0087	1.5412	0.9940	0.0174
31	12	0.0094	1.1742	0.9433	0.0174
27	11	0.0096	1.1742	0.9900	0.0174
33	11	0.0070	1.9081	0.9433	0.0174
Pareto portfolios	No. of stocks	Portfolio return (%)	Relative dividend yield (%)	Beta coefficient (%)	Mean absolute deviation (%)
32	11	77.778	67.745	52.115	63.793
28	11	80.556	67.745	49.457	63.793
31	12	87.037	51.613	52.115	63.793
27	11	88.889	51.613	49.657	63.793
33	11	64.815	83.873	52.115	63.793

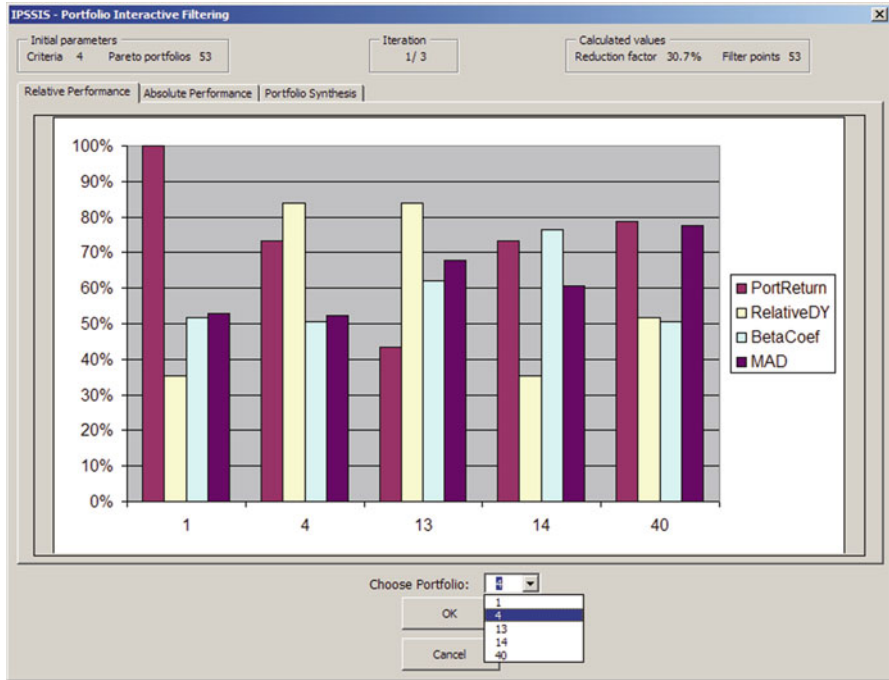


Fig. 4.7 Accomplishment (%) of the optimal performance per portfolio after the first iteration

objective; and Portfolio 13 was rejected owing to its extremely poor performance in the portfolio’s return objective. Subsequently, the decision space contracted around Portfolio 4, and the second iteration was launched.

4.4.3.2 Second Iteration

In the second iteration, four new portfolios (plus Portfolio 4), representative of a new contracted search space, were proposed to the DM. Again, the IPSSIS system provided a graphical representation of the accomplishment of the optimal performance regarding the four objective functions. The choice of the experts after the second iteration was Portfolio 32. The rationale behind this particular choice had to do with the fact that part of the very satisfactory relative dividend yield performance of Portfolio 4 (83.873%) was sacrificed as an offset for improving the performance of both portfolio return objectives (from 73.148% to 77.778%) and MAD (from 52.358% to 63.793%) (see Table 4.6). Simultaneously, the choice of Portfolio 32 resulted in slight improvement of the beta coefficient objective (from 0.9716 to 0.9433 in absolute values). Also, Portfolio 24 was rejected owing to its extremely poor performance regarding the MAD objective, and Portfolio 12 was rejected because of its mediocre performance regarding all the objective functions. The search space now contracted around Portfolio 32.

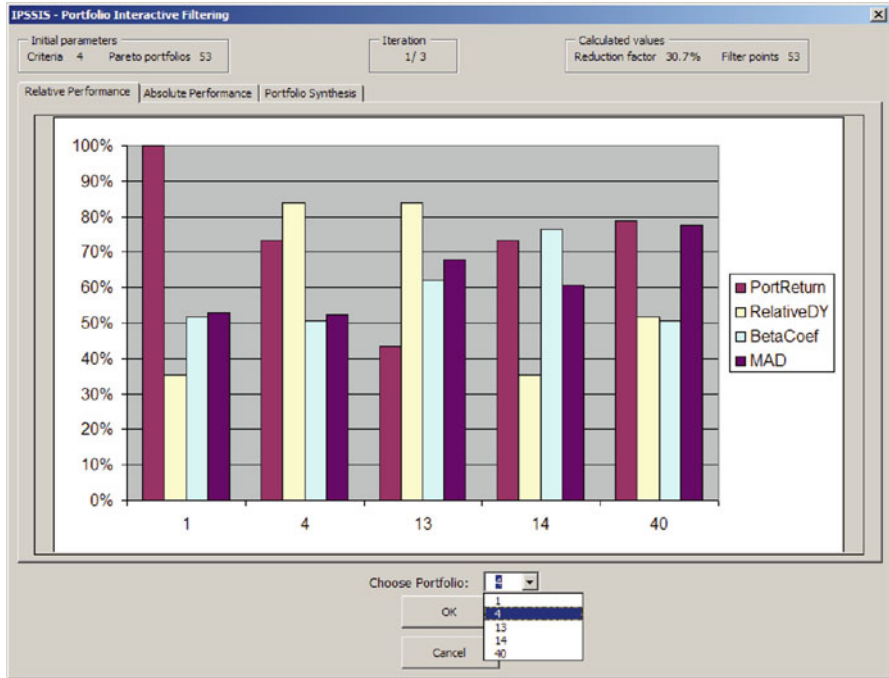


Fig. 4.8 Accomplishment (%) of the optimal performance per portfolio after the first iteration

4.4.3.3 Third Iteration

Finally, in the third iteration, five portfolios, representative of the reduced search region around Portfolio 32, were again proposed to the DM. As far as some statistics of the final five portfolios, a total of 14 securities participated in their synthesis (which means that 46 securities from the initial set stocks were absent). Also, 11 of these securities were high capitalization stocks and three securities low-medium capitalization stocks. The minimum number of stocks that a portfolio contains is 11, and the maximum number is 12. Among the final portfolios, the experts explicitly stated their final preference for Portfolio 28, the synthesis of which is shown in Fig. 4.8. Portfolio 28 maintained the attained values of Portfolio 32 in terms of relative dividend yield and MAD objectives plus it had an improved relative performance in the portfolio return objective (from 77.778% to 80.556%). A small part in the portfolio beta coefficient performance was sacrificed for this enhancement, but the final portfolio's absolute beta value was considered affordable. Finally, Portfolios 27 and 31 were rejected because of their poor performance regarding the relative dividend yield objective, and Portfolio 33 was rejected owing to its unsatisfactory performance in the portfolio's return objective (Fig. 4.9).

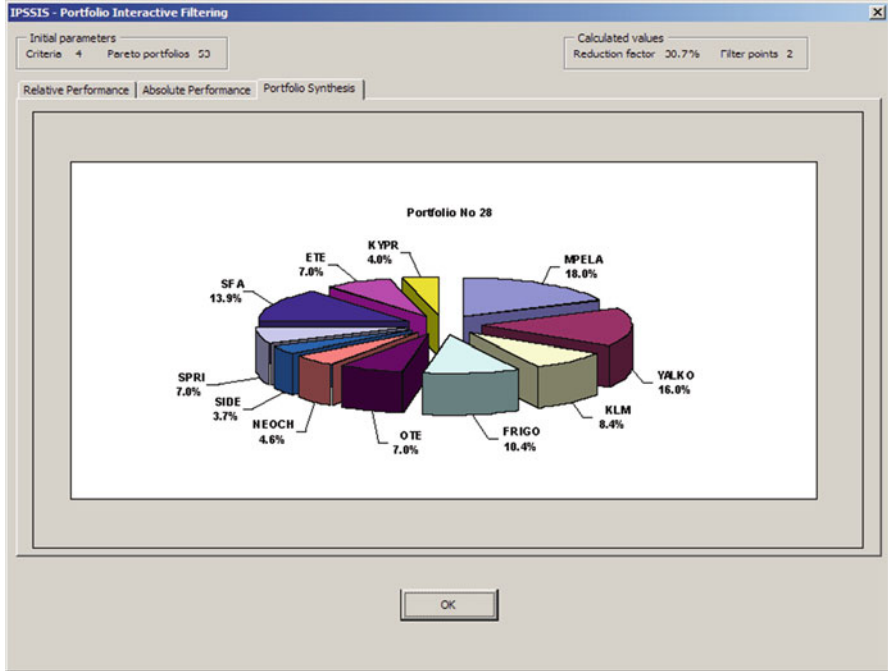


Fig. 4.9 Synthesis of the final portfolio (Portfolio 28)

4.5 Conclusions

It was our purpose in this chapter to present an integrated MCDM methodological approach for equity portfolio construction and selection. The proposed approach, based on the MMP framework, is implemented through a mixed-integer multiobjective linear programming model accompanied by an interactive filtering process to assist the DM when making his final choice among the Pareto optimal solution set. The IPSSIS, a fully parameterized, multiobjective portfolio optimization DSS, applies the proposed approach in an attempt to support the DM effectively in making well-structured investment decisions according to his particular IPS.

