

Productivity and Efficiency Evaluation of US Mutual Funds

Mohammad Reza TAVAKOLI BAGHDADABAD—National University of Malaysia
(Mr_tavakkoli@yahoo.com), *corresponding author*

Afsaneh NOORI HOUSHYAR—National University of Malaysia (a_nh86@yahoo.com)

Abstract

In this paper assess the relative performance of US mutual funds using a non-parametric method such as data envelopment analysis (DEA). In particular, we assess the changes of mutual funds' total productivity using the DEA-based Tornqvist productivity Index. The findings show significant losses in mutual funds' productivity over the period 2000–2012, which has attracted the attention of US market regulators and policymakers. This paper presents some significant and important implications because we introduce the potential sources of operational inefficiency and unproductiveness. Using a panel logit model, it is revealed that a significant negative relationship exists between the efficiency and productivity and the size and management fee of mutual funds, a result that may be associated with the microstructure of the US stock market. Moreover, it is found that there is a significant positive relationship between the efficiency and productivity and the age and incentive fee of mutual funds. Average productivity growth in the US mutual fund industry is equal to 0.98, which hints at its unsatisfactory performance over the studied period. Finally, we present the findings versus the notion of the mean-variance (MV) efficiency of mutual funds.

1. Introduction

Mutual funds are professional organizations whose investments come from their own financial sources in a diversified portfolio and redeem their shares in the net asset value (NAV) upon request of the shareholder. These are among the most successful firms in modern investment markets (Tavakoli Baghdadabad, 2013). They are collective investment tools that pool the financial resources of individual investors to purchase the most attractive assets and to derive maximum benefit from them with respect to risk-adjusted returns. These funds have the advantages of being able to reduce risk and in their professional management of the portfolio diversification they propose to shareholders. However, the downside of the funds consists in the fact that there can be conflicts of interest among shareholders who tend to maximize their expected returns and the fact that fund managers try to maximize their compensation using fund assets (Tavakoli Baghdadabad et al., 2013).

The problem of optimal portfolio choice has attracted significant attention due to the pioneering works of Markowitz (1952) and Tobin (1958). In relation to modern portfolio mean-variance (MV) theory, investors attempt to maximize their own utility in terms of risk preferences among all the possible MV efficient portfolios. MV efficiency is theoretically defined as the ability of a group of securities to generate the minimum levels of risk for a certain expected return or, alternatively, to earn the maximum returns for a certain level of risk.

Another issue of portfolio efficiency is the evaluation of portfolio performance. The most common ratios are those of Sharpe (1966), Treynor (1965), and Jensen (1968), whose measures are based on the capital asset pricing model (CAPM) and evaluate excess returns of a portfolio adjusted for the return variability employing the standard deviation. However, over the last three decades, following the CAPM equilibrium model proposed by Sharpe (1964) and Lintner (1965), researchers have introduced different parametric measures to evaluate portfolio performance.

However, all of the applied measures involve two essential problems in the literature. The first problem concerns the selection of a desirable benchmark that is closely associated with the attributes of the normal performance of a fund. According to modern portfolio theory, the benchmark return is the strategy of comparable risks that incorporate investment in a risk-free security and tangent portfolio to include all the risky securities. Different studies attribute the sensitivity of portfolio performance assessment to the measures used (Lehman and Modest, 1987). The disadvantage of the conventional performance measures is their inability to combine the different costs imposed on fund shareholders. Mutual fund investors incur a series of indirect and direct charges that ultimately decrease their received net return. These costs include sale charges such as the front- and back-end loads and marketing, administrative and operational costs, which are mostly proxied by funds' expense ratios. A series of investigations such as those conducted by Carhart, Prather et al. (2004) and Babalos et al. (2009) examined the effect of costs on fund returns and found a negative relationship between the cost of funds and performance.

The inherent problems of conventional performance measures can be effectively improved using an alternative non-parametric measure that was primarily proposed by Murtrhi et al. (1997) and based on the well-known Charnes et al. (1978) method, namely data envelopment analysis. This method is extensively employed in areas outside of finance, such as operational management research, to calculate relative measures of efficiency. DEA can evaluate individual funds' investment performance through their relative efficiency compared with peer group portfolios. It does this by making the efficiency frontier from a linear combination of a perfectly efficient portfolio and by specifying portfolio deviations from the frontier that show performance inefficiency as slack.

We address the important issue of funds' performance evaluation by incorporating the financial aspects as well as the operational ones. More specifically, we use the non-parametric DEA method to evaluate the performance of a large universe of US mutual funds. We further evaluate the changes of mutual funds' total productivity using the Tornqvist index. The DEA approach allows us to calculate inefficient relative measures of the individual output and input factors to identify the source(s) of performance inefficiency. However, the developed structure of the US mutual fund industry incorporated with the big sizes and the liquidity of US stock exchanges make the US an interesting case. Specifically, we seek to determine whether the percentage of mutual fund assets influences the successful performance of a mutual fund investment strategy and provides us the big and liquidity capitalization of the US stock market.

Mutual funds' technical (operational) efficiency is a crucial issue for both investors and managers. In particular, investors believe that the different charges imposed on the funds are effectively applied in their best interest and that the funds

use their existing resources in the most productive way. Moreover, managers are concerned about the efficiency of mutual funds because the long-term success of the delegated nature of active management is closely related to the adoption of practices that employ clients' investment purposes effectively.

