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Rating Mutual Funds Through an Integrated DEA-based Multicriteria Performance Model: Design and Information Content

Vassilios Babalos
Michael Doumpos
Nikolaos Philippas
Constantin Zopounidis

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RATING MUTUAL FUNDS THROUGH AN INTEGRATED DEA-BASED MULTICRITERIA PERFORMANCE MODEL: DESIGN AND INFORMATION CONTENT

Vassilios Babalos[1], **Michael Doumpos**[*2], **Nikolaos Philippas**[3], **Constantin Zopounidis**[2]

[1] Technological Educational Institute of Kalamata

Department of Finance & Auditing, Greece

E-mail: vbabalos@gmail.com

[2] Technical University of Crete

Department of Production Engineering and Management

Financial Engineering Laboratory

University Campus, 73100 Chania, Greece

E-mail: {mdoumpos, kostas}@dpem.tuc.gr

[3] University of Piraeus

Department of Business Administration

80, Karaoli and Dimitriou Str, Piraeus, Greece

E-mail: philipas@unipi.gr

[*] Corresponding author: Phone: +30-28210-37318, Fax: +30-28210-69410, E-mail: mdoumpos@dpem.tuc.gr

RATING MUTUAL FUNDS THROUGH AN INTEGRATED DEA-BASED MULTICRITERIA PERFORMANCE MODEL: DESIGN AND INFORMATION CONTENT

Abstract

There is a growing literature that employs nonparametric frontier methods in order to evaluate the performance of investment funds. This paper proposes an integrated approach for analyzing the efficiency and performance of mutual funds. The methodology combines data envelopment analysis (DEA) with a multicriteria decision aid (MCDA) methodology. DEA is employed to assess the relative efficiency of mutual funds in terms of their return, size, gross expense ratio, turnover rate, and risk. In a second stage, a multicriteria approach is employed to develop an overall performance measure on the basis of the DEA efficiency results. The resulting model evaluates all mutual funds in a common basis and enables comparisons over time. The methodology is applied on a large sample of more than 500 US mutual funds over the period 2003–2010. The analysis is implemented under three different time-window periods (one, three, and five year evaluations) and the results are compared against the fund ratings provided by Morningstar.

Keywords: Mutual funds, Performance appraisal, Multicriteria analysis, Data envelopment analysis, Efficiency

JEL codes: G11, C61, C67, C44

1. INTRODUCTION

Mutual funds remain the most popular investment vehicle among individual investors in the US. Despite the decline that followed the outbreak of the global financial crisis of 2008, combined assets of mutual funds in the US at the end of 2010 amounted to $11.8 trillion, while worldwide mutual fund assets stood at the end of 2010 at $24.7 trillion (Investment Company Institute, 2011). According to Turtle and Zhang (2012), 90 million individuals hold mutual funds in the United States, and of these individuals, 65% have more than half of their financial assets invested in mutual funds.

A major challenge faced by the mutual fund industry is the proper assessment of the performance of actively managed portfolios. Given the delegated nature of active management industry, the plethora of offered funds (the number of available open-end funds in the US at the end of 2010 was 7,580) and the existing framework with respect to investors' selection, fund rating agencies have become an integral part of the investment process. Morningstar was the first to introduce the well-known mutual fund rating system in 1986 that has attracted attention from both investors' and the academic community and has become the key ingredient that investors and financial advisors use when formulating their investment strategies.

The issue of whether managers of active portfolios add value still remains controversial. Traditional performance measures compare the return of the examined portfolio with the return of a properly defined unmanaged portfolio (benchmark return) after accounting for all aspects of investment risk. The evolution of financial theory has contributed substantially to the proper definition of systematic risk sources that should be accounted for when evaluating the performance of skilled fund managers.

In this context, the single factor evaluation model introduced by Jensen (1968) has been replaced by multi-factor models motivated mainly by the pioneer findings of asset pricing studies such as Fama and French (1993, 1996). In particular, the ability of mutual funds' managers to achieve superior risk-adjusted returns compared to passively managed portfolios has been extensively studied by a broad range of authors starting with the seminal works of Treynor (1965), Sharpe (1966), and Jensen (1968). Several issues have been examined, such as the performance persistence in mutual fund rankings (Gruber, 1996; Carhart, 1997), the relation between performance, fund attributes, and economies of scale (Prather et al., 2004; Chen et al., 2004), the role of chance in portfolio performance (Kosowski et al., 2006; Fama and French, 2010), and the importance of incorporating economic indicators in predicting future market movements (Jha et al., 2009; Kosowski, 2006).

However, traditional performance measures namely the Treynor ratio (1965), the Sharpe ratio (1966), and Jensen's alpha (1968) are plagued with two shortcomings that have spurred the academic and practitioners' research for the past couple of decades. First, they are rooted in CAPM theory, thus being exposed to standard criticism made against it (Roll, 1977, 1978). In addition, they fail to incorporate explicit and implicit costs associated with running and managing a mutual fund (Ippolito, 1993). As a result, a strand of literature has embarked on adopting production measurement techniques such as frontier analysis, and more specifically data envelopment analysis (DEA), as a tool for assessing managed fund performance. Such an approach can tackle effectively the aforementioned limitations of traditional performance measures providing a more holistic approach in the context of portfolio performance assessment.

The extensive appeal of DEA-based performance measures is motivated mainly by the simultaneous handling of multiple outputs and input measures, including risk-return attributes, transaction costs, and the cost of obtaining and using information (Ippolito, 1993), which have a non-negligible impact on fund performance. In the same vein, as Glawischnig and Reichmann (2010) pointed out, the derivation of input and output weights endogenously and a single real number performance index provided by DEA appear as the most desirable properties in favor of the method. DEA is a nonparametric approach that has been originally introduced for investigating the productive efficiency of public, not-for profit decision making units. Shortly after, the method has entered into the financial sector with many applications in measuring not only banks' performance (Berger and Humphrey, 1997, Fethi and Pasiouras, 2010) but also traditional mutual funds' performance (Murthi et al., 1997; McMullen and Strong, 1998; Galagedera and Silvapulle, 2002; Basso and Funari, 2001, 2005; Lozano and Gutiérrez, 2008; Zhao et al., 2011) and more recently for alternative funds (Gregoriou, 2003; Gregoriou et al., 2005).