The contribution of both the proposed approach and the corresponding DSS is a multitiered one. The DM’s preference system is effectively incorporated in the decision-making process by fully taking into consideration his investment policy objectives and constraints regarding the portfolio structure. The proposed approach is equipped with a powerful multiobjective optimization method, the “augmented ϵ -constraint method.” This method allows expansion of the single-objective formulation of the classic theory through the incorporation of additional objectives beyond the expected return and the risk. It must be noted that the proposed DSS can use any combination of the four objective functions, providing significant flexibility to the

DM. It results in the generation of solution space of the relevant Pareto optimally efficient portfolios. The introduction of binary variables provides more realistic and flexible modeling as it allows the expression of logical and other conditions that cannot be expressed in a conventional linear programming model. Finally, the interactive procedure we employed gradually drives the DM to his most preferred choice by expressing his subjective preferences.

Within this multicriteria framework, the fundamental aim of the proposed portfolio construction and selection approach is to assist investors in improving the quality of their decisions, along with effectively implementing their investment strategies.

Chapter 5

Portfolio Performance Evaluation

5.1 Introduction

The multiple criteria decision-making (MCDM) modeling framework provides a solid methodological basis to resolve the inherent multidimensional nature of the problem. It has the advantage of incorporating into the decision process, the preferences of any particular investor. Traditional theoretical approaches do not take the investor's specialized individual goals into account sufficiently. The MCDM framework builds realistic models by assessing, in addition to the two basic criteria of return and risk, a number of other criteria.

In this chapter, we introduce the need for a multicriteria approach to model the problem of portfolio performance evaluation, taking into account: (a) the limits related to the Markowitz conventional theory, the results from estimation of the models, and the philosophy of the optimization approach; and (b) the behavior of investors, who, in addition to the above-mentioned anomalies, could have criteria in mind beyond risk and return.

5.2 Proposed Approach

5.2.1 General Description

The aim of the proposed approach (Xidonas et al. 2010a) is the evaluation, and finally the selection, of equity portfolios. The proposed approach (Fig. 5.1) was developed in close cooperation with a panel of specialists (portfolio managers and trading experts). Their contribution was of catalytic impact at all the stages of the collaboration.

At the first stage of the approach, the set of portfolios under evaluation was determined and the criterion set constructed. According to the proposed approach, the criterion set developed consisted of specialized measures that are widely used by

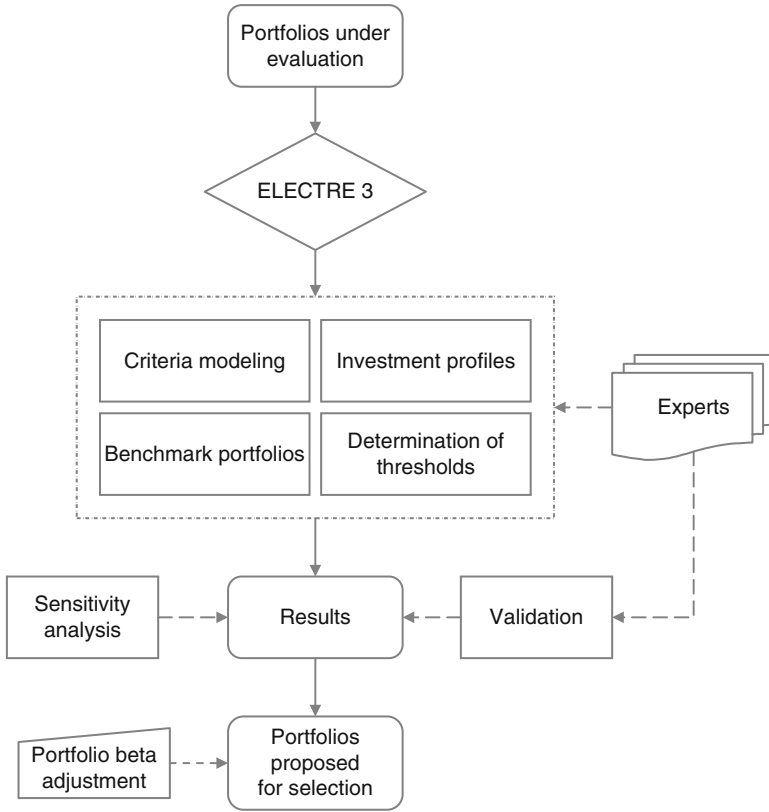


Fig. 5.1 Logical diagram of the proposed approach

practitioners in the field for evaluating the performance of equity portfolios. Some of the measures employed are the well-known risk-adjusted performance ratios of Sharpe, Jensen, and Treynor, the M^2 and T^2 measures, the portfolio's value at risk (VaR), and the conventional measures of mean and standard deviation (volatility) of capital return.

One of the methodology's main features is the potential to incorporate investment profiles that reflect the whole range of the investment policy spectrum. Under this rationale, the resistance-to-change weighting system (Rogers and Bruen 1998) was chosen for the formulation of three investment profiles: conservative, balanced, aggressive. The contribution of the experts was also important when determining the technical parameters (preference and indifference thresholds) of the ELECTRE III multicriteria decision aid ranking method, which was employed for the portfolio evaluation process.

Three hypothetical equity portfolios (one for each investment profile) were utilized benchmark portfolios in the evaluation. These portfolios participated in the ranking process like all the alternative portfolios, and their relative position in the

rankings provided the decision-maker (DM) with fruitful information and supported him up to his final choice.

At the final stage of the proposed approach, the sensitivity of the obtained results was tested, with its validation conducted by the experts. The appropriate portfolio was finally selected by adjusting the betas of the top-ranked alternatives to the investment profile of the potential DMs and their attitudes towards risk.

The critical choice of the ELECTRE III method for evaluating the equity portfolios was based mainly on its remarkable conformity to the nature of the portfolio selection problem (Hurson and Zopounidis 1995, 1997), the extended use the ELECTRE family framework in many financial decision-making problems (Xidonas and Psarras 2009), and the fact that it can easily take into account data of imprecise character. Also, the strict constraint that the experts put in place for obtaining a ranking result of the alternative portfolios (and not a classification of them in predefined categories) was the final critical reason that led to the choice of employing the ELECTRE III.

5.2.2 ELECTRE III Method

ELECTRE III (Roy 1978; Rogers et al. 2000) uses a pseudo-criterion, with its indifference and preference thresholds, explicitly to make allowances for any imprecision/uncertainty in the data. ELECTRE III comprises two distinct phases: (a) construction of the outranking relation, and (b) exploitation of the outranking relation.

5.2.2.1 Constructing the Outranking Relation

ELECTRE III defines the degree of outranking of b by a , $S(a,b)$ (or aSb) in terms of its concordance index $C(a,b)$ and its discordance index $D(a,b)$. The following concordance index is computed for its ordered pair (a,b) of actions:

$$C(a,b) = \frac{1}{W} \sum_{j=1}^n w_j c_j(a,b)$$

where

$$W = \sum_{j=1}^n w_j$$

and

$$c_j(a,b) = 1 \text{ if } g_j(a) + q_j(g_j(a)) \geq g_j(b)$$

or

$$c_j(a,b) = 0 \text{ if } g_j(a) + p_j(g_j(a)) < g_j(b)$$

otherwise

$$c_j(a, b) = \frac{g_j(a) - g_j(b) + p_j(g_j(a))}{p_j(q_j(a)) - q_j(g_j(a))}$$

where p_j is the strict preference threshold for criterion j , and q_j is the indifference threshold for criterion j . $C(a, b)$ represents the percentage of weights of the criteria that concord with the proposition “ a outranks b .”

Note: if $q_j(g_j(a)) = p_j(g_j(a))$, $\forall a, j$, the structure becomes a semiorder one, based on the threshold model.

Thus,

$$C(a, b) = \frac{1}{W} \sum_{j: g_j(a) + q_j(g_j(a)) \geq g_j(b)} w_j$$

The definition of discordance uses a veto threshold $v_j(g_j(a))$ such that the outranking of b by a is refused if

$$g_j(b) \geq g_j(a) + v_j(g_j(a))$$

The discordance index for its criterion j is as follows:

$$D_j(a, b) = 0 \text{ if } g_j(b) \leq g_j(a) + p_j(g_j(a))$$

$$D_j(a, b) = 1 \text{ if } g_j(b) > g_j(a) + v_j(g_j(a))$$

otherwise

$$D_j(a, b) = \frac{g_j(b) - g_j(a) - p_j(g_j(a))}{v_j(g_j(a)) - p_j(g_j(a))}$$

The degree of credibility of outranking of b by a is defined as follows:

$$S(a, b) = C(a, b) \text{ if } D_j(a, b) \leq C(a, b), \forall j$$

otherwise

$$S(a, b) = C(a, b) \prod_{j \in J(a, b)} \frac{(1 - D_j(a, b))}{1 - C(a, b)}$$

where $J(a, b)$ is the set of criteria for which $D_j(a, b) > C_j(a, b)$.

The degree of credibility of outranking is thus equal to the concordance index where no criterion is discordant. Where discordances do exist, however, the concordance index is lowered in direct relation to the importance of those discordances.

5.2.2.2 Exploiting the Outranking Relation

The algorithm for ranking all options yields two preorders, each constructed in a different way. The first preorder is obtained in a descending manner, selecting the best-rated options initially and finishing with the worst (descending distillation). The second preorder is obtained in an ascending manner, selecting first the worst rated options and finishing with the assignment of the best (ascending distillation). The construction of these two preorders requires the qualification score for each option, which is calculated using the following procedure.

First, let λ_0 equal the maximum value of $S(a, b)$ for all option pairs.

$$\lambda_0 = \max_{a, b \in A} \{S(a, b)\}$$

A cutoff level of outranking λ_1 is defined as a value close to λ_0 such that:

$$\lambda_1 = \lambda_0 - s(\lambda_0)$$

where $s(\lambda_0)$ is called the discrimination threshold.