Our analysis reinforces the literature in several ways. Firstly, we evaluate the relative efficiency of a large universe of US mutual funds. Secondly, we evaluate the productivity of the US mutual fund industry using the Tornqvist index to examine the changes in funds' total productivity. To address this issue, we employ the revised Carhart's risk-adjusted returns similar to Edwards and Caglayan (2001) for the first time as an output measure. Thirdly, we seek the interaction between the two new factors of incentive and management fees with funds' efficiency and productivity on a capital market with unique attributes such as liquidity and big capitalization. Fourthly, we examine the impacts of the recent crisis (2007–2008) on the productivity and efficiency of the US mutual fund industry.

In order to conduct a sensitivity analysis, we extend our work to explore the relationship between funds and their size as reported by Coelli et al. (1998). In line with Grinblatt and Titman (1989) and Murthi et al. (1997), we seek the interaction between asset size and funds' efficiency and productivity in addition to the two factors added to our study, incentive and management fee.

This study is organized as follows: Section 2 provides a description of our research hypotheses. Section 3 reviews the relevant literature. Section 4 provides the details of the sample and variables, and the computations of our risk-adjusted returns. Section 5 presents the DEA method and the Tornqvist productivity index. Section 6 reports our empirical findings. Finally, Section 7 presents our concluding remarks and possible policy implications.

2. Research Hypotheses

We specify our research hypotheses as follows:

Hypothesis 1: Total productivity of US mutual funds is enhanced by a series of institutional variations.

Productivity change of a mutual fund can be determined by comparing its efficiency over successive periods. Specifically, we evaluate the relative efficiency of the US mutual fund industry using a number of variables to assess outputs and inputs which integrate the funds' operational characteristics as well as financial ones. Similar to the existing literature, productivity can be theoretically decomposed into two components of technological change and technical efficiency change, employing the robust inference to know how privately-managed mutual funds must be operated and organized. Since the fund management process is the key determinant of returns for shareholders, it is the issue of numerous studies in the context of delegated portfolio management. This concurs with Jensen (1968), who suggests a relationship between funds' underperformance and known benchmarks. Due to the multi-aspect process of fund management, which offers an approach to collecting investors' money, investing securities in a range of financial services and using a range of supporting products, there is the evitable necessity of evaluating the technical efficiency of mutual funds. These evaluations support the mutual fund industry by bringing forth better governance and greater transparency. Garcia (2010) indicates that despite significant legis-

lative remedies imposed on the Portuguese pension fund industry, there are still possibilities to achieve operational efficiency.

Hypothesis 2: US mutual funds are efficient MV.

Markowitz's (1952) MV theory shows that investors can construct an MV efficient portfolio by benefiting from diversification to achieve the maximum expected returns on a given level of risk determined by the portfolio returns' variance. Specifically, an investor may effectively decrease the risk of his investment by allocating his wealth to a range of securities. Thus, mutual funds can be a desirable form of investment for those individuals who do not have sufficient wealth to make a fully diversified portfolio. One of the key advantages of the non-parametric DEA method is the recognition of the slack variables as indicative of inefficient sources. These variables show whether portfolio managers employ their resources inefficiently. Thus, by examining the slacks of our risk variable, we can infer whether the funds hold MV-efficient portfolios (Murthi et al., 1997).

Hypothesis 3: When the size of a mutual fund increases, the possibility of a more efficient and productive fund also increases.

Despite the conflicting findings, this hypothesis is a basis for our perception of the role of funds in finance and in the economy, such as the role of economies of scale in the active management industry. A better understanding of this issue would naturally be desirable for investors, particularly in light of the significant outflows that US mutual funds experienced during the recent decades. Furthermore, scalability of the funds is strongly associated with the persistence of fund performance (i.e. Berk and Green, 2004). As for delegated attributes of active management, the existence of economies of scale in the mutual fund industry can also provide implications for the agency relationship between shareholders and managers, and lead to the best compensation contract among them. A positive relationship between performance and fund size can be indicative of economies of scale (i.e. Otten and Bams, 2002).

Moreover, there is an approach in which a larger fund size can have a detrimental impact on mutual fund performance due to the trading costs of liquidity or price effects (Perold and Salomon, 1991). This means that smaller funds have very significant superiority over larger ones because trading may be done without any significant effect on the asset price. This follows Chen et al. (2004), who posit that a small fund may easily invest all of the financial resources in the best way, whereas a shortage of liquidity forces a larger fund to invest financial resources in relatively inferior ways. Grinblatt and Titman (1989) and Prather et al. (2004) investigated the impacts of fund size on performance and found that funds with the smallest net asset values showed the best performance.

Hypothesis 4: An increase in a mutual fund's management fee, age and incentive fee leads to an increase in the possibility of funds being more efficient and productive.

Despite the conflicting findings, similarly as in the case of fund size, this hypothesis is a basis for our perception of the role of economies of scale in the active management industry. The evidence shows the significant impacts of our variables on portfolio performance. In the context of the incentive fee, the evidence shows that

funds with higher incentive fees can attract the best managers and subsequently earn higher performance. Steri et al. (2009) found that incentive fees have a statistically significant and positive impact on funds' performance.