However, despite its usefulness for efficiency evaluation, DEA results do not allow the comparison of all mutual funds in a common setting, as each fund is evaluated under a different weighting of the available input-output variables. Furthermore, in basic DEA models all efficient funds are considered equal, thus not allowing the investor to discriminate between them. The existing approaches to handle these issues include alternative DEA models that could provide a ranking of the funds (Adler et al., 2002), or multi-stage analyses based on linear regression techniques (McDonald, 2009; Wang, 2011). In this paper, we employ a multicriteria methodology based on a nonlinear additive value function. The resulting model resembles the efficiency estimates of DEA, but it can also be used for performance evaluation and benchmarking purposes. Its additive form makes the model easy to comprehend and implement to any set of funds, independently on the sample used to obtain the DEA efficiency estimates. The multicriteria model provides insights into the relationship of several fund appraisal criteria with the overall performance and efficiency of the funds.

In the above context, this paper adds some important contributions to the relevant literature. Firstly, we contribute to the ongoing research that is concerned with a more accurate ranking of funds based on nonparametric techniques. In line with recent findings of Lamb and Tee (2012) and Premachandra et al. (2012) who concluded that DEA efficiency estimates of fund performance might be plagued with substantial bias and could be misleading, we opt for an innovative two-stage process of performance evaluation, with the advantages discussed above. Furthermore, the constructed multicriteria model can be considered as an alternative simple model to Morningstar's rating system, combining a small set of relevant performance attributes. Through the DEA efficiency analysis and the multicriteria modeling approach, we re-examine the role of risk-return criteria in mutual funds' performance under different evaluation horizons, investigate the role of the recent crisis, and analyze the relationship between the efficiency/performance of the funds and their investment policies. Finally, the comparative analysis of the obtained multicriteria evaluation of the funds with the ratings of Morningstar provides insights on the connections between the ratings and the efficiency of the funds.

The combination of DEA with the multicriteria methodology is applied to a sample of US no-load equity managed funds. First, we examine their efficiency in the traditional sense using up to date data over the period 2003–2010 and then, following Murthi et al. (1997), we provide updated evidence on the existence of a link between managed fund ratings and efficiency on the basis of the multicriteria evaluation results.

The remainder of the paper is structured as follows. Section 2 describes the techniques used in the paper, including data envelopment analysis as well as the multicriteria evaluation procedure. Section 3 is involved with the description of the data set, whereas section 4 presents in detail the obtained results. Finally, section 5 concludes the paper and discusses some possible future research directions.

2. METHODOLOGY

2.1 Data Envelopment Analysis

Data envelopment analysis (DEA; Charnes et al., 1978; Cooper at al., 2006), is a nonparametric frontier technique where efficiency of a particular entity is measured by its distance from the best practice frontier constructed by the best entities within a sample. It is a well-established methodology for the evaluation of the *relative* efficiencies of a set of comparable entities (decision making units, DMUs), which transform multiple inputs into multiple outputs. DEA is based on linear programming (LP) techniques without imposing restrictive assumptions on the functional relationship between inputs and outputs, thus providing nonparametric estimates of the efficiency of each DMU in comparison to an empirical best practice frontier.

In a fund appraisal setting, assume that there are data on K inputs and M outputs for N funds. For fund i these are represented by the vectors $\mathbf{x}_i$ and $\mathbf{y}_i$, respectively. The $K \times N$ input matrix $\mathbf{X}$, and the $M \times N$ output matrix $\mathbf{Y}$, represent the data for all funds. Then, the efficiency of fund i is measured by the ratio:

$$\theta_i = \frac{\mathbf{u}_i \mathbf{y}_i}{\mathbf{v}_i \mathbf{x}_i} \in [0,1]$$

where $\mathbf{u}_i, \mathbf{v}_i \geq \mathbf{0}$ are weight vectors corresponding to the outputs and inputs for fund i. DEA provides an assessment of the relative efficiency of a fund compared to a set of other funds. Under constant returns to scale (CRS) and assuming an input orientation, the maximum efficiency of fund i can be estimated through the LP formulation introduced by Charnes et al. (1978), which is expressed in dual form as follows (CCR model):

$$
\begin{array}{ll}
\min & F = \theta_i^C - \varepsilon(\mathbf{e}\mathbf{s}_i^x + \mathbf{e}\mathbf{s}_i^y) \\
\text{Subject to:} & \mathbf{X}\boldsymbol{\lambda} - \theta_i^C \mathbf{x}_i + \mathbf{s}_i^x = \mathbf{0} \\
& \mathbf{Y}\boldsymbol{\lambda} - \mathbf{s}_i^y = \mathbf{y}_i \\
& \boldsymbol{\lambda},\ \mathbf{s}_i^x,\ \mathbf{s}_i^y \geq \mathbf{0},\ \theta_i^C \in \mathbb{R}
\end{array} \tag{1}
$$

where $\mathbf{s}_i^x$ and $\mathbf{s}_i^y$ are the vectors of slack variables for the inputs and outputs, respectively, indicating the improvements that an inefficient fund should achieve in order to become efficient, $\mathbf{e}$ denotes a vector of ones, and $\varepsilon \approx 0$ is a small positive constant that allows the solution procedure to give first priority on the optimization of θ_i^c. Denoting by F^* the value of the objective function of problem (1) at its optimal solution, fund *i* is classified as efficient if $F^* = 1$ (i.e., if the efficiency score is $\theta_i^C = 1$ and the slacks are zero). Otherwise, if $F^* < 1$ then fund i is classified as inefficient. Variable returns to scale (VRS) can be introduced by simply adding the convexity constraint $\lambda_1 + \cdots + \lambda_N = 1$ to the above model. This constraint ensures that a fund is benchmarked only against other units of similar size. The resulting model is known as the BCC model (Banker et al., 1984).