For a given pair of options (a, b) , a outranks b at the cutoff level λ_1 if the following conditions are met: $aS^{\lambda_1}b$ iff $S(a, b) > \lambda_1$ and $S(a, b) > s(S(a, b))$.

In other words, a outranks b if the degree of credibility of outranking for a over b is greater than the cutoff level, and the degree of credibility for a over b is greater than that for b over a by more than the discrimination threshold. If these two conditions hold, it can be stated that it is significantly more credible that a outranks b than that b outranks a .

From the outranking relation in the previous equation, the strength and weakness of each option a at the cutoff level λ_1 is determined as follows.

The strength of the option $p_A^{\lambda_1}(a)$ is defined by: $p_A^{\lambda_1}(a) = \left| \left\{ b \in A / aS_A^{\lambda_1}b \right\} \right|$

The weakness of the option $f_A^{\lambda_1}(a)$ is defined by: $f_A^{\lambda_1}(a) = \left| \left\{ b \in A / bS_A^{\lambda_1}a \right\} \right|$

The qualification of option a in relation to a set of options A , $q_A^{\lambda_1}(a)$, is defined by:

$$q_A^{\lambda_1}(a) = np_A^{\lambda_1}(a) - f_A^{\lambda_1}(a)$$

This indicator expresses clearly the relative positions of the options within the set A .

5.2.2.3 Distillation

The algorithm used in the distillation proceeds on the basis of lowering the cutoff level λ from λ_0 to zero. Two distillation procedures are employed, the downward and upward systems.

5.2.2.4 Downward Distillation Procedure

For the first chosen cutoff level λ_1 , the subset \bar{D}_1 of the best options within A , is obtained from:

$$\bar{D}_1 = \left\{ a \in A / q_A^{\lambda_1} = \bar{q}_A = \text{Max}_{x \in A} q_A^{\lambda_1}(x) \right\}$$

which is the subset of options within A having the greatest qualification score.

The procedure continues for those options belonging to \bar{D}_1 , this time trying to distinguish between them on the basis of a new second outranking relation defined by the cutoff level λ_2 , such that:

$$\lambda_2 = \lambda_1 - s(\lambda_1)$$

The process is repeated until the k^{th} step is reached when the first distillate consists of only one option, called a singleton, such that $\text{If } |\bar{D}_1| = 1$, then one option only has been selected.

If the first distillate contains more than one option, the process continues for those options within \bar{D}_1 , progressively lowering λ . At each step, those options not having the maximum qualification score are eliminated until the k^{th} step is reached, at which the distillate is either a singleton or two or more options are declared indistinguishable. This set, called the first distillate, is denoted as \bar{C}_1 , the highest-ranking option or options on the basis of the first downward distillation procedure. *If* $|\bar{D}_1| > 1$, and $\lambda_k = 0$, then on the basis of the available information it is not possible to decide between the options remaining in \bar{D}_k , and each is considered to have equal ranking for the purposes of the downward procedure.

When going from the k^{th} to the $(k+1)^{\text{th}}$ step, the cutoff level λ_k is replaced by λ_{k+1} using the following transformation:

$$\lambda_{k+1} = \text{Max}_{\left\{ \begin{array}{l} S(a,b) < \lambda_k - s(\lambda_k) \\ a,b \in D_k \end{array} \right\}} S(a,b) \text{ where } s(\lambda) = \alpha * \lambda + \beta$$

The second distillation then commences, using the same procedure, this time with the set of options A_1 , containing all the options in A except those within \bar{C}_1 , i.e. $A_1 = A / \bar{C}_1$.

This time λ_0 is set equal to the maximum remaining degree of credibility of the outranking score $S(a,b)$ for the remaining options. Thus, \bar{C}_2 , the singleton or group of options in the second rank according to the downward distillation procedure, is obtained. Then, the distillation procedure is applied again to $A_2 = A_1 / \bar{C}_2$ to obtain \bar{C}_3 . The algorithm proceeds until no options remain to be ranked. This process is called a descending distillation chain, yielding a first complete preorder.

5.2.2.5 Upward Distillation Procedure

Here, for the initial derived cutoff level λ_1 , the subset \underline{D}_1 of the worst options within A are selected such that:

$$\underline{D}_1 = \left\{ a \in A / q_A^{\lambda_1} = \underline{q}_A = \text{Min}_{x \in A} q_A^{\lambda_1}(x) \right\}$$

which is a subset of options within A having the smallest qualification scores.

Again, if this subset contains more than one option, the procedure continues for those options belonging to \bar{D}_1 , again trying to distinguish between them on the basis of a lower cutoff level λ_2 , repeating this procedure until the set contains only one option, or the cutoff level has diminished to zero and all options remaining within the subset are declared equal. The remaining option or options are declared the first distillate of the ascending chain, and the second distillation commences on all options except those from the first distillate. Selection is again on the basis of the smallest qualification score. The upward procedure is completed when all options have been assigned a rank.

Thus, a second complete preorder called the ascending order chain is obtained, in which the options having the smallest qualifications are systematically left aside. Final rankings are obtained through a combination of these two preorders.

The algorithm for ranking the options by the above two procedures can be described as follows:

Let A be the complete set of options to be ranked

1. Set $n = 0$, put $\bar{A}_0 = A$ (descending) or $\underline{A}_0 = A$ (ascending).
2. Set $\lambda_0 = \text{Max}_{a,b \in \bar{A}_n, a \neq b} S(a,b)$ or $\lambda_0 = \text{Max}_{a,b \in \underline{A}_n, a \neq b} S(a,b)$.
3. Put $k = 0$, $D_0 = \bar{A}_n$ (descending) or $D_0 = \underline{A}_n$ (ascending).
4. From among all the credibility scores that are less than $\lambda_k - s(\lambda_k)$, the one having the maximum value is chosen as follows:

$$\lambda_{k+1} = \text{Max}_{\left\{ \begin{array}{l} S(a,b) < \lambda_k - s(\lambda_k) \\ a,b \in D_k \end{array} \right\}} S(a,b)$$

If $\forall a,b \in D_k, S(a,b) > \lambda_k - s(\lambda_{k+1})$, put $\lambda_{k+1} = 0$

5. The λ_{k+1} -qualification scores for all options within D_k are calculated
6. The maximum or minimum λ_{k+1} -qualification score is obtained: \bar{q}_{D_k} (descending) \underline{q}_{D_k} (ascending).
7. The following set is then obtained

$$\bar{D}_{k+1} = \left\{ a \in D_k / q_{D_k}^{\lambda_{k+1}}(a) = \bar{q}_{D_k} \right\} \text{ (descending) or}$$

$$\underline{D}_{k+1} = \left\{ a \in D_k / q_{D_k}^{\lambda_{k+1}}(a) = \underline{q}_{D_k} \right\} \text{ ascending}$$

8. If $|\bar{D}_{k+1}| = 1$ or $|\underline{D}_{k+1}| = 1$ or $\lambda_{k+1} = 0$, proceed to step 9, otherwise put $k = k + 1$, $D_k = \bar{D}_k$ (descending) or $D_k = \underline{D}_k$ (ascending) and go to Step 2.

9. $\bar{C}_{n+1} = \bar{D}_{k+1}$ is the group of options carried through the $(n+1)^{th}$ downward distillation, termed the $(n+1)^{th}$ distillate of the downward procedure.
 $\underline{C}_{n+1} = \underline{D}_{k+1}$ is the group of options carried through the $(n+1)^{th}$ upward distillation, termed the $(n+1)^{th}$ distillate of the upward procedure.
- Put $\bar{A}_{n+1} = \bar{A}_n / \bar{C}_{n+1}$ (descending) or $\underline{A}_{n+1} = \underline{A}_n / \underline{C}_{n+1}$ (ascending).
- If $\bar{A}_{n+1} \neq \emptyset$ or $\underline{A}_{n+1} \neq \emptyset$, put $n = n+1$ and proceed to Step 2. Otherwise, end the distillation.

5.2.3 Actors Involved in the Decision-Making Process

Decisions are rarely made by a single individual. Even if responsibility for the decision ultimately rests with a well-identified individual, the decision is generally the product of an interaction between this individual's preferences and those of others. Indeed, in many cases, the final decision might not be the responsibility of or influenced by single individuals. It could involve entities, (i.e., an elected or appointed body or a board of directors). It could also involve a group (community) with less than well-defined boundaries (i.e., a professional lobby). These actors (individuals, entities, communities) are what we call stakeholders, in that they have an important interest in the decision and can intervene to directly affect it through the value systems they possess. Additionally, there are those who do not actively participate in shaping the decision but who are affected by its consequences and whose preferences must be considered when arriving at a decision (third parties).

The various stakeholders within a decision process might be relatively diverse, having different objectives and conflicting value systems. Therefore, a specific application of decision aiding is rarely comprehensive enough to benefit all of them. For this reason, decision aiding almost always requires that a particular stakeholder is identified (decision maker). Identifying a DM entails specifying the objectives under which he or she operates. Often, the DM may not have the background to perform the decision aid. In this case, the one performing the aid (analyst or facilitator) is generally different from the DM.

In the application presented here illustrating the proposed methodology, no real DM or private or institutional investor was involved. The experts who participated in the study stated, at all the collaboration stages, their personal preferences. Under these circumstances, it could be said that the roles of the DM and the analyst are an amalgam of the experts' contributions.

5.2.4 Criteria Modeling

The proposed methodology is grounded in a series of interviews with experts. The international literature concerning the assessment of corporate performance was taken into account as well.