The fund's age is a control variable employed by both Tufano and Sevick (1997) and Del Guercio et al. (2003) to examine the fund fee. Age is measured as the number of years since the fund's establishment. Younger funds may be subsidized by sponsors, resulting in lower fees. Alternatively, newer funds may experience high start-up costs and require that higher fees be charged. Chevalier and Ellison (1997) showed that younger funds exhibit greater inflow sensitivity to good performance. The idea is that younger or newer funds' immediate performance is more informative to investors who are learning the ability of the funds' unproven management. However, the age of funds has a positive relationship with performance (Edwards and Caglayan, 2001). Older and younger funds may exhibit various behaviors that can have a significant impact on expenses. In this context, Ferris and Chance (1987) and Chevalier and Ellison (1997) found a negative relationship between a fund's age and expenses. The evidence shows that the relationship can be either negative or positive. A negative sign would signal the existence of learning economies: older funds have a more efficient process and, as a result, they can lead to lower expenses. On the other hand, a positive sign can describe, similarly as Del Guercio and Tkac (2002) and Korkeamaki and Smythe (2004), whether age has a negative impact on funds' growth so that older funds can charge higher fees to compensate for their slower pace of growth. Finally, Do et al. (2005) and Koh et al. (2003) found no impact of funds' age on performance.

The management fee is also one of the most important costs among operating expenses; it is the compensation provided to the management company for supervising the portfolio and executing its operation (Geranio and Zanotti, 2005). Mutual fund managers are under constant pressure to deliver good returns because their management fees depend on the investment performance (Yuan et al., 2008). Grinblatt and Titman (1994) conclude that management fees are negatively related to funds' performance, whereas the remaining non-management expenses are uncorrelated with US equity fund risk-adjusted returns. Golec (1996) reports that management fees have a positive impact on performance while funds that keep their operating expenses low tend to show better performance. Examining a sample of Swedish equity funds, Dahlquist et al. (2000) conclude that performance is negatively related to management fees. Korkeamaki and Smythe (2004) document no such relationship in the case of Finnish funds. Finally, Renneboog et al. (2008) report that the management fee significantly decreases the risk-adjusted returns of funds.

Consistent with these findings, we consider age, the management fee and the incentive fee as three other determinants of performance in order to know whether they have a significant impact on US mutual funds' productivity and efficiency.

3. Literature Review

In the review of literature on evaluating the performance of mutual funds, the major focus has been on the parametric approaches including reward-to-volatility measures (Treyner, 1965; Sharpe, 1966), regression-based abnormal return measures (Treyner and Mazuy, 1966), and Jensen's (1968) and Carhart's (1997) alphas as reported by Romacho and Cortez (2006). Murthi et al. (1997) first applied the DEA method

on a sample of 2,083 funds in an evaluation of the performance of US equity-based mutual funds. They found a significant positive relationship between Jensen's alpha and the efficiency index for all of the selected funds. The model specification included the mean gross returns as output, and the expense ratio, the standard deviation of returns, the load and the turnover as inputs. Basso and Funari (2001) used both a single input-output approach and an extended version of the DEA method to incorporate a stochastic dominance indicator as the output. They used several risk ratios (standard deviation, semi-standard deviation and beta), redemption and subscription costs as inputs, and the mean returns and percentage of periods that funds are non-dominated as outputs. Their purpose was to assess the performance of a sample of 47 Italian funds in terms of the classes of balance, equity and bond over the period 1997–1999. Their findings emphasized the importance of redemption and subscription costs in specifying the fund rankings. Murthi and Choi (2001), using outputs and inputs reported in Murthi et al. (1997), indicated a relationship between the MV and cost-return efficiency by connecting a DEA-based performance measure and Sharpe measure. They used a new performance measure over the sample of 731 US equity-based funds and seven various classes of funds. A significant finding described that more than 90% of aggressive growth funds showed increasing returns to scale. Funds' turnover and load were specified as the main sources of slack among all of the funds' classifications. Galagadera and Silvapulle (2002) employed DEA to evaluate the relative performance of a sample of 257 Australian mutual funds over the period 1995–1999. Minimum primary investment and several time periods (one, two, three and five years) over the mean returns were used as inputs. Their findings proposed that scale efficiency is the major source of technical efficiency and that both are greater for risk-averse funds with high positive net security flows.

Sengupta (2003) investigated the relative performance of a sample of 60 US funds over the period 1988–1998. He used raw returns as the output and expense, load, turnover, skewness of returns and risk (standard deviation or beta) as inputs. More than 70% of funds were identified as efficient, but with significant deviations in the fund classifications. The examination of slacks showed no negative significant impact of standard deviation on funds' efficiency; this supports the assertion that funds are efficient MV efficient. Anderson et al. (2004) evaluated the relative performance of US real estate mutual funds (RMFs) with a data range from 28 RMFs in 1997 to 110 in 2001 over the period 1997–2001. They used raw return as the output and a series of inputs such as various costs, loads, and a standard measure of the funds' risk (standard deviation). Their findings showed that 12b-1 fees and loads were responsible for funds' operating inefficiency. Daraio and Simar (2006) introduced a robust non-parametric performance measure based on the concepts of the order-m frontier. Their sample included 3,000 US mutual funds over the period 2001–2002. They employed mean raw return as the output and expense ratio, standard deviation, the fund's size and turnover as inputs. Their findings showed that the majority of funds do not benefit from the economies of scale resulting from the unique structure of the mutual fund industry such as shareholder services and portfolio management of a variety of customers and securities. Specifically, the analysis of slacks proposes that, in some classifications, funds do not lie on the MV efficiency frontier. Lozano and Gutierrez (2008) investigated the relative efficiency of a sample of 108 Spanish funds employing six different DEA-based

models including the second-order stochastic dominance. The models use various measures of risk as the output and mean returns as the input. Babalos et al. (2012) evaluated the productivity and efficiency of Greek equity-based funds using the DEA-based Malmquist productivity index over the period 2003–2009. They employed the expected returns as the output and the funds' capital, risk and expense ratio as the input.