The combination of the results obtained under from the CCR and BCC models (CRS vs VRS) provides a decomposition of the global efficiency as follows:

$$\theta_i^C = \theta_i^V \theta_i^S$$

where $0 \leq \theta_i^V \leq 1$ is the pure efficiency score obtained under the BCC model and $0 \leq \theta_i^S \leq 1$ is the scale efficiency factor. Thus, the inefficiency of a fund can be attributed to inefficient operation (e.g., too small θ_i^V), disadvantageous exogenous conditions (corresponding to scale inefficiency), or both.

The characteristics of DEA, and in particular a) the lack of restrictive assumptions on the form of the production function that relates inputs to outputs and b) the possibility of using simultaneously multiple inputs and outputs, which can be specified by different units of measurement, have made it a popular efficiency analysis technique with numerous applications in many domains. In addition to efficiency estimates, DEA also supports the identification of the sources of inefficiency, as well as the specification of performance targets.

2.2 Multicriteria Evaluation Approach

The results obtained with DEA provide useful indications on the relative efficiency of the funds. However, in the context of DEA, each fund is evaluated with different weightings of the input and output variables, thus making it difficult to interpret the results in a common setting that would be applicable to all funds. Furthermore, DEA does not discriminate among efficient cases, as they all receive the same efficiency score. Alternative techniques, such as stochastic frontier analysis (Coelli et al., 2005), address some of these shortcomings, but they assume specific input-output functional forms and their implementation with multiple outputs is often troublesome (Whiteman, 1999).

In this study, we enhance the results of DEA through the development of a global multicriteria evaluation model, common for all funds. Such a model would be particularly useful to investors and analysts, as it can be easily used for benchmarking purposes without requiring performing the DEA analysis every time one needs to evaluate the performance of a single fund. The global evaluation model is built through a multicriteria disaggregation approach based on the global efficiency scores obtained with DEA under the CCR model. The objective of the multicriteria model building process is to introduce a common model applicable to all funds that best replicates the DEA efficiency scores. The multicriteria model has an additive (nonlinear) form:

$$V(\mathbf{x}_i) = \sum_{j=1}^{n} w_j v_j(x_{ij}) \in [0,1]$$

where w_j is a nonnegative tradeoff constant for performance attribute j and $v_j(x_j)$ is the corresponding marginal value function normalized between 0 and 1. The marginal value functions have a functional-free piecewise linear monotone form (increasing for return/profit related criteria and decreasing for cost or risk criteria) providing a decomposition of the aggregate result (global value) in terms of individual assessments at the attributes' level.

The development of the additive model is performed through a nonparametric regression approach based on the solution of the following optimization problem:

$$\begin{array}{ll} \min & \sum_i (\sigma_i^+ + \sigma_i^-) \\ \text{s.t.} & V(\mathbf{x}_i) + \sigma_i^+ - \sigma_i^- = \theta_i^C \quad \forall i \\ & V(\mathbf{x}_*) = 0,\ V(\mathbf{x}^*) = 1 \\ & \sigma_i^+,\ \sigma_i^- \geq 0 \qquad\qquad \forall i \end{array}$$

where $\mathbf{x}_*$ and $\mathbf{x}^*$ denote the anti-ideal and ideal funds, respectively, defined on the basis of the worst and best performances of all funds in the sample on the evaluation criteria. The above formulation seeks to find an optimal additive value model that minimizes the sum of absolute deviations between the models estimates $V(\mathbf{x}_1)$, $V(\mathbf{x}_2)$, …, and the DEA efficiency scores θ_1^C, θ_2^C, …, for all funds in the sample (the nonnegative error variables σ_i^+, σ_i^- define the absolute error for each fund i as $\sigma_i^+ + \sigma_i^- = |V(\mathbf{x}_i) - \theta_i^C|$). Adopting a piecewise linear modeling approach for the marginal value functions, enables the reformulation of the above optimization problem in a linear programming form. Examples of the transformation procedure in the context of ranking and classification problems can be found in Jacquet-Lagrèze and Siskos (1982) as well as in Doumpos and Zopounidis (2002).

The resulting additive evaluation model constitutes a global evaluation measure for each fund, estimated under a setting which is common to all funds, and over different time periods.

3. DATA DESCRIPTION

The combined DEA-MCDA approach described in the previous section is applied to a sample consisting of more than 500 no-load US equity funds that were in existence for at least one year during the period 2003–2010. Only no-load funds have been included in our analysis so as to avoid the complexity of the variety of expenses charged in different fund share classes. Index funds, exchange traded funds (ETFs) and other non-traditional mutual funds such as target-date funds have been excluded from the sample. The source of input-output data variables is the comprehensive Morningstar Direct database. The sample spans 20 different investment categories as officially defined by Morningstar, whereas the number of funds in the sample ranges between 376 in 2003 and 505 in 2010. Our results are robust to the effects of survivorship bias (Brown et al., 1992) since we employ a variable number of funds avoiding to limit the analysis to funds that operate during the entire period.

The collected data for the sample funds include annual raw returns, total year-end assets, capital flows, and some funds' operational characteristics including their gross expense ratio and turnover ratio. The gross expense ratio measures the total expenses incurred by the fund while the turnover ratio indicates how often a fund manager alters the composition of the fund's portfolio. Moreover, the annualized standard deviation of fund returns has been included as a risk variable.

A fairly common approach employed in measuring funds' efficiency is to consider various mutual funds' cost and risk variables as inputs and a proper measure of return as one of the outputs. In particular, Murthi et al. (1997) and Murthi and Choi (2001) used the standard deviation of returns, the expense ratio, loads, and turnover as inputs and the mean gross return as output. Sengupta (2003) in a later study employed raw returns as output and loads, expenses, turnover, risk (standard deviation or beta), and the skewness of returns as inputs in his model. Other studies focusing on US funds include Anderson et al. (2004), who examined the efficiency of real estate funds employing a series of inputs such as loads, various costs, and a standard measure of funds' risk (standard deviation) and raw return as output, while Daraio and Simar (2006) utilized standard deviation, expense ratio, turnover, and fund size as inputs and mean return as output.