Initially, experts were involved to help identify and select the criteria that were most appropriate for use in the evaluation of portfolio performance. The end objective was to select the most attractive criteria based on the DM's investment policy. In the second stage, emphasis was placed on determining the weights of the selected criteria and the value of the corresponding thresholds. The contribution of experts, in this phase too, was significant. Finally, there was a validation stage where the results were tested with their assistance.

An initial set of portfolio performance measures were chosen from the international literature (Sharpe et al. 1999; Bodie et al. 2004; Reilly and Brown 2005; Jones 2006) on the basis of their popularity and effectiveness. After a series of meetings with the experts, some additional financial ratios were proposed, with others considered unnecessary. With the agreement of all of the experts, the criterion set was constructed (Table 5.1). The measures used were categorized into three major dimensions: return, risk, and risk adjustment.

5.2.5 *Determination of Weight*

The assignment of importance weightings to each criterion is a crucial issue in the application of all versions of the ELECTRE model (with the exception of ELECTRE IV). Because it is a noncompensatory decision aid model, the interpretation of weights is different than for a compensatory system such as the multiattribute utility theory (MAUT) (Keeney and Raiffa 1993). Within ELECTRE, the weights used are not of constant scale but are simply a measure of relative importance of the criteria involved. Rogers et al. (2000) distinguished four methods to weight criteria for use within ELECTRE: (a) the direct weighting system (Hokkanen and Salminen 1997); (b) the Mousseau system (Mousseau 1995); (c) the "pack of cards" technique (Simos 1990); and (d) the "resistance-to-change" grid (Rogers and Bruen 1998).

The method chosen for determining weights was the resistance-to-change grid. This method represents an improvement on the other approaches because: (a) it is relatively simple and straightforward; (b) it has a theoretical basis within the psychology of human preference relationships; (c) the weights obtained can be directly connected, in theoretical terms, to the DM's concept of personal importance; and (d) the method has been widely in a large number of real-world applications.

Finally, it is worth noting that the experts involved in the application found the resistance-to-change grid weighting method extremely friendly and perceivable and expressed satisfaction with the obtained weighting results. Tables 5.2–5.5 provide the analytical presentation of the resistance-to-change grids for the criterion sets of all three investment profiles.

Table 5.1 Criteria set for the evaluation of equity portfolios

Criterion	Mathematical formula	Description	Dimension	Criterion direction
g_1 Portfolio return	$E(r_p) = \sum_{i=1}^m w_i E(r_i)$ <p>where w_i is the proportion of security i in a portfolio that consists of m assets; and $E(r_i)$ is the expected return of security i (for a single share the capital return per share is defined as: $r_i = \frac{P_t - P_{t-1} + D_t}{P_{t-1}}$, where r_i is the return on a share in period t, P_t is the share price in period t, P_{t-1} is the share price in period $t-1$, and D_t is the dividend that the share gives to the investor in period t)</p>	The portfolio expected return is the weighted average of the expected returns of the individual assets of which the portfolio consists. The rate of return is the main criterion recognized by all financial and micro-theories to explain the investor's behavior	Return	Max
g_2 Portfolio volatility	$\sigma_p^2 = \sum_{i=1}^m w_i^2 \sigma_i^2 + \sum_{i=1}^m \sum_{j \neq i}^m w_i w_j \sigma_{ij} = \sum_{i=1}^m \sum_{j=1}^m w_i w_j \sigma_{ij}$ <p>where i and j are the set of pair of assets in the portfolio; w_i and σ_i are correspondingly the proportion and the volatility of the i-th asset in the portfolio; and m is the number of securities in the portfolio</p>	Portfolio volatility or portfolio variance is the conventional measure of risk. More specifically, it represents the portfolio's nonsystematic risk	Risk	Min
g_3 Value at risk	$VaR_p = \sqrt{w_i^2 \sigma_i^2 + 2 \sum_{i,j} w_i w_j \sigma_i \sigma_j \rho_{i,j}}$ <p>where i and j are the set of pair of assets in the portfolio; w_i and σ_i are correspondingly the proportion and the volatility of the i-th asset in the portfolio; and $\rho_{i,j}$ is the correlation between assets i and j</p>	Value at risk measures the worst expected loss under normal market conditions over a specific time interval at a given confidence level. Another way of expressing this measure is that VaR is the lowest quantile of the potential losses that can occur within a given portfolio during a specified time period	Risk	Min

g_4	Sharpe ratio	$S = (\bar{r}_p - \bar{r}_f) / \sigma_p$ <p>where \bar{r}_p is the expected return of the portfolio; \bar{r}_f is the expected risk free rate; and σ_p is the portfolio's standard deviation</p>	Sharpe's ratio divides average portfolio excess return over the sample period by the standard deviation of returns over that period. It measures the reward to (total) volatility trade-off	Risk adjustment	Max
g_5	Treynor ratio	$T = (\bar{r}_p - \bar{r}_f) / b_p$ <p>where \bar{r}_p is the expected return of the portfolio; \bar{r}_f is the expected risk free rate; and b_p is the portfolio's beta</p>	Treynor's ratio gives excess return per unit of risk, but it uses systematic risk instead of total risk	Risk adjustment	Max
g_6	Jensen ratio	$J = \bar{r}_p - [\bar{r}_f + b_p(\bar{r}_M - \bar{r}_f)]$ <p>where \bar{r}_p is the expected return of the portfolio; \bar{r}_f is the expected risk free rate; \bar{r}_M is the expected return of the market portfolio; and b_p is the portfolio's beta</p>	Jensen's ratio is the average return on the portfolio over and above that predicted by the CAPM, given the portfolio's beta and the average market return. Jensen's ratio is also known as the portfolio's alpha value	Risk adjustment	Max
g_7	M ² measure	$M^2 = \bar{r}_p^* - \bar{r}_f$ <p>where \bar{r}_f is the expected risk-free rate; and r_p^* is the expected return of the "adjusted" portfolio. (It is assumed that the managed portfolio P is mixed with a position in T-bills so the complete or "adjusted" portfolio, denoted by P^*, matches the volatility of the market index.)</p>	The M ² measure focuses on total volatility as a measure of risk, but its risk-adjusted measure of performance has the easy interpretation of a differential return relative to the benchmark index.	Risk adjustment	Max
g_8	T ² measure	$T^2 = T - (\bar{r}_p - \bar{r}_f)$ <p>where T is the Treynor ratio; \bar{r}_p is the expected return of the portfolio; and \bar{r}_f is the expected risk-free rate</p>	The T ² measure is produced after subtraction of the market excess return from the Treynor ratio. Thus, the difference between the return on the Treynor ratio line in and the security market line is obtained at the point where the beta coefficient is equal to 1	Risk adjustment	Max

Table 5.2 Resistance-to-change grid for the conservative profile

g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	Blanks	X	Sum	Weight
Portfolio return	Portfolio volatility	Value at risk	Sharpe ratio	Treynor ratio	Jensen ratio	M ² measure	T ² measure				
Portfolio return		X				X		5	0	5	20.8
Portfolio volatility								6	0	6	25.0
Value at risk			X	X	X	X	X	0	1	1	4.2
Sharpe ratio				I	I			2	1	3	12.5
Treynor ratio					I			2	1	3	12.5
Jensen ratio								2	1	3	12.5
M ² measure							I	0	2	2	8.3
T ² measure								0	1	1	4.2

Table 5.3 Resistance-to-change grid for the balanced profile

g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	Blanks	X	Sum	Weight
Portfolio return	Portfolio volatility	Value at risk	Sharpe ratio	Treynor ratio	Jensen ratio	M ² measure	T ² measure				
Portfolio return		X				X		5	0	5	20.8
Portfolio volatility							X	5	0	5	20.8
Value at risk			X	X	X			0	1	1	4.2
Sharpe ratio				I	I			2	1	3	12.5
Treynor ratio					I			2	1	3	12.5
Jensen ratio								2	1	3	12.5
M ² measure							I	0	2	2	8.3
T ² measure								0	2	2	8.3

Table 5.4 Resistance-to-change grid for the aggressive profile

g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	Blanks	X	Sum	Weight
Portfolio return	Portfolio volatility	Value at risk	Sharpe ratio	Treynor ratio	Jensen ratio	M ² measure	T ² measure				
Portfolio return								7	0	7	29.2
Portfolio volatility		X				X		4	0	4	16.7
Value at risk			X	X	X	X	X	0	1	1	4.2
Sharpe ratio				I	I			2	1	3	12.5
Treynor ratio					I			2	1	3	12.5
Jensen ratio								2	1	3	12.5
M ² measure							I	0	2	2	8.3
T ² measure								0	1	1	4.2

5.3 Application and Results

5.3.1 *Field of Application*

The proposed methodology presented was applied to data concerning portfolios whose equities were traded in the American Stock Exchange (ASE). The ASE was selected because of the availability of data. It was quite difficult to gather complete and reliable financial data about other European and non-European stock exchanges. However, it is important to note that the usefulness of the proposed methodology is not affected by the fact that it is applied only to the ASE. The type of data employed in this application are also available to analysts and investors in other countries. Also, no assumptions were made concerning the special characteristics of the stock exchange.

The composition of the ten portfolios participating in the evaluation process is summarized in Table 5.5 (bold-type figures indicate high capitalization equities, and non-boldtype figures indicate medium-low capitalization equities).