However, there are key differences between our study and the existing literature. First, we use the Tornqvist index to assess the productivity of funds because it is a better index than Malmquist when considering only a decision-making unit (DMU) for our analysis. Second, we investigated the interaction between funds' efficiency and productivity and the management and incentive fees. In line with earlier studies, we used the expected returns as the output and the funds' capital, risk and expense ratio as the input.

4. Data and Description

The efficiency frontier needs data on different outputs and inputs for our DMUs. Data was collected from a comprehensive sample of 11,522 US mutual funds over the period 2000–2012. Our research period and sample were selected based on the availability of data. The initial purpose of our analysis was to evaluate the total performance of mutual funds with DEA from an investor's perspective and our purpose was to minimize the inputs for a given level of output. As such, we used the DEA input-oriented model. Then, using balanced panel data on the US mutual funds (11,522 funds over a 12-year period with 144 observations), we estimated changes in the funds' total productivity using the Tornqvist index. A commonly encountered deficiency in the DEA-based financial literature was the existence of negative numerical values in the output or input variables, which contradicted the non-negative assumption of the basic DEA methods. In order to eliminate the impacts of this problem, a number of alternative methods were proposed (see, for example, Ali and Seiford, 1990). A transformation of basic and original data along with the use of a translation-invariant DEA model such as an additive model are the most popular methods of resolving negative data problems. With respect to this issue, we used an output measure which is always non-negative and financially significant as

$$W = 1 + R_j \tag{1}$$

where R_j is the actual return generated by fund j over the sample period. It is proxied using the annualized risk-adjusted returns from a multi-factor model as revised in Carhart's model. Thus, W denotes the final value at the end of the investment period of one unit $C_0 = 1$ invested in the fund.

Annual fund data such as age, total expenses and total net assets in dollars were collected from the mutual funds' annual reports. We employed the net asset value (NAV) of the US mutual funds, US S&P 500 returns as proxied by general index returns, and the risk-free rate as proxied by three-month Treasury bills. The sources of the mutual funds' NAVs and annual reports were the reports available in Morningstar. The long-term government bond interest rate, the short-term risk-free rate, the long-term corporate interest rate and the long-term government interest rate

were extracted from the Bloomberg database. Moreover, the data of Carhart's factors were extracted from Kenneth French's website (i.e. Du et al., 2009).

In the empirical application of the DEA model, we used multiple inputs such as the funds' capital, risk (the standard deviation of returns) and total expense ratio. An expense ratio includes the overall costs and operational and administrative costs as well as management fees incurred by the funds. The annualized standard deviation of the returns was considered as another input because investment risk is a key input for investors and an essential factor when interpreting returns. However, since our output was determined by the general value of our investment, we considered the primary capital invested in the funds as an input. Moreover, we assumed that the similar primary outlay $C_0 = 1$ was invested in all of our sample funds.

4.1 Risk-Adjusted Returns

The raw returns of our funds were computed using the following standard formula:

$$R_{pt} = (NAV_{pt} - NAV_{pt-1}) / NAV_{pt-1} \quad (2)$$

where NAV_{pt} denotes the NAV for mutual fund p over time t .

It is a common procedure for mutual fund management firms to publicize their funds' high returns in the financial press in order to keep existing investors and to attract new ones. Even so, raw returns are not an indicator of managerial ability because they do not consider funds' various exposures to systematic risk sources. Jensen (1968) proposes a risk-adjusted return ratio based on the standard CAPM model. However, in order to consider the excess returns made by strategies of tactical asset allocation, which extracts the contradictions of the CAPM model such as value strategies or size, we used a multi-factor performance evaluation model. Similar to Edwards and Caglayan (2001), we used the revised Carhart's six-factor model, which decomposes excess fund returns into excess market returns, returns made by selling bigger stocks (small minus big) and by purchasing smaller stocks, returns made by purchasing stocks with larger book-to-market ratios (value) and by selling stocks with lower book-to-market ratios (growth), returns made by purchasing and selling stocks with low and high past-year returns (MOM), returns made due to differences between the long-term government bond interest rate and the short-term risk-free rate, and returns made due to differences between the long-term corporate interest rate and the long-term government interest rate. Carhart's four-factor model is described by the intercept of regression as follows:

$$R_{pt} = \alpha_{pt} + \beta_{0p}R_{mt} + \beta_{1p}SMB + \beta_{2p}HML + \beta_{3p}MOM + \beta_{4p}TERM + \beta_{5p}DEF + \varepsilon_{pt} \quad (3)$$

where R_{pt} is the mutual fund's excess return, R_{mt} is the excess returns of the market portfolio, SMB is the difference in returns between the portfolio of big and small stocks, HML is the difference in returns between the portfolio of low book-to-market ratio and high book-to-market stocks, MOM is the difference in returns between the portfolio of losing and winning stocks over the previous year, TERM is the long-term bond spread (the difference between the long-term government bond interest rate and the short-term risk-free rate), and DEF is the default factor (the difference between the long-term corporate interest rate and the long-term government interest rate).