The deviation from the median return (DMR) is used to define the single output variable in our DEA model. In particular, the output variable is defined as 1+DMR, which indicates the dollar worth of an investment in a fund in comparison to its peers. This specification ensures that the output variable is positive, thus avoiding problems that arise when negative data are introduced in DEA. Furthermore, using DMR instead of raw returns enables the evaluation of the efficiency of the funds in our panel data set, while implicitly controlling for the performance of the market and funds' risk-taking strategy at the same time. In other words, a high return may be simply the result of the manager adopting a risky investment strategy. Additionally, this specification avoids "double-counting" raw returns which are related to the changes in the funds' assets. As far as the input variables are concerned, these include the gross expense ratio (GER), the turnover rate (TRN), assets (ATS), and the annualized standard deviation of returns (STD).

For the purposes of the multicriteria evaluation process, the assets variable is replaced by capital flow (CFL). While a fund's assets is a useful variable for measuring its efficiency in the input/output context of DEA, it is not particularly useful in a multicriteria performance evaluation setting, as it is not possible to define a clear-cut (positive or negative) association between the assets of a fund and its suitability/attractiveness as an investment option for a particular investor. On the other hand, capital flow combines information provided both by assets and returns. In particular, for a fund at year t its flow is defined as $[A_t - (1+r_t)A_{t-1}]/A_{t-1}$, where A_t represents the fund's assets at the end of year t and r_t is its return over year *t*. Thus, a large capital flow for a mutual fund indicates that the fund is capable of attracting new investors (thus being more preferable for an investor compared to a fund with a low or negative flow). The interaction between performance and fund flows has been extensively documented in various studies (Sirri and Tufano, 1998; Zheng, 1999) whereas the current study is the first to the authors' knowledge that employs fund flows in the efficiency analysis framework of DEA.

Except for the inclusion of the funds' flow, two additional categorical indicators related to the funds' investment style, are also used for the development of the multicriteria model. The first indicator (SZT) is used to take into consideration whether the funds are focused on large, medium, or small capitalization stocks, whereas the second indicator (GRT) distinguishes between growth, blend, and value funds. Both indicators are taken from the classifications of Morningstar.

Table 1 presents the annual averages of all variables (except for the two aforementioned categorical indicators), throughout the period of the analysis, whereas the correlations between the variables are given in Table 2. Summary statistics contain valuable information regarding the behavior of the employed variables. It is worth noting (column DMR in Table 1) that the average fund managed to offer a positive (though modest) return in excess of industry's average return even during adverse market conditions. Apart from this, our attention is drawn to the substantial shrinkage of funds' average size that took place from 2007 to 2008 following the outburst and ramifications of the global financial turmoil. Specifically, the average fund size dropped from 1,204.39 million US$ in 2007 to 754.89 million US$ in 2008. Another interesting feature revealed by Table 1 is the significant increase in funds' overall risk from 2007 and onwards. In particular, the funds' risk level during the 2-year period from 2007 to 2008 more than doubled as a result of the increased volatility in the financial markets.

Insert Table 1 & Table 2 about here

On the basis of the available data, all subsequent analyses are implemented for time-horizons of one, three, and five years. In the first case (one-year horizon) the funds are evaluated in year t using only the data available for that year. In the second setting (three-years horizon), the funds are evaluated in year t using data for a time-period of three years (i.e., years t, $t-1$, and $t-2$), whereas in the five-years setting, the evaluation at year t is based on data up to $t-4$. The examination of these three settings enables the consideration of different investment policies as well as the analysis of different situations with regard to the available historical data. For instance, the one-year horizon analysis would be more interesting for short-term investors who focus their decisions on the most recent available data. Furthermore, this scheme enables the evaluation of newly established funds, which lack historical data over longer time periods.

Overall, the one-year data set has 3,666 fund-year observations, the three-year data set has 2,587 observations, and the five-year data consist of 1,595 cases. In the multi-year data, the deviation from the median cumulative return over the period under consideration is the output variable, whereas the averages (over the corresponding period) are used to define the inputs for the expense ratio, turnover ratio, assets, and standard deviation. Similarly, the average is also used for the capital flow ratio in the second stage of the analysis.

4. RESULTS

4.1 DEA Results

Table 3 summarizes the average efficiency scores (CCR, BCC, scale) under all three time horizon settings and for all years in the time period of the analysis. Under an one-year horizon, the results for the period 2003–2006 show an increasing efficiency trend, which is reverted in 2007 and declined at a stronger pace in 2008, before showing some stabilizing trend in 2009 and 2010. Similar trends are also observed in the results obtained with a time horizon of three and five years (the similarities between the three settings are verified by the correlations shown in Table 4, which are all significant at the 1% level). In all cases, 2008 is clearly the worst year. Of course, the two multi-year models are less responsive to annual data changes as they do not rely on the data of a single year. Thus, under these settings the efficiency of the funds in the sample in 2009 and 2010 continued to decline due to the negative effect that the 2008 data still have. As far as the scale effect is involved, this is stronger in the multi-year horizon results (with a clearly increasing trend in the results under a horizon of five years). On the other hand, in the results for the one and three-years horizons, the scale effect is weaker and its time trend is less clear. This finding may be related to the well documented “dilution effect” (Greene and Hodges, 2002) that results from inflows that funds experience either due to rising stock markets or because of a fund’s recent superior track record. In other words, when a fund performs well it is natural to be compensated by disproportionately large inflows by investors, but when “fresh” cash is pooled with the fund’s rest risky assets it dilutes fund’s overall performance. This in turn may show up as a weaker scale effect in the short term since fund managers are not able to invest available cash in an optimal manner. Another plausible explanation for the dilution effect is associated with the open-end structure of traditional funds and their statutory obligation to retain a significant portion of their assets in cash or cash-equivalent form in order to meet promptly investors' redemptions.

Insert Table 3 & Table 4 about here

Table 5 provides a breakdown of the CCR and BCC efficiency scores in terms of the two indicators related to the investment style of the funds. In both the size and growth style indicators, the "sectors" entry includes all funds not classified by Morningstar into the main style/growth classes. These are funds that invest in specific equity sectors (e.g., financials, communications, technology, etc.) and represent about 16% of the sample. It is clearly evident that funds investing in large capitalization stocks and value funds have performed better (on average). Funds investing in mid-cap stocks have also outperformed funds investing in small stocks, whereas funds investing in specific business sectors performed similarly to funds investing in small stocks. In terms of the growth style, blend funds outperformed growth funds, whereas funds investing in specific sectors performed slightly worse than growth funds. However, it is worth noting that the differences are not consistent over time. For instance, as illustrated in Figure 1 for the one-year horizon setting, the differences are more noticeable over the period 2003–2007.