Alternative portfolios consisted of miscellaneous securities from the ASE and covered a broad spectrum of business activities to take into account the major issue of the diversification effect (see Statman 1987; Brennan 1975). The study period included weekly-based closing prices between January 1, 2004 and June 30, 2007. Table 5.6 summarizes the values of the ten alternatives, including the three benchmark portfolios, in regard to the eight selected criteria. Benchmarks 1, 2, and 3 are three hypothetical portfolios chosen by the experts to participate in the evaluation process. Benchmark portfolio 1 was constructed to represent the profile of a conservative (against risk) investor, and benchmark portfolios 2 and 3 were constructed to represent the profiles of investors with preferences, respectively, for a balanced portfolio and an aggressively chosen (risky) portfolio.

The preference and indifference thresholds for the eight selected criteria are shown in Table 5.7. The contribution of the experts here was of crucial importance. Their invaluable experience with security analysis and asset management was critical to obtaining reliable results. Also invaluable were the plethora of statistical data to which they had access.

5.3.2 *Results and Discussion*

The software (version 3.1b) used in the current case study for implementation of the ELECTRE III method is licensed to the Laboratory for Analysis and Modeling of Decision Support Systems (LAMSADE) of the University of Paris-Dauphine. It was developed at the Institute of Computing Science of the Technical University of Poznan. The results obtained after application of the proposed approach for performance evaluation of the alternative equity portfolios are summarized in Fig. 5.2. Each ranking graph corresponds to one of the three investment profiles (conservative, balanced, aggressive).

Table 5.6 Performance matrix

	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8
Portfolios	Portfolio return	Portfolio volatility	Value at risk	Sharpe ratio	Treynor ratio	Jensen ratio	M ² measure	T ² measure
1	0.009	0.0241	5,612	0.3317	0.0077	0.0043	0.0037	0.0042
2	0.0083	0.0233	5,413	0.3137	0.0077	0.0039	0.0033	0.0041
3	0.0077	0.0242	5,621	0.2773	0.0070	0.0033	0.0025	0.0035
4	0.0089	0.0228	5,312	0.3460	0.0078	0.0043	0.0040	0.0042
5	0.0086	0.0229	5,316	0.3326	0.0080	0.0042	0.0037	0.0044
6	0.0088	0.0228	5,300	0.3424	0.0076	0.0042	0.0039	0.0041
7	0.0084	0.0227	5,279	0.3261	0.0073	0.0038	0.0036	0.0037
8	0.0081	0.0228	5,310	0.3111	0.0074	0.0037	0.0032	0.0039
9	0.0081	0.0225	5,224	0.3162	0.0068	0.0034	0.0033	0.0033
10	0.0075	0.0233	5,424	0.2788	0.0068	0.0031	0.0025	0.0033
Benchmark 1	0.0076	0.0226	5,258	0.2920	0.0073	0.0034	0.0028	0.0038
Benchmark 2	0.0082	0.0233	5,420	0.3090	0.0072	0.0037	0.0032	0.0037
Benchmark 3	0.0088	0.0240	5,583	0.3250	0.0071	0.0039	0.0035	0.0036

Table 5.7 Determination of thresholds

	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8
	Portfolio return	Portfolio volatility	Value at risk	Sharpe ratio	Treynor ratio	Jensen ratio	M ² measure	T ² measure
$q_j [g_j(a)]$	0.0002	0.0003	75	0.0134	0.0003	0.0001	0.0003	0.0003
$p_j [g_j(a)]$	0.0007	0.0005	300	0.0298	0.0005	0.0005	0.0006	0.0005

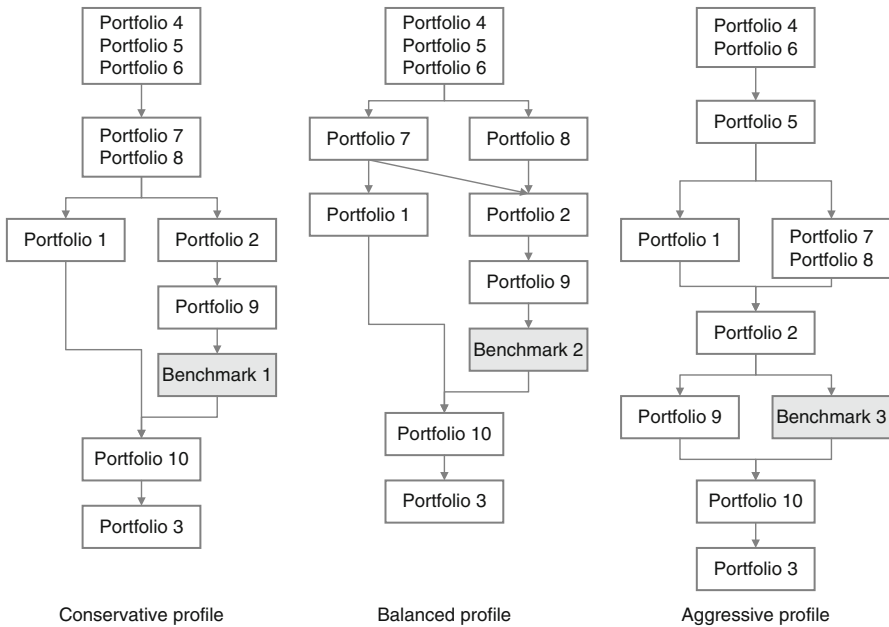


Fig. 5.2 Final graphs of results for each investment profile

Table 5.8 Portfolio betas of the alternative and benchmark portfolios

Portfolio	Beta coefficient	Portfolio	Beta coefficient
1	1.04	8	0.95
2	0.95	9	1.04
3	0.95	10	0.95
4	1.02	Benchmark 1	0.90
5	0.95	Benchmark 2	1.00
6	1.02	Benchmark 3	1.10
7	1.02		

Regarding the ranking results of the conservative versus risk investment profile, note that Portfolio 5 is the most appropriate choice for the risk-averse DM because it is at the top of the three ranked portfolios and has the lowest beta coefficient ($b_p=0.95$) when compared to Portfolios 4 and 6 (i.e., has the lowest systematic risk) (see Table 5.8). Portfolio 8 ($b_p=0.95$) might also be an alternative for further study because it also enjoys low systematic risk. The conservative Benchmark portfolio 1 has been ranked fairly low. Portfolios 1, 2, and 9 are at the middle of the rankings, and Portfolios 10 and 3 have the worst rankings according to the evaluation process.

The ranking results of the balanced investment profile indicate that Portfolio 4 is the most appropriate choice for the neutral DM as it belongs at the top of all three portfolios and has a beta coefficient ($b_p=1.02$) that is closest to the beta of the market portfolio ($b_p=1$) in comparison to Portfolios 4 and 6. Portfolio 7 ($b_p=1.02$) might also be an alternative for further study because it has a beta coefficient close to the market portfolio beta. The balanced Benchmark Portfolio 2 has been ranked fairly low. Portfolios 1, 2, and 9 are at the middle of the rankings, and Portfolios 10 and 3 have the worst rankings according to the evaluation process.

The ranking results of the aggressive against risk investment profile indicate that Portfolio 4 is the most appropriate choice for the risk-seeking DM because it belongs at the top in two portfolios and has a higher capital return ($r_p=0.0089$) than Portfolio 5. Portfolio 5 might also be an alternative for further study because it has a high capital return as well as risk ($r_p=0.0086$). The aggressive Benchmark Portfolio 3 has again been ranked fairly low, and Portfolios 10 and 3 have the worst rankings.

The analysis also showed that in all three cases the benchmark portfolios had a fairly poor performance, a fact that has to be studied further by the experts. Also, Portfolios 10 and 3 are, in all cases, represent bad portfolio compositions, and Portfolios 1, 2, and 9 constitute alternatives that consistently perform poorly. Overall, the core of alternatives consisted of Portfolios 4 and 5, which might effectively reflect the entire investment policy spectrum. The experts also stated that the potential to build a portfolio consisted of Portfolios 4 and 5, in proportions that reflect the risk-tolerance policy of the DM. That is, considering the case of a conservative investor, there is the potential to build a portfolio consisted partly of Portfolio 5 ($b_p=0.95$) (biggest proportion) and partly of Portfolio 4 ($b_p=1.02$) (smallest proportion).

5.3.3 *Sensitivity Analysis and Validation of Results*

The ranking of alternatives with the ELECTRE III method remains dependent on the values of various thresholds and indices of importance. Therefore, in most cases, sensitivity analysis is recommended. In the application that has been presented, the sensitivity analysis was conducted with respect to criteria weights. A large number of weighting scenarios examined (its generation rationale had to do with low, random, and simultaneous fluctuations on the weights of the baseline scenarios) and the obtained sorting results had no or extremely slight variation compared to the results of the baseline scenarios. It has to be remembered that the ELECTRE III method is a direct pairwise methodology. For each option, the outranking relations derived are under consideration with the other alternatives (not with category profile limits, as with the ELECTRE Tri method). It thus tends to be more sensitive than the indirect pairwise-based ELECTRE methods to the presence of “clones” (i.e., options close to each other in regard to their criterion valuations). This is why assessing the stability of the obtained results is of crucial importance.

The proposed methodology also contains a final validation stage, where the results were tested with the assistance of experts, whose contribution in this last phase was significant. They expressed their satisfaction with the final results. More precisely, they confirmed that the results were in categorical concurrence with the set of high-performance portfolios that they heuristically manage in their everyday practice. Among the securities of the final proposed portfolios, they identified “winning” equities of the ASE with respect to the particular time period of the application. Moreover, even in cases of equities that participated in the top-ranked portfolios but were not recognized by the experts as direct investment opportunities (as confirmed by the market), both chances and hints were given for further study and potential detection of mispriced securities.