5. Methodology

We evaluated the relative efficiency of US mutual funds with the non-parametric DEA method employed in the construction of production functions. This methodology was extended by Charnes et al. (1978) and widely used to evaluate the relative performance of DMUs including social and financial firms that adopt multiple purposes and/or multiple input structures. The DEA method investigates the maximum potential output from a given set of inputs. For each DMU, it assigns an efficiency indicator relative to the best operating DMU in a certain group. It determines the given optimal weights and the best level of efficiency (equal to 1) only with the most efficient units. The DEA efficiency measure for DMU j is the ratio of a weighted sum of outputs to a weighted sum of inputs as follows:

$$h = \frac{\sum_{r=1}^t u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \quad (4)$$

where $j = 1, 2, \dots, n$ is the number of DMUs, $i = 1, 2, \dots, t$ is the number of outputs and $i = 1, 2, \dots, m$ is the number of inputs. y_{rj} denotes the amount of output r for DMU j , x_{ij} is the amount of input i for DMU j , u_r is the weight allocated to output r , and v_i is the weight allocated to input i .

As already described, the most efficient DMUs are attributed by an efficiency indicator equal to 1: at least with the most desirable weights; these DMUs are not able to be dominant over the other DMUs in the set. Thus, the DEA approach results in a Pareto efficiency indicator in that the efficient DMUs lie on the efficiency frontier (see Charnes et al., 1994). In order to calculate the DEA efficiency measure for a DMU, $j_0 \in \{1, 2, \dots, n\}$, consistent with Charnes et al. (1994), we find the optimal alternative for the following linear programming problem:

$$\begin{aligned} \max_{\{v_i, u_r\}} h_0 &= \frac{\sum_{r=1}^t u_r y_{rj_0}}{\sum_{i=1}^m v_i x_{ij_0}} \\ s.t. \quad &\frac{\sum_{r=1}^t u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1 \quad j = 1, \dots, n \\ &u_r \geq \varepsilon \quad r = 1, \dots, t \\ &v_i \geq \varepsilon \quad i = 1, \dots, m \end{aligned} \quad (5)$$

where ε denotes a small positive number to ensure that the weights do not take a value equal to zero. The value of optimal objective function, which is computed in (5), shows the efficiency measure allocated to the captured target DMU j_0 . The efficiency indicators of other DMUs are calculated by solving the same problems for each DMU in turn.

The aforementioned fractional drawback is converted on an equivalent linear programming problem. By arranging $\sum_{i=1}^m v_i x_{ij_0} = 1$, we obtain the so-called input-oriented Charnes et al.'s (CCR) linear model as follows:

$$\begin{aligned}
 & \max \sum_{r=1}^t u_r y_{rj_0} \\
 & s.t. \sum_{i=1}^m v_i x_{ij_0} = 1 \\
 & \sum_{r=1}^t u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0 \\
 & -u_r \leq -\varepsilon \quad r = 1, \dots, t \\
 & -v_i \leq -\varepsilon \quad i = 1, \dots, m \quad j = 1, \dots, n
 \end{aligned} \tag{6}$$

The optimization problem computes the values of $t + m$ variables, which are the weights u_r and v_i with respect to $n + t + m + 1$ constraints.

5.1 Change in Total Factor Productivity

There are two common methods to explore changes in total productivity, such as the parametric and non-parametric DEA methods. However, due to some criticisms of parametric methods (e.g. Farrell, 1957), the studies concentrate on non-parametric methods.

Primary studies on analyzing the changes in total productivity have been carried out by Koopmans (1951) and Solow (1957). They used a non-parametric DEA technique to examine the changes in total productivity. Nishmizu and Page (1982) decompose these changes into technological and technical efficiency changes. In order to evaluate the changes in productivity, Tornqvist (1936) and Caves et al. (1982) proposed new methods such as the DEA-based Tornqvist and Malmquist productivity indices to evaluate the technological and technical efficiency changes. However, due to the nature of the Malmquist productivity index, which makes a comparison of the productivity changes among different DMUs, it is only used when there is more than one DMU in our sample. Thus, when only employing one DMU, similar to our present study which employs the US mutual fund industry, another methodology must be used as the Tornqvist productivity index.

5.1.1 Tornqvist Productivity Index

As described in the previous section, the Malmquist productivity index is a DEA-based model that compares changes in the total productivity of different DMUs during a limited time period. In other words, due to the comparative nature of the Malmquist index in computing the productivity changes for more than one DMU, the index will not be appropriate if only a single DMU is available. In order to solve this problem, the Tornqvist productivity index is employed. Unlike the Malmquist index, this index is a useful tool for calculating productivity over a definite time series and estimating productivity growth using the output and input elasticity.