Table 6 presents the average improvements estimated through the DEA-BCC model that the inefficient funds in the sample should have achieved in terms of the input and output variables. Observing the results in Table 6 we conclude that the turnover rate is the main source of inefficiency for our sample funds, although it exhibits a declining tendency. For example, during 2006 alone, the average fund could operate on the efficient frontier provided it diminished its trading activities by around 13%. Our finding clearly indicates a negative impact of turnover on fund performance and contributes to the ongoing debate relating to the interaction between fund performance and trading activity (Christoffersen and Sarkissian, 2011). Another advantage of DEA-like performance evaluation methods is that they allow us to infer funds' portfolio diversification by simply examining the slacks of the risk variable. Hence, with respect to the risk variable, we observe that it exhibits near zero slacks for five consecutive years (2003–2007). As stated earlier, the slacks of the risk variable have only picked-up from 2008 and onwards during the years of increased volatility in the financial markets. In line with previous findings (Murthi et al., 1997; Sengupta, 2003), we infer that during this 5-year period US funds hold mean-variance efficient portfolios. Finally, both fund size and the expense ratio variable seem to play an insignificant role in funds' inefficiency.

Insert Table 6 about here

4.2 Global Multicriteria Evaluation Model

For the development of the multicriteria evaluation model, the CCR global efficiency scores of the funds are regressed against the deviation from median return, the gross expense ratio, the turnover ratio, risk, capital flow, as well as the two indicators related to the investment style of the funds (size style-SZT and growth style-GRT). Table 7 presents some fitting statistics, namely R^2, mean absolute error (MAE), and root mean square error (RMSE) for all multicriteria models (MCDA) developed for different time horizons. For comparison purposes, the results of tobit regression are also reported. It is evident that the models developed through the nonparametric multicriteria approach are (in all cases except for the five-years horizon) more consistent with the efficiency scores of the CCR model.

Insert Table 7 about here

Table 8 presents the criteria tradeoff constants in all three additive evaluation models, together with their 95% confidence intervals estimated through a bootstrap procedure (1,000 bootstrap samples). The funds' returns (DMR) and risk (STD) are clearly the dominant performance factors, whereas all the other criteria account for about 18–20% in the models. Interestingly, the relative importance of the return variable decreases in the models developed for shorter time horizons, whereas the relative importance of risk increases. The latter might be associated with the tendency of managers to engage into risk-shifting actions in the short-term as if they compete in a tournament (Brown et al., 1996; Chevallier and Ellison, 1997). The objective of this risk-taking behavior on behalf of the managers is to improve the performance of their fund and attract more inflows that will ultimately enlarge their funds' asset base and their asset-based compensation. However, when a fund is evaluated in a longer horizon (3-year or 5-year periods), this risk-altering strategy appears weakened. Therefore, the riskiness of the fund should be a serious concern for investors that select funds based on short-term evaluations. Among the rest of the criteria, the turnover rate is the most important one confirming its strong interaction with performance as in the case of slack variables analyzed earlier. The two indicators related to the investment style of the funds have marginal contribution in the models, with the size factor (SZT) being consistently more important compared to the growth type criterion (GRT). The relatively low importance of these two variables is in line with the observations made earlier on their inconsistent relationship with the efficiency of the funds over time (Figure 1).

Insert Table 8 about here

Figure 2 presents the marginal value functions of the three most important criteria (DMR, STD, TNR). These functions indicate the way that the funds are evaluated on the corresponding criteria. In all three models developed for different time horizons, the marginal value functions have similar forms, thus indicating a robust behavior of the three models on the way that the DMR, STD, and TNR criteria are taken into consideration for the evaluation of the funds. The concave-like form of the function for the return criterion and the convex form for risk and the turnover rate imply that the performance and efficiency of the funds are better explained in the context of risk aversion.

Insert Figure 2 about here

Table 9 summarizes the average multicriteria performance scores over the period of the analysis. The observed trends are similar to the ones obtained through DEA, showing an increase over the period prior to the crisis (2003–2006), followed by a considerable decrease over the next period.

Insert Table 9 about here

Figure 3 illustrates the relationship between the multicriteria scores and the Morningstar's ratings of the sample funds. The star rating system of Morningstar is the most popular investment tool for mutual funds. Morningstar assigns 1 to 5 stars to mutual funds according to their risk-adjusted performance over a three year period, within their relative peer group. Stars are computed for all funds that are in existence provided that are at least three years old. The funds with risk-adjusted ratings in the top 10% of their peer group are designated with five stars, the next 22.5% receive four stars, the next 35% receive three stars, the next 22.5% receive two stars, while the lowest 10% of funds in each peer group receive one star. Figure 3 illustrates the multicriteria scores at every year t, averaged for each rating class of Morningstar for years t and $t+1$. The results indicate that there is strong monotone and positive relationship between the multicriteria scores of the funds and the Morningstar's ratings both in the same year as well as one year ahead. This was also confirmed by the Kruskal-Wallis nonparametric test on the differences between the scores across the rating classes, which indicated that they are all statistically significant at the 1% level. As expected the relationship with the Morningstar's rating is stronger for the multicriteria model developed for a horizon of three years, as the ratings of Morningstar are also constructed using data over a period of three years.

Insert Figure 3 about here

In order to further test the relationship between the results of the multicriteria model and the ratings of Morningstar, a rating is constructed on the basis of the multicriteria scores of the funds in the sample. The rating is defined following the same approach used by Morningstar. In particular, in each year t the funds are classified in five groups defined on the basis of the multicriteria scores of the funds in year t. Funds in the top 10% are rated as 5*, the next 22.5% are rated as 4*, the next 35% receive three stars, the following 22.5% receive two stars, and the lowest 10% of funds are classified in the 1* group. Table 10 presents the overall confusion matrix (constructed over all years) between the rating of Morningstar and the three-years multicriteria rating. The agreement rate (percentage of cases where the two ratings coincide) is 37.6%, whereas in 84.3% of the cases, the differences are up to one notch. The Kendall's τ correlation coefficient is 0.45 (statistically significant at the 1% level). Full details on the association between the two ratings in all years of the analysis and under different time horizons are given in Table 11, which presents the Kendall's τ correlation coefficients between the multicriteria ratings in each year t, and the Morningstar's ratings in years t and $t+1$. The multicriteria ratings developed under a three and five-years horizon are consistently strongly associated with the ratings of Morningstar, whereas the association is weaker for the multicriteria evaluation based on data of a single year.