5.4 Conclusions

A multicriteria approach for equity portfolio comparisons based on outranking relations was presented here along with a comprehensive literature review of the coherent methodologies. We illustrated how this multicriteria approach makes it possible to integrate, within the portfolio selection process, the conventional mean-variance (MV) model with additional relevant criteria. Our approach is founded on the idea that portfolio selection is a problem with an inherent multidimensional nature. The fact that the proposed approach is capable of helping the DM select a portfolio that satisfies his spectrum of investment desires as much as possible makes it a powerful decision support tool. The methodology that has been presented can be a useful tool for investors (private or institutional) and professionals in the field in regard to evaluating and selecting their portfolios.

The special features and contribution of the approach presented are outlined as follows.

- Incorporation of the DM's (private or institutional investor) preference system by taking into account his or her investment policy constraints. The proposed approach allows taking into consideration both the DM's preference system and the analyst's professional experience.
- Incorporation in the decision process of several criteria (conventional ones and more sophisticated risk-adjusted performance measures) that on a realistic basis represent the way a professional (asset manager or trading expert) supports the client's (private or institutional investors) strategies and decisions.
- The ELECTRE III method that was chosen for the evaluation process is well adapted to the nature of the portfolio selection problem. Also, the extended and effective use of the ELECTRE family framework in many financial decision-making problems was one more critical factor for choosing this particular methodology.

Further work that may be considered for broadening the proposed approach can be summarized as follows.

- Embodiment of the methodology in a decision support system so real-time investment decisions to be supported.
- Expansion of the criterion set to include additional portfolio performance measures, according to the preference system of the user.
- Expansion of the methodology's focus to include additional asset classes.
- Expansion of the methodological framework by introducing an initial portfolio construction component (i.e., a continuous optimization technique) for optimal allocation of wealth in the available securities. (The output of this additional phase would be input for the proposed portfolio performance evaluation approach.)

Chapter 6

Applied Portfolio Management

6.1 Introduction

Ever since Professor Markowitz introduced his modern portfolio theory (MPT), applications faced numerous constraints. These constraints dictated that professionals adopt either important assumptions or reengineered models. In this chapter, we focus on those elements that drive today's professional world.

6.2 Tools Employed

Probably the most debatable elements of the formation of the investment policy of any organization are the tools employed to implement the strategic views (usually) of an investment committee. Professionals are divided into several categories, as is the theory itself. One can then exercise fundamental activities, quantitative techniques, and technical analysis within the essence of the investment committee's insights regarding the whole system. Although asset management should be a pure and fully recognizable procedure, in fact every organization changes the tools, the mix, and sometimes the importance of each to produce a "secret sauce." From a marketing point of view, this procedure is important for achieving diversification and creating the "mystery" of the organization. From a finance point of view, the scope of any operation is none other than profit maximization given the means and market conditions. Research in the area of behavioral finance has highlighted several human anchors that drive the industry itself. We have no intention to create an exhaustive list of tools, but we want to help the

reader understand the equipment the professionals have at hand. The following sections describe some of these tools.

6.2.1 Strategic Market Evaluation

Exactly the same way that research companies provide strategic research regarding opportunities in several market sectors, the beginning of the long investment journey begins with the market evaluation form, a strategic viewpoint. There are few participants who can conduct research in every market worldwide. Mostly markets are assessed at a high level on the basis of secondary research, which in turn is conducted by sell-side analysts. Note that sell-side analysts usually cover only markets and asset classes in which there is expressed demand either size-wise or situation-wise. Fundamental information is also publicly available, with the recent Internet explosion creating terabytes of information daily. There is an ongoing debate regarding the quality of publicly available information and the implications of the process capabilities an organization must have to make use of that vast amount of information.

Another question has to do with the marginal improvement of the overall evaluation on the basis of the next mega-, tera-, or petabyte of additional information. It is my view that serious expert systems based on Google-type searching algorithms should be employed in the future to scan all available information, assess it, and finally summarize it so it can be at least slightly more useful to the evaluation procedure. In every case, an evaluation step is critical to justify the focus of the asset management process.

6.2.2 Focus Group Definition

“Focus group” is a term is used widely in market research. In fact, it is a small group of people selected in a special way to represent the general public. In asset management, a focus group is a small group of companies targeted to represent the market(s). As an organization, its interests lie mainly in terms of companies’ size and liquidity. Obviously, an organization cannot analyze the whole population of interest economically. Some investee targets, however, offer extremely low liquidity—or low enough to restrict asset managers from selecting them. We should also keep in mind that different funds can follow different focus groups depending on their general criteria or investment target. For example, in general, sizable companies and index members are selected to participate in focus groups; but this strategy would not be applicable to a fund specializing in investing in, for example, small capitalization companies or distress opportunities. As a result, a more targeted focus group would be selected by the managers and the investment committee to cater to the fund’s needs.

6.2.3 *Relative Value Analysis*

Institutional and professional bond markets refer to the term “relative value” when comparing the prices of two or more bonds. More precisely, they refer to the additional yield an investor can capitalize by investing in a fixed-income asset rated below the top-rated bonds. Similarly, investors measure the perceived market value, or relative value, of a corporate bond by measuring its yield spread relative to a designated benchmark. A key measure of relative value of a corporate bond is its “swap spread,” which is the basis point spread over the interest-rate swap curve. It is a measure of the credit risk of the bond. The same concept is used when equities are in question. Relative valuation dictates that the value of a company is determined in relation to how similar companies are valued. The most common way to apply relative value analysis to equities is by creating a group of comparable companies (often industry peers) and calculating their multiples, such as the price/earnings (P/E) ratio, price to book value (P/BV), and enterprise value to earnings before interest, taxes, depreciation and amortization (EV/EBITDA), among others. The analyst then compares those multiples to justify over- or undervaluation of the company under examination. Relative value analysis is quite simple and can be applied quickly, but it can also lead to serious mistakes. Comparing values versus industry peers, benchmarks, indices, or rating levels can justify (or not) current valuation. In most circumstances, it provides little or no information regarding the overall state of the asset class. Therefore, it is important that any application be followed by a strategic market evaluation. Note that future estimates that are used for relative value analysis should not be based on historical figures as they can direct a decision in a completely wrong direction.

6.2.4 *Technical Analysis*

Technical analysis bases the determination of a future direction of an asset price on past prices and volumes. Technicians use several methods, such as charts, patterns, indicators, and waves, among others. Different techniques may ignore the existence of the other or be used in collaboration to provide insight regarding the trend, momentum, price levels, or pivotal points. Basically, this method analyzes market supply and demand for any specific instrument. To that extent, it is essential that liquidity (i.e., the size of supply and demand that results in transactions) is high enough and that the market is deep. According to basic assumptions, the market discounts everything and moves in trends and past trends to repeat itself. Obviously, these assumptions imply a number of others, such as the imminent dissemination of information to all participants, which is not always the case. In fact, technical analysis is used in practice most commonly to evaluate very short-term periods in markets where liquidity is extremely high. Any attempt to use it with neglected stocks characterized by limited free float should be circumscribed to the identification of those characteristics for which is also useful.

6.2.5 Behavioral Variables

Most financial and economic theory has its basis in the notion of rationality that characterizes the actions of individuals based on all the available information in the decision-making process. An alternative approach has been developed in an attempt to better understand and explain how emotions and cognitive errors influence investors and the decision-making process. Many researchers believe that the study of psychology and other social sciences can shed considerable light on the efficiency of financial markets and explain many stock anomalies. For example, some believe that the outperformance of value investing comes from investors' irrational overconfidence in exciting growth companies and from the fact that investors generate pleasure and pride from owning growth stocks. Monitoring behavioral variables can help the asset manager identify periods when psychological pressure over actions is more significant than other decision-making determinants. That pressure can drive market prices to extremes in one or the other direction, which cannot be justified using any other tool. More important than this is the fact that behavioral variables can provide leading information to identify possible market extremes. People trade for both cognitive and emotional reasons. They trade because they think they have information when they have nothing but noise; and they trade because trading can bring the joy of pride when decisions turn out well.

6.2.6 Exceptional Targets

Regardless of the investment tool used, the asset management process may set specific targets to be achieved. It is well known that for most asset management organizations exceptional performance is a common target. To our view, this is more a vision or mission and less tactical target. Alternatively, it may be a set of criteria that shapes the way people in the organization perform. Nevertheless, setting performance—most times on a relative basis—or risk targets in most circumstances drive the whole procedure to some conditionality. In this respect, the use of any selection process should produce results that comply with the original target set. Conditional asset management, today partly provoked by marketing strategies and diversification needs, increasingly direct the procedure to become quantitative-oriented and computer-based. Such developments leave it to the managers to set criteria and micro-tune the strategy model. In the end, however, they should follow its suggestions with no “extra” insight. Managerial insight now has to be directed on a higher level—that of strategic asset allocation. This, then, takes us back to leaving the tactical allocation to techniques such as those described in this book.

6.3 Evaluation of Market Conditions

6.3.1 *Macroeconomic and Microeconomic Models*

A macroeconomic model is an analytical tool designed to describe the operation of the economy of a country or region. These models are usually designed to examine the dynamics of aggregate quantities such as the gross domestic product, total income earned, the level of employment, and the level of prices. There are two basic models: Classical and Keynesian, which after the 1970s transformed to New Classical and New Keynesian following changes in the global economy. As for their type, they are simple theoretical models. During the 1940s and 1950s, economists set out to construct quantitative models to describe the dynamics of the real economic data. These models estimated the relations between the economic variables using time series analysis. These models are used today for forecasting purposes. There is another type called the dynamic stochastic general equilibrium (DSGE). Based on what is called “optimal choice” of economic participants or agents, these agents try to find prices that equate supply and demand in every market. As with DSGE, they are computable general equilibrium models that mainly focus on long-run relations. This makes them more appropriate for studying the long-term implication of permanent policies such as taxes. In this limited reference of a huge subject, we should not ignore the Lucas critique, named for Robert Lucas’s work on macroeconomic policymaking. It argues that it is naive to try to predict the effects of a change in economic policy entirely on the basis of relations observed in historical data, especially highly aggregated historical data.