Let us define the data of a DMU over n years, including m input and s output. The DMU over the K -th period has the input vector, $X^K = (x_1^k, x_2^k, \dots, x_m^k)$, and the output vector, $Y^K = (y_1^k, y_2^k, \dots, y_s^k)$. In addition, the period $k + 1$ has the input vector, $X^{K+1} = (x_1^{k+1}, x_2^{k+1}, \dots, x_m^{k+1})$, and the output vector, $Y^{K+1} = (y_1^{k+1}, y_2^{k+1}, \dots, y_s^{k+1})$, thus if we consider a DMU with respect to the constant return to scale and the output-oriented approach, then the input value of the Tornqvist index is computed as follows:

$$TQ_X = \prod_{i=1}^m \left[\frac{X_i^{k+1}}{X_i^k} \right]^{ex_i}, \quad \sum_{i=1}^m ex_i = 1 \quad (7)$$

where ex_i is the geometric average of i -th input elasticity over the periods K and $K + 1$, which is computed by Eq. (8), and X_i is the desired input over the periods K and $K + 1$.

$$ex_i^k = \frac{r_i^k x_i}{\sum_i r_i^k x_i}, \quad ex_i^{k+1} = \frac{r_i^{k+1} x_i}{\sum_i r_i^{k+1} x_i} \quad (8)$$

The magnitude of TQ_X shows the changes in input during two consecutive years which are computed using the elasticity of each input multiplied by the total output where r_i is the weight of inputs over the periods k and $k + 1$. Similarly, the output value of the Tornqvist index is computed as follows:

$$\sum_{j=1}^s ey_j = 1, \quad TQ_Y = \prod_{j=1}^s \left[\frac{y_j^{k+1}}{y_j^k} \right]^{ey_j} \quad (9)$$

where ey_j is the geometric average of j -th output elasticity over the periods k and $k + 1$ which is computed by Eq. (10), and y_i is the desired output over the periods k and $k + 1$.

$$ey_j^{k+1} = \frac{q_j^{k+1} y_j}{\sum_j q_j^{k+1} y_j}, \quad ey_j^k = \frac{q_j^k y_j}{\sum_j q_j^k y_j} \quad (10)$$

where q_j is the weight of outputs over the periods k and $k + 1$.

The amount of TQ_Y shows the changes in output during two periods which are computed by the elasticity of each output, thus the total productivity changes are computed as follows:

$$TFPG_{k,k+1} = \frac{TQ_Y}{TQ_X} \quad (11)$$

Efficiency changes are also computed for the two periods k and $K + 1$ as follows:

Table 1 Characteristics of the Variables over the Period 2000–2012

Variables	Mean	Maximum	Minimum	Standard deviation
Revised Carhart alpha (%)	0.002	20.12	-14.26	5.31
Assets (mil. dollars)	294.15	671.13	34.22	147.02
Total expense ratio	0.044	0.082	0.004	0.05
Age (in years)	19.01	35.12	1.11	5.36
Risk	0.241	0.652	0.002	0.071

Notes: The table reports the descriptive statistics of our mutual funds' attributes over the sample period. It includes the annualized Carhart's alpha, total assets in USD million, the total expense ratio, the mutual funds' age assessed in years from inception, and the total risk determined by the annualized standard deviation of our returns.

$$EC_{k,k+1} = \frac{EFF_{k+1}}{EFF_k} \quad (12)$$

The values in the numerator and denominator are efficiency scores over the periods k and $k + 1$, respectively. Eq. (11) and (12) help us to compute the technological changes (TC) as

$$TC_{k,k+1} = \frac{TFPG_{k,k+1}}{EC_{k,k+1}} \quad (13)$$

The results of Eq. (13) follow two important interpretations:

- If TC becomes greater than one, it implies technological progress of the US mutual fund industry during a definite period (two consecutive years), and if TC becomes less than one, the interpretation will be the opposite.
- If the Tornqvist index becomes greater than one, it implies total factor productivity (TFP) growth during a definite period (two consecutive years), and if the Tornqvist index becomes less than one, the interpretation will be the opposite.

6. Results

6.1 Basic Results

We computed a relative indicator of efficiency using the DEA approach on all of the mutual funds in our sample. We use a common input-oriented DEA method in which the value of an efficient fund relative to other funds is reported with a value of 1. A DEA measure less than 1 implies that the fund is inefficient relative to others. The score of an inefficient mutual fund is computed based on the difference between our efficiency measure and 1; larger differences imply greater inefficiency of our funds.

Table 1 provides some descriptive statistics of our input and output variables. It reports that average mutual funds show slight over-performance (0.2%) relative to known benchmarks, while it charges 4.4% of total assets as expenses. This is substantially greater than the international standard. In addition, *Table 1* reports that there is much heterogeneity among our funds, with a standard deviation higher than the mean for the majority of our listed variables.

Figure 1 Mean Efficiency Score over the Period 2000–2012

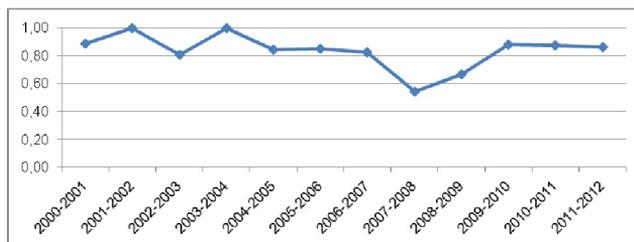


Figure 1 indicates the evolution of funds' mean efficiency over the sample period. It shows that the average efficiency of US funds is relatively not at a high level (above 0.93 on average), while detecting a significant variation. Specifically, mean efficiency varies from 0.89 in 2000–2001 to 0.867 in 2011–2012, confirming a long-run downward trend. In addition, during the period 2007–2008, the funds suffered a significant depression in their efficiency levels due to the effects of the global financial crisis.