Insert Table 10 & Table 11 about here

5. CONCLUSIONS

The vast amount of options available to investors through mutual funds of different types, has attracted considerable research and practical interest on the development and implementation of proper procedures for mutual fund performance appraisal. In this paper, an efficiency evaluation perspective was adopted for a sample of US no-load funds over the period 2003–2010. The analysis was implemented at two stages taking into consideration the risk-return characteristics of the mutual funds, as well as their operational attributes and investment style.

The combination of DEA with a multicriteria technique enabled not only the evaluation of the funds' efficiency, but also the construction of an operational model that provides a global evaluation in a common setting for all funds, aggregating multiple attributes of the funds' operation, performance, and investment style. The multicriteria model also provides useful indications on the factors that best describe the funds' efficiency.

The application on a sample of about 500 US funds, re-confirmed the importance of risk-return attributes. Return was found more important in a longer horizon setting, whereas risk was the decisive factor in short evaluation horizons. The turnover rate was the most important among the operational characteristics of the funds, while indicators related to the investment style of the funds were not found to have a consistent effect. The results of the comparative analysis to the ratings of Morningstar indicate that these ratings are closely related to the efficiency of the funds.

Future research could consider among others the extension of the analysis to other fund markets (outside US) and different types of funds, the examination of the funds' efficiency persistency over time in comparison to risk-adjusted measures, as well as the construction, management and evaluation of portfolios of mutual funds.

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Table 1: Annual means of all variables for the sample funds

Years	DMR (%)	GER (%)	TNR (%)	ATS (million US$)	STD (%)	CFL (%)
2003	3.976	1.402	83.253	1,061.83	14.275	34.789
2004	1.050	1.355	74.587	1,110.04	11.961	27.233
2005	1.056	1.321	72.462	1,135.22	11.778	26.606
2006	–0.070	1.317	82.381	1,158.05	10.456	24.889
2007	1.088	1.262	81.457	1,204.39	11.518	10.154
2008	0.265	1.306	93.769	754.89	26.270	3.607
2009	3.067	1.388	94.193	908.34	23.945	11.342
2010	1.265	1.324	83.890	991.77	21.017	7.697

Table 2: Correlation matrix

	DMR	GER	TNR	ATS	STD
GER	0.079				
TNR	0.041	0.176			
ATS	0.010	–0.311	–0.117		
STD	0.109	0.064	0.167	–0.082	
CFL	0.279	0.169	0.019	–0.083	–0.089

Table 3: Averages of the DEA efficiency scores

	One year			Three years			Five years		
	CCR	BCC	Scale	CCR	BCC	Scale	CCR	BCC	Scale
2003	0.455	0.526	0.864	–	–	–	–	–	–
2004	0.506	0.545	0.928	–	–	–	–	–	–
2005	0.505	0.541	0.932	0.459	0.519	0.886	–	–	–
2006	0.546	0.579	0.943	0.508	0.545	0.932	–	–	–
2007	0.502	0.560	0.896	0.507	0.542	0.935	0.584	0.772	0.757
2008	0.399	0.429	0.931	0.547	0.579	0.946	0.511	0.637	0.803
2009	0.385	0.455	0.846	0.503	0.558	0.902	0.483	0.579	0.835
2010	0.390	0.422	0.926	0.404	0.427	0.945	0.468	0.550	0.852

Table 4: Correlations of efficiency scores under different time horizons

	CCR		BCC	
	3-years	5-years	3-years	5-years
1-year	0.792	0.648	0.767	0.601
3-years		0.798		0.895

Table 5: Efficiency scores by funds' styles

	Size style	CCR	BCC	Growth style	CCR	BCC
1 year	Large	0.505	0.543	Value	0.499	0.541
	Mid-cap	0.431	0.474	Blend	0.482	0.520
	Small	0.411	0.457	Growth	0.443	0.485
	Sectors	0.414	0.486	Sectors	0.414	0.486
3 years	Large	0.564	0.615	Value	0.570	0.614
	Mid-cap	0.497	0.528	Blend	0.545	0.593
	Small	0.458	0.495	Growth	0.493	0.532
	Sectors	0.474	0.530	Sectors	0.474	0.530
5 years	Large	0.535	0.682	Value	0.531	0.664
	Mid-cap	0.501	0.600	Blend	0.518	0.655
	Small	0.465	0.556	Growth	0.499	0.610
	Sectors	0.493	0.594	Sectors	0.493	0.594

Table 6: Average suggested percentage improvements under the BCC model

Horizon	Variables	2003	2004	2005	2006	2007	2008	2009	2010
1-year	DMR	4.86	3.79	3.69	4.11	5.54	3.51	5.41	3.19
	GER	0.38	0.89	0.27	0.43	0.16	0.06	0.15	0.19
	TNR	7.33	9.98	9.53	13.01	10.63	2.72	3.33	2.60
	ATS	1.02	2.59	2.29	3.63	1.56	0.00	0.25	0.01
	STD	0.12	0.10	0.04	0.03	0.15	2.54	1.47	0.60
3-years	DMR	–	–	7.84	5.34	5.35	3.77	4.31	4.59
	GER	–	–	1.13	1.06	0.74	0.42	0.24	0.19
	TNR	–	–	7.68	10.24	9.42	3.65	2.40	1.88
	ATS	–	–	3.16	4.42	3.80	0.80	0.21	0.03
	STD	–	–	0.19	0.12	0.07	0.66	2.53	4.34
5-years	DMR	–	–	–	–	11.65	2.66	3.86	5.78
	GER	–	–	–	–	1.72	1.26	0.51	0.24
	TNR	–	–	–	–	12.70	6.26	4.40	3.41
	ATS	–	–	–	–	4.51	1.80	1.06	0.65
	STD	–	–	–	–	0.12	0.43	1.48	2.40