The strength of microeconomics comes from the simplicity of its underlying structure and its close touch with the real world. Basically, microeconomics is the study of supply and demand along with their interaction in different markets. Several fields are studied under this general description, including labor economics, industrial organization, international economics, and public finance, among others. In other words, microeconomics is basic, and in the end everything is supply and demand. Structuring and using models for different markets is essential to any selection process, from the setup of a small store to the portfolio mix of multinational, fully diversified organizations. Quite detailed, and in some cases appropriately describing the specific environment, models are built for organizations under scrutiny from every fundamental analysis team worldwide. Models are reevaluated, rescheduled, and reconsidered as often as the macroeconomic environment calls for important changes in basic assumptions.

6.3.2 *Corporate Actions*

A corporate action is an event initiated by a public company that affects the securities (equity or debt) issued by the company. Some corporate actions, such as a dividend

(for equity securities) or coupon payment [for debt securities (bonds)], may have a direct financial impact on the shareholders or bondholders. Another example is the “call” (early redemption) of a debt security. Other corporate actions such as a stock split may have an indirect impact, as the increased liquidity of shares may cause the price of the stock to rise. Other corporate actions, such as a name change, have no direct financial impact on the shareholders.

The primary reasons for companies to use corporate actions are the following.

- Return profits to shareholders
- Influence the share price
- Corporate restructuring

Corporate actions are classified as voluntary, mandatory, or mandatory with choice.

In any case, corporate actions affect the company’s microenvironment. There are also circumstances where the macroenvironment may be affected. For example, share capital increases and any type of capital injection directly affect the expected return on equity (ROE). The question arising here is the possibility, or capacity, the company has to maintain its historical ROE, especially after massive share capital increase (SCI). Portfolio managers should compare historical ROEs with expected ones on the basis of less effective use of the new capital according to the law of marginal returns. Fundamental analysts tend to believe that historical ROEs will be achieved again after a short period of adjustment, usually between 12 and 18 months. This is based on what actually happens in most cases.

Another example comes from the mergers and acquisitions (M&As) arena. M&As refers to the aspect of corporate strategy, corporate finance, and management that deals with buying, selling, dividing, and combining different companies and similar entities. This is done to can aid, finance, or help an enterprise grow rapidly in its sector or location of origin, or in a new field or new location, without creating a subsidiary, other entity, or using a joint venture. The distinction between a “merger” and an “acquisition” has become increasingly blurred in various respects (particularly in terms of the ultimate economic outcome), although it has not completely disappeared. In any M&A case, portfolio managers should examine the final benefits for their own shareholding stake. Deals that appear accretive to the shareholders are based on the assumption of client loyalty to the new entity the same way they were loyal to the separate corporations. Their loyalty is subject to a number of parameters but definitely to the final corporate culture of the organization after the amalgamation. On the other hand, unification costs (usually underestimated) and perplexed situations (such as a merger with a simultaneous SCI) may drive uncertainty seriously higher with respect to the final outcome, which is another issue to be considered.

Finally, a common corporate action is the stock split. A “stock split” or “stock divide” increases the number of shares in a public company. The price is adjusted such that the “before and after” market capitalization of the company remains the same, and dilution does not occur. Options and warrants are included.

For example, a company has 100 shares of stock priced at \$50 per share. The market capitalization is $100 \times \$50$ or \$5,000. The company splits its stock two for one. There are now 200 shares of stock, and each shareholder holds twice as many shares. The price of each share is adjusted to \$25. The market capitalization is $200 \times \$25 = \$5,000$, the same as before the split.

Ratios of two-for-one, three-for-one, and three-for-two splits are the most common, but any ratio is possible. Splits of four for three, five for two, and five for four are used although less frequently. Investors sometimes receive cash payments in lieu of fractional shares.

It is often claimed that stock splits, in and of themselves, lead to higher stock prices; research, however, does not bear this out. What is true is that stock splits are usually initiated after a large run up in share price. Momentum investing suggests that such a trend would continue regardless of the stock split. In any case, stock splits do increase the liquidity of a stock; there are more buyers and sellers for ten shares at \$10 than one share at \$100. Some companies have the opposite strategy: By refusing to split the stock and keeping the price high, they reduce trading volume and volatility.

Other effects could be psychological. If many investors believe that a stock split will result in an increased share price and so purchase the stock, the share price tends to increase. Others contend that the management of a company, by initiating a stock split, is implicitly signaling its confidence in the future prospects of the company.

In a market where there is a high minimum number of shares, or a penalty for trading in so-called odd lots (a nonmultiple of some arbitrary number of shares), a reduced share price may attract more attention from small investors. These small investors have negligible impact on the overall price.

Obviously it is important to understand what the investors' reactions as a result of a split will be, which is a function of their financial literacy and understanding of corporate actions and market price changes. It is quite common to observe different reactions in the market place from what was expected as a result of momentum, behavioral issues, news highlighting, and so on. A portfolio manager is never in a position to estimate herding implications in market prices and at the same time increased or decreased liquidity as a result of investors' interest of the same direction. Target price definition, a subject analyzed later in the chapter, is a superior guide to decision-making under these circumstances.

6.3.3 Risk Analysis and Alternative Options

Risk analysis is a technique to identify and assess factors that may jeopardize the success of a project or of achieving a goal. This technique also helps define preventive measures to reduce the probability of these factors from occurring and identify

countermeasures to deal with these constraints successfully when they develop, thereby averting possible negative effects on the competitiveness of the company.

Two fundamental types of financial risks exist:

Systematic risk: Systematic risk influences a large number of assets. A significant political event, for example, could affect several of the assets in a portfolio. It is virtually impossible to protect oneself against this type of risk.

Unsystematic risk: Unsystematic risk is sometimes referred to as “specific risk.” This kind of risk affects a small number of assets. An example is news that affects a specific stock such as a sudden strike by employees. Diversification is the only way to protect oneself from unsystematic risk.

Now that the fundamental types of risk are determined, let us look at more specific types of risk.

Credit or default risk: Credit risk is the risk that a company or individual will be unable to pay the contractual interest or principal on its debt obligations. This type of risk is of particular concern to investors who hold bonds in their portfolios. Government bonds, especially those issued by the federal government, have the least amount of default risk and the lowest returns, whereas corporate bonds tend to have the highest amount of default risk but also higher interest rates. Bonds with a lower chance of default are considered to be investment grade, whereas bonds with higher chances are considered junk bonds. Bond rating services, such as Moody’s, allows investors to determine which bonds are investment grade, and which bonds are junk.

Country risk: Country risk refers to the risk that a country will not be able to honor its financial commitments. When a country defaults on its obligations, it harms the performance of all other financial instruments in that country as well as other countries with whom it has relations. Country risk applies to stocks, bonds, mutual funds, options, and futures that are issued in a particular country. This type of risk is most often seen in emerging markets or countries that have a severe deficit.

Foreign-exchange risk: When investing in foreign countries, one must consider the fact that currency exchange rates can change the price of the asset. Foreign-exchange risk applies to all financial instruments that are in a currency other than your domestic currency. As an example, if you are a resident of America and invest in some Canadian stock in Canadian dollars, even if the share value appreciates you may lose money if the Canadian dollar depreciates in relation to the American dollar.

Interest rate risk: Interest rate risk is the risk that an investment’s value will change as a result of a change in interest rates. This risk affects the value of bonds more directly than that of stocks.

Political risk: Political risk represents the financial risk that a country’s government will suddenly change its policies. This is a major reason why developing countries lack foreign investment.

Market risk: Market risk is the most familiar of all risks. Also referred to as volatility, market risk is the day-to-day fluctuations in a stock’s price. Market risk applies mainly to stocks and options. As a whole, stocks tend to perform well during a bull

market and poorly during a bear market—volatility is not so much a cause but an effect of certain market forces. Volatility is a measure of risk because it refers to the behavior, or “temperament,” of the investment rather than the reason for this behavior. Because market movement is the reason people can make money from stocks, volatility is essential for returns. The more unstable the investment, the more chance there is that it will experience a dramatic change in either direction.

In the market place, under any risk assumptions there are three alternatives in asset management, according to the investors’ expectations.

1. Long. Given the portfolio exposure, an investor can increase asset participation in it. It is usually following expectations of an upward market.
2. Short. This is a decrease of portfolio exposure to a given asset or asset class. A short position can also be taken as a negative position from the beginning. Based on negative expectations with respect to the asset in question, a portfolio manager can set its portfolio to earn from the downturn of the asset price.
3. Do nothing. This is an alternative for a constructed portfolio. If there is no change in expectations, there is no need to change portfolio allocation just because third parties call for it. Sell-side analysts often come with reviews on equities, bonds, and other assets. From time to time, they simply change price targets, sometimes following the markets, and create exit and entry signals. A portfolio manager should consider all available information but does not need to adjust its strategy unless the expectation really changes.