Table 2 reports the scores of DEA efficiency for the whole sample in each period separately. It can be seen that there are only two periods with efficiency, meaning that the bulk of our funds are away from the efficiency frontier, thus indicating the sources of inefficiency among the funds (which will be investigated in detail later). The average efficiency score of our whole sample is 0.838, implying a low level of efficiency. For the mutual funds' management styles this is low, showing a range between 0.626 at the lowest to 0.862 at the highest for the subclasses of Blend and Equity Income, respectively.

Moreover, the DEA model appraises inefficient variables or slack measures based on efficiency scores which are interpreted as the difference between the target output and input values and the period's real values. It is then possible to determine the fundamental factors that are responsible for a mutual fund's (period's) inefficiency and to investigate how to improve inefficient funds (periods).

Panel A of Table 3 shows the mean values of our slack measures for the sample periods. Consistent with Murthi et al. (1997), we investigate the mean of inefficiencies in individual inputs. Specifically, we assess fund managers' degrees of inefficiency based on risk measures and certain cost. Mutual funds are the preferred investment tool for individuals because they offer a low cost for a diversified portfolio. A mutual fund's expense ratio determines the general costs of managing and running a fund including management fees and other administrative and operational costs. It is referred to as the fund's overall expenses ratio to its average net assets over each year. A few possible descriptions are reported as the relationship between funds' performance and cost. Acting in an information-inefficient form, as reported by Grossman and Stiglitz (1980), informed investors must be rewarded greater returns than uninformed investors (Ippolito, 1989). However, different expenses are deducted from fund assets, inevitably causing performance erosion (see Carhart, 1997; Chen et al., 2004; Babalos et al., 2009).

We investigated another input variable with respect to portfolio diversification, which is the funds' investment risk. *Table 3* reports that both the risk measure

Table 2 Efficiency Scores of the Whole Sample of Funds and Management Styles Thereof

Period	Total Sample	Blend	Contrarian	Emerging Markets	Equity Income	Geographically Focused	Growth and Income	Index Fund	Long-Short	Market Neutral
2000–2001	0.890	1.000	0.876	0.893	0.872	0.835	1.000	0.873	0.675	0.795
2001–2002	1.000	0.83	0.821	0.838	0.817	1.000	0.8631	0.818	0.620	0.740
2002–2003	0.809	1.000	1.000	0.812	0.791	0.754	0.8371	0.792	0.594	0.714
2003–2004	1.000	0.844	0.835	0.852	0.831	0.794	0.8771	0.832	0.634	0.754
2004–2005	0.845	0.84	1.000	0.848	0.827	0.79	0.8731	0.828	0.630	0.750
2005–2006	0.853	0.848	0.839	0.856	0.835	0.798	0.8811	0.836	0.638	0.758
2006–2007	0.828	0.823	0.814	0.831	0.810	0.773	0.8561	0.811	0.613	0.733
2007–2008	0.543	0.538	0.529	0.546	0.525	0.488	0.5711	0.526	0.328	0.448
2008–2009	0.668	0.663	0.654	0.671	0.650	0.613	0.6961	0.651	0.453	0.573
2009–2010	0.880	0.875	0.866	0.883	0.862	0.825	1.000	0.863	0.665	0.785
2010–2011	0.874	0.869	0.860	1.000	1.000	0.819	1.000	1.000	0.659	1.000
2011–2012	0.867	0.862	0.853	1.000	0.849	1.000	0.8951	0.850	1.000	0.772
Average	0.838	0.626	0.807	0.826	0.862	0.791	0.806	0.829	0.833	0.838
No of efficient periods	2	2	2	2	1	2	3	1	1	1
No of inefficient periods	10	10	10	10	11	10	9	11	11	11

Notes: The table reports the DEA-CRS annual efficiency scores for mutual funds over the period 2000–2012. The number of efficient (inefficient) periods is reported at the bottom.

Table 3 Mean Slacks in Inputs

Panel A: Mean absolute slacks			
Period	Capital	Expenses	Risk
2000–2001	0.000	0.001	0.009
2001–2002	0.000	0.003	0.010
2002–2003	0.000	0.005	0.013
2003–2004	0.000	0.004	0.013
2004–2005	0.000	0.009	0.016
2005–2006	0.000	0.011	0.019
2006–2007	0.029	0.020	0.032
2007–2008	0.023	0.022	0.024
2008–2009	0.000	0.010	0.017
2009–2010	0.000	0.014	0.016
2010–2011	0.000	0.005	0.011
2011–2012	0.000	0.004	0.008
Mean	0.004	0.009	0.015

Panel B: Relative slacks (absolute slack/mean value of inputs)			
2000–2001	0.000	0.003	0.011
2001–2002	0.000	0.005	0.013
2002–2003	0.000	0.007	0.015
2003–2004	0.000	0.006	0.014
2004–2005	0.000	0.007	0.015
2005–2006	0.000	0.011	0.019
2006–2007	0.029	0.022	0.035
2007–2008	0.024	0.026	0.028
2008–2009	0.000	0.011	0.014
2009–2010	0.000	0.010	0.012
2010–2011	0.000	0.008	0.011
2011–2012	0.000	0.007	0.009
<i>Mean</i>	0.004	0.010	0.016

Notes: The table reports the mean of relative mean slacks and the absolute slacks, which are computed as the absolute mean slack in the output or input divided by the mean value of outputs/inputs. Slacks show that an output (input) needs to be reduced (increased) in order for our mutual fund to achieve relative efficiency of 1. Panel A reports the results for the estimated mean absolute slacks while Panel B represents our computed relative slacks.

and expense ratio determined by the standard deviation of returns show significant slacks across our sample period. For example, over the period 2003–2004, a fund needed to decrease expenses by 0.004 units and risk levels by 0.013 units in order to operate on the efficiency frontier. It also revealed that inputs must consume more magnitude under crisis conditions in order to operate on the efficiency frontier. This means that they had to consume capital by 0.023 units, expenses by 0.022 units and risk levels by 0.024 units over the crisis period 2007–2008. This implies inefficient performance of our funds in crisis conditions.

Panel B of *Table 3* reports the relative mean slacks which are defined as the absolute mean slack in the input divided by the mean value of inputs. Using the relative slacks, it is possible to measure the marginal effect of each input variable

Table 4 Changes in Technical and Technological Efficiency (Productivity) for US Mutual Funds over the Period 2000–2012

Period	Change in technical efficiency	Technological change	Change in Pure technical efficiency	Change in scale efficiency	Tornqvist Index (TFP change)
2000–2001	1.001	0.938	1.001	1,000	0.939
2001–2002	0.969	0.962	0.969	1,000	0.932
2002–2003	0.971	0.957	0.971	1,000	0.929
2003–2004	0.934	0.958	0.934	1,000	0.895
2004–2005	1.075	0.952	1.075	1,000	1.023
2005–2006	1.001	0.950	1.001	1,000	0.951
2006–2007	0.921	0.821	0.921	0.929	0.756
2007–2008	0.816	0.902	0.816	0.844	0.736
2008–2009	0.968	0.931	0.968	0.938	0.901
2009–2010	0.972	0.982	0.972	1,000	0.955
2010–2011	1.492	0.981	1.492	1,000	1.464
2011–2012	1.295	0.989	1.295	1,000	1.281
Mean	1.035	0.944	1.035	0.976	0.980

Notes: The table reports the results of our estimated output-oriented Tornqvist productivity index over the period 2000–2012. Column (2) represents the changes in technical efficiency while column (3) represents the technological changes. Columns (4) and (5) report the changes in pure technical efficiency and scale efficiency, respectively. The changes in total factor productivity (TFP determined by Tornqvist index) are reported in column (6). All of the Tornqvist index averages are geometric means.

on our funds' efficiency. As described earlier, the computation of slack variables allows us to determine whether fund managers allocate their various resources efficiently. A notable result is that the risk of our funds, as determined by the standard deviation of returns, shows non-zero slacks for our sample funds. This result contradicts the notion of the MV efficiency of the portfolio. Among the other input variables, overall expenses report larger slacks with a relative slack of 0.01, confirming the prior evidence (Babalos et al., 2009) that expenses may erode funds' performance.

6.2 Tornqvist Productivity Index

This section provides an evaluation of the performance of US mutual funds in terms of changes in their total productivity over the period 2000–2012. This analysis gives additional insights on the performance of the US mutual fund market. In order to perform our analysis, we adopted the non-parametric efficiency frontier approach, which allows computing the Tornqvist productivity index (Tornqvist, 1936) in terms of the DEA methodology. However, in accordance with Nemoto and Goto (2005) and Feng and Serletis (2010), there are different formulations in the Tornqvist index. In line with the same studies, we estimated an output-oriented Tornqvist index in terms of DEA. Output-oriented models are employed to identify technical inefficiency in terms of the proportional decrease in using our inputs. The scores of our funds' total productivity changes are reported in *Table 4*. The change in the funds' total productivity can be theoretically decomposed into a technical efficiency change (diffusion or catch-up term), which determines the changes of the funds that worsen

or improve in efficiency, and a technological efficiency change (frontier-shift or innovation term), which shows the changes in our estimated frontiers between two periods. Technological change in the mutual fund industry is the outcome of innovations such as investing in a new manner or using new techniques and practices with the purpose of attaining superior risk-adjusted returns. For further analysis, we decomposed the technical efficiency change into a scale-efficient change and pure efficiency change, which is associated with funds' size. The pure technical efficiency change can be an indicator of enhanced managerial abilities or even an upgraded management structure, which brings forth a better balance between output and input, effective decision-making, accurate reporting and so on. A value higher than one implies an improvement in our utilized technology. The periods are ranked in terms of the value of the Tornqvist index, as reported in column (6) of *Table 4*. Values of the Tornqvist index higher than one imply overall productivity gains for our relevant funds during a given period.

The findings propose that the total productivity of US mutual funds shows an annual mean equal to 0.98 over the period 2000–2012. This indicates the weakness of innovation in our sample funds during the research period due to insufficient investment in new technologies and a lack of upgrading of managerial ability. More specifically, the US mutual funds experienced an essential productivity loss over the period 2000–2012, which implies a major concern for US policymakers.

The fourth column