Table 7: Model fitting statistics

Horizon	Models	R^2	$100\times$MAE	$100\times$RMSE
1 year	MCDA	0.501	7.315	11.006
	Tobit	0.385	8.644	11.802
3 years	MCDA	0.616	6.892	10.873
	Tobit	0.558	8.099	11.268
5 years	MCDA	0.503	8.932	12.322
	Tobit	0.505	8.987	11.971

Table 8: Criteria tradeoff constants (in %) and 95% confidence intervals

	One year	Three years	Five years
DMR	24.24	35.14	62.89
	[18.49, 31.74]	[32.47, 41.75]	[52.19, 66.80]
GER	6.80	1.12	0.90
	[4.15, 12.55]	[0.81, 2.18]	[0.69, 1.58]
TRN	9.54	12.70	8.04
	[7.92, 11.64]	[10.30, 14.17]	[5.55, 12.99]
STD	55.52	46.41	18.71
	[40.70, 61.00]	[40.32, 48.33]	[15.34, 27.22]
CFL	1.41	2.74	7.52
	[1.11, 2.79]	[1.43, 4.33]	[4.87, 11.00]
SZT	1.98	1.34	1.57
	[1.30, 2.73]	[0.72, 2.06]	[0.48, 3.27]
GRT	0.51	0.55	0.37
	[0.38, 1.41]	[0.35, 1.16]	[0.26, 0.55]

Table 9: Average multicriteria scores

	1-year	3-years	5-years
2003	0.440	–	–
2004	0.495	–	–
2005	0.493	0.538	–
2006	0.528	0.581	–
2007	0.477	0.577	0.548
2008	0.345	0.465	0.497
2009	0.358	0.414	0.465
2010	0.372	0.399	0.443

Table 10: Confusion matrix between the ratings of Morningstar and the multicriteria model (3-years horizon)

		Multicriteria rating				
		1*	2*	3*	4*	5*
Morningstar rating	1*	50.44	30.53	13.27	4.42	1.33
	2*	19.20	36.60	30.00	11.80	2.40
	3*	5.45	26.90	41.00	21.56	5.09
	4*	0.46	10.69	41.07	33.13	14.66
	5*	0.00	8.19	29.24	31.58	30.99

Table 11: Kendall's τ correlations between the multicriteria and the Morningstar's ratings

	1 year		3 years		5 years	
	t	$t+1$	t	$t+1$	t	$t+1$
2003	0.15	0.17	–	–	–	–
2004	0.10*	–0.09*	–	–	–	–
2005	–0.04*	0.10*	0.32	0.31	–	–
2006	0.03*	–0.02*	0.21	0.08*	–	–
2007	0.19	0.28	0.30	0.25	0.49	0.13
2008	0.43	0.38	0.54	0.43	0.44	0.33
2009	0.16	0.19	0.61	0.53	0.49	0.40
2010	0.32	0.00	0.65	0.00	0.58	0.00
Overall	0.17	0.15	0.45	0.33	0.50	0.29

Note: All correlations are significant at the 1% level, except those marked with *

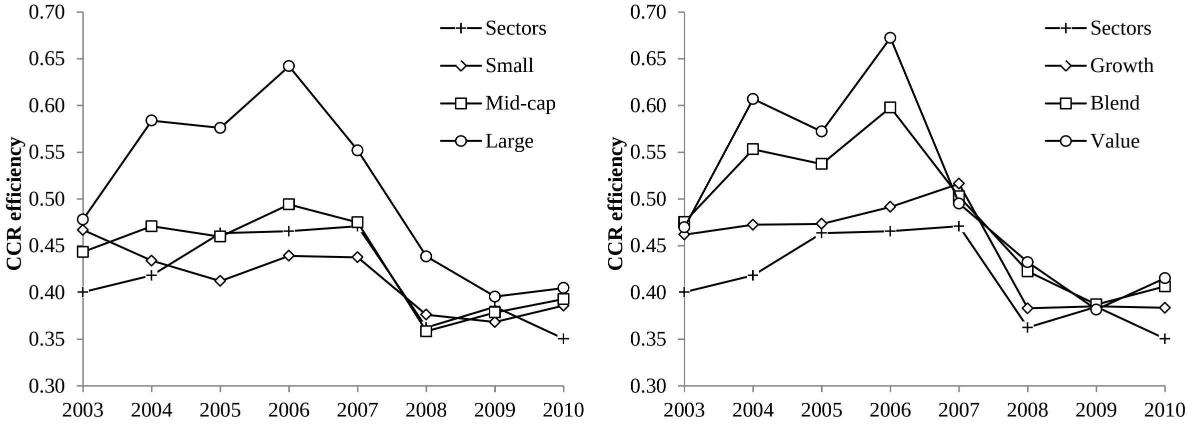

Figure 1: Average efficiency scores over time for different types of mutual funds (1-year horizon)

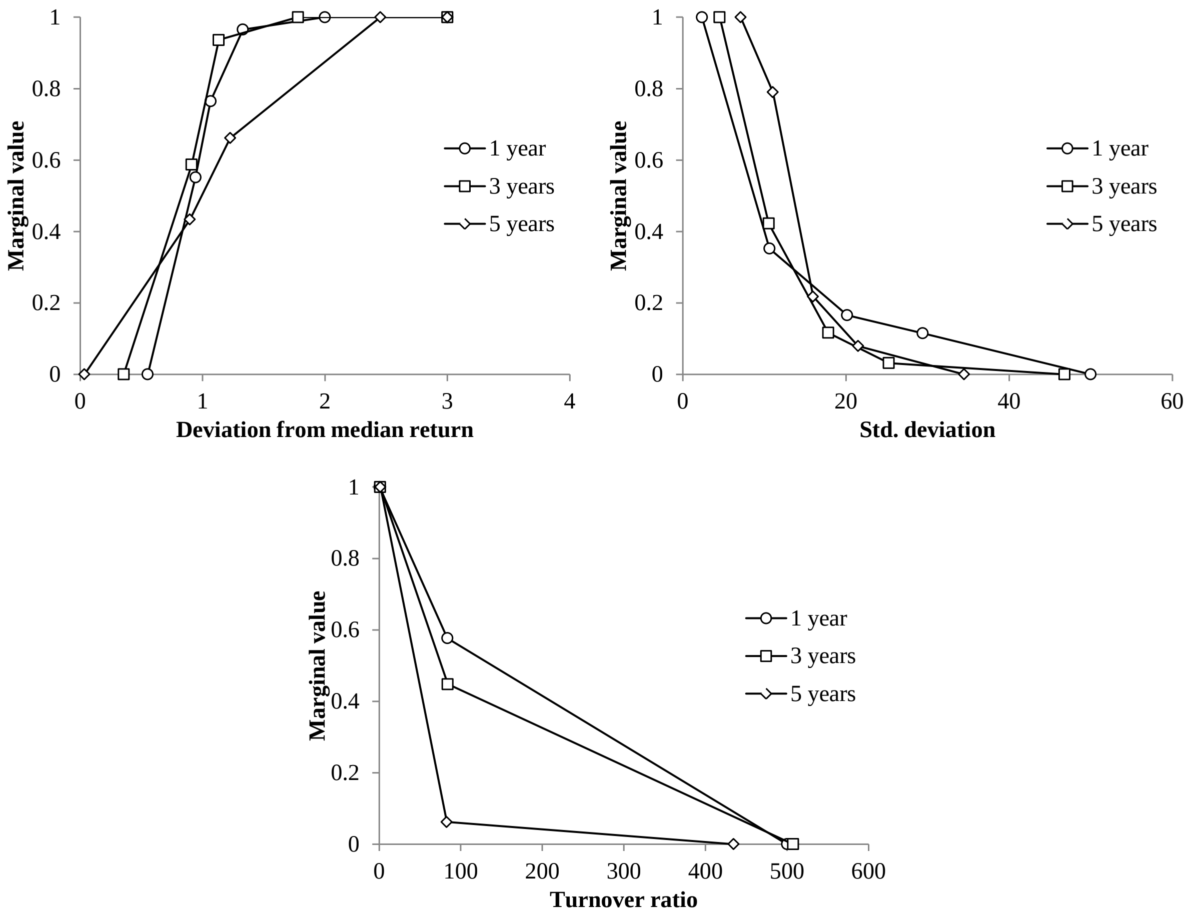

Figure 2: Marginal value functions

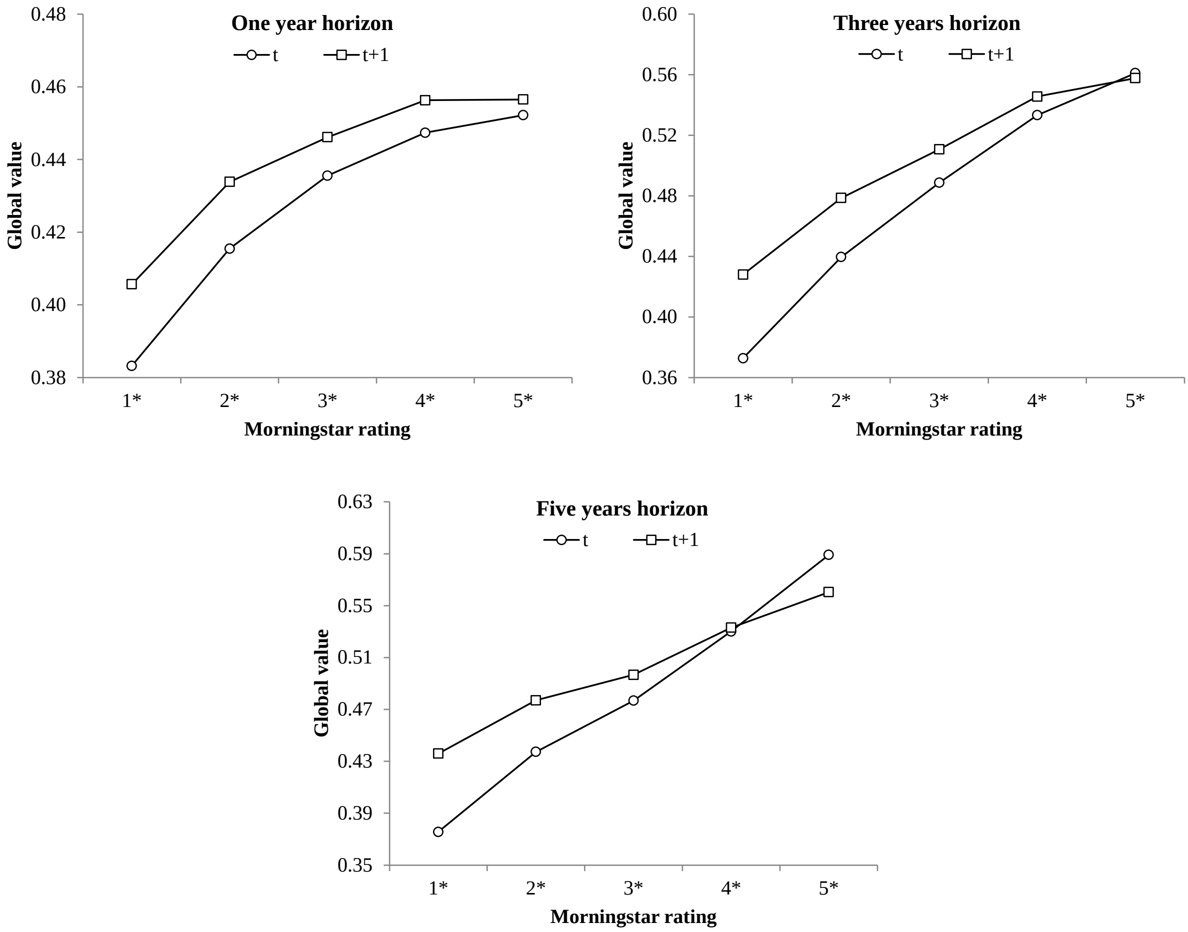

Figure 3: Average global scores vs the ratings of Morningstar