(a) Corporate strategy optimization (twofold concept):

1. Maximize value of enterprise: Stockholders are always interested in acquiring the maximum potential of their stakes upside. Enterprise value (EV) is the most important element of the value of their stockholding. The pressure for EV maximization has been intense in previous years; and stakeholders demand for it, along with precious bonuses for achieving it, have directed many decisions. Increased ROE has been a serious metric of that value year after year, and the fight for increased ROE has been the managements’ priority. There are several cases in which, to achieve increased ROE, risks were underestimated. In these cases, huge organizations have fallen. Portfolio managers are also interested—as stakeholders—in EV maximization but in respect to a shorter horizon than majority shareholders. That shorter horizon—according to some researchers it is less than 12 months—have intensified managements’ efforts to achieve this goal in the short term.
2. Minimize equity. The other side of the same coin, where maximization of EV is the number one priority, is equity minimization. It is the will of the shareholders’ to dedicate as little capital as possible, as it will enhance ROE and subsequently the EV. This could be the result of a risk aversion of those that have already succeeded in their previous investments, the limited capital directed toward startup companies, the quick expansion of computer technologies, or a combination of all of these possibilities. In all cases, it is

accepted that all possible measures will be taken to avoid a capital increase. A recent example is the fallen American banks, which proved that their equity, considering the extent of their business, was quite low.

- (b) Initial public offering (IPO): An initial public offering can take place only when the pre-IPO shareholders believe they have achieved EV maximization. Otherwise, they have no real interest in selling part of their organization. Another issue to consider is the equity minimization principle. In other words, is it possible to continue achieving high ROEs when new capital is injected into the company? Usually, funds optimization is achieved when funds are in scarcity. An IPO offers serious fresh cash, in most cases in multiples of existing equity; and there is no track for excess ROE for that new level of equity. Also, managers tend to undertake extra risks or invest in less attractive projects after an IPO. The portfolio manager must consider that when the owner has an IPO in mind he has already decided on the optimization mix. In this respect, the valuation misjudgment of the owner will be the profit of the portfolio manager.

Generally, corporate actions need to be trivially considered and judged for the final decision. Easy “bets” do not exist in the market place. Either needed cash or value optimization drives the decisions. In both circumstances, the investor must decide whether new cash will generate subsequent value for the new shareholders or if value optimization has not yet been achieved. To reach that decision, a valuation of the asset is as important as the deal that is to be signed.

6.3.4 Target Price Definition

Most successful investors worldwide have insisted on knowing the value of the asset they are considering. The idea behind it is very simple: If one buys a mispriced asset, be careful that the real value is higher than the market. There are several methods for asset valuation, and it is not our intent to present them here. It is extremely important, however, for the portfolio manager to have, from the very beginning of an investment, the exit value. We call that exit value the “target price.” It should be known before any market action. There are three issues to be considered during this procedure.

1. The portfolio manager should exit the position as soon as the target price is achieved or go on “hold” if the macroeconomic conditions alter. Valuations do not change every moment or at least frequently enough to justify opinion change. Once the target price is achieved, the goal of the portfolio manager is fulfilled; and exit from the position is justified. Obviously, market momentum can drive prices higher or lower from any price target, but this is not something we can calculate or incorporate in management. Sometimes execution of an order is allocated to a trader who is trying to capture that market sentiment. On the other hand, when macroeconomic conditions change, such as long-term interest rates,

the portfolio manager should adjust his or her price targets based on the new data that is known or seriously anticipated.

2. A country's risk is an essential element of the value of any asset in it. If country risk is under consideration, it is irrational to keep target prices unchanged. It is probably the sole most important macroeconomic factor that affects prices across the board. Increased country risk affects economic as well as market conditions. In reflex markets, prices will deteriorate to the level at which extra risk will be incorporated in the price. Very basic fundamentals justify the new price.
 - (a) Business sense. Is there real demand for the business? Even if there is demand, will that generate enough profits to justify assets?
 - (b) Locality. When there is reason for local production, or existence, there is local business value.
 - (c) Change of business models. During intense changes, historically business models change. What use is there to making if the profits no longer exist? Look for models that will arise through this change.
3. Beware of estimation (valuation) errors. Market sentiment is highly directive when target prices are defined. During an uptrend, most sell-side analysts adjust their target prices higher after every quarter. The economic cycle is unfolding, and the market is pricing stocks because of the expected growth. The procedure can drive target prices to unsustainable levels through micro or macro variables. In some circumstances, a combination of the best macro and micro situations are employed to justify current market prices. There is always an action to be taken—be sure to take the proper one.

6.3.5 Supernormal or Nonconstant Expected Growth

All portfolio managers are in search of companies that will achieve supernormal growth. They are looking for the organization that will bring multiple returns for every euro invested. Brilliant ideas, modern projects, and new markets are always on track for those new kings of the financial marketplace. We have no doubt that this kind of “pick” offers the portfolio with extra return, an impeccable marketing tool in today's asset management world.

There are several issues we have to consider when we are searching for this non-constant growth, knowing that only a small portion of those efforts remain long enough to return their gain to their shareholders.

1. Today's markets value rapid gratification of their expectations; and when a successful business started in a garage, its value is further applauded after a series of successes. Such examples are Google, Apple, and Facebook. Even when we consider those examples successful, there were hundreds of other efforts in the same direction that were also highly priced but never made it.

2. Like it or not, there are no fundamental tools to proceed in realistic valuations in these cases. Hence, target prices should be determined through intuition and heuristics. When intuition takes place in a seriously scientific environment, the result can be all over the place. We have seen heuristic multiples to justify prices or even form target prices with disappointing results. This should not be a betting structure. It should be a fundamentals principled valuation. In some cases, however, value can simply not be derived.
3. A portfolio manager should always consider that existing shareholders try to achieve maximization of their value. Furthermore, to that extent they incorporate a selling price for all existing and expected results that someone is willing to pay. Existing shareholders try to acquire the maximum the market is willing to offer toward their optimization process.
4. To avoid negative surprises, portfolio managers should examine the following.
 - (a) Ability to maintain growth rates. It is not always possible to achieve high growth rates, especially when invested capital multiplies. If a super-growing company becomes a stable one with a multimillion or even billion injection, valuation should be made on that basis.
 - (b) Profit capabilities. Profit capability is part of the growth rate problem. There is also the case in which size deficiency can lead to lower profits directly or higher risks and adjusted lower returns.
5. When expected growth is much higher than the growth domestic product, serious justification is needed. If it cannot be achieved, some of this growth should not be valued in the model. Otherwise, the hypothetical value of the investment will be much higher than the existing one. As a result, a higher level of risk will be inserted in the portfolio.

6.4 Conclusions

We presented the fundamental elements that drive today's professional asset management world. More specifically, the basic tools were described, such as strategic market evaluation, focus group definition, relative value analysis, technical analysis, various behavioral variables, and the definition of exceptional targets. Finally, techniques were introduced that help evaluate market conditions. The discussions focused in macroeconomic and microeconomic models, corporate actions, risk analysis and alternative options, rules for target price definition, and supernormal or nonconstant expected growth issues.

Chapter 7

Conclusions

In the introduction of this book, three strong needs regarding the future of portfolio management became apparent: (a) enhancement of current investment management processes and ontologies; (b) improvement of the computational effectiveness of contemporary financial engineering models; and (c) augmentation of the operational transparency and regulation in the markets.

The methods, tools, and analytical tools presented deal directly with the above objectives and assist in enhancement of the state of the art by:

1. Introducing innovative and integrated investment business analytical tools and frameworks.
2. Launching new powerful, robust decision support by algorithmic tools and mechanisms.
3. Exploiting multiple risk metrics and standardized risk management procedures within a fertile coalition.

We also advocated establishing an integrated methodological framework for supporting decisions that concern the management process of portfolios. It can be effective under the strongly volatile and uncertain conditions of contemporary financial environment. Our objective was to contribute to parameters identification of every investment profile and their interrelations. Finally, we offered an elaboration of a transparent and consistent decision support framework for our clients.

Our approach roughly consisted of the following three components: (a) stock selection; (b) portfolio optimization; and (c) performance evaluation. More specifically, the first component deals with selection of the most attractive asset classes and securities through evaluation of the macro and micro economic climate and analysis of the underlying capital market expectations. Then, in the second component, complex optimization models are developed to engineer finely tuned portfolios. The second component also focuses on realization of a selection procedure to meet the needs of our clients' profile and policy statement. The third component emphasizes an evaluation of the portfolios on the basis of a broad grid of portfolio performance measures.

Our philosophy aspires to heal the pathology of the related current knowledge level and to constitute the starting point for reforming and improving the conventional, stereotyped investment practices. Also, it comprises an antisystemic tailor-made equity portfolio engineering approach because it departs from the point that state-of-the-art models finish, proceeding further in the implementation of complex, specialized investment management strategies.

We examined the contribution of various multiple criteria decision-making (MCDM) technology methodologies in the multidimensional character of portfolio management decisions. The MCDM modeling procedure provides advantages in the area of portfolio management and generally in financial decision-making, including: (a) the possibility of structuring complex evaluation financial problems; (b) construction of both quantitative and qualitative criteria in the evaluation process; (c) transparency in the evaluation, allowing good argumentation in financial decisions; and (d) introduction of sophisticated, flexible, realistic scientific methods in the financial decision-making process. Of course, the most important of all aspects is that MCDM enables the decision-maker to participate actively in the financial decision-making process and helps him or her understand the peculiarities and special features of the real-world problem he or she faces.

The discrete methodologies we have presented may be integrated into a robust MCDM framework for equity portfolio construction and selection. The contribution of the proposed models in the process of designing portfolios is significant and can be proven valuable for portfolio managers, financial analysts, and investors in managing their portfolios. Further work that may be considered for broadening the proposed approaches, can be summarized as follows: (a) embodiment of the proposed methodologies in an integrated decision support system so real-time investment decisions can be supported; and (b) expansion of the methodologies' focus so as to include additional asset classes, such as bonds, derivatives, and others.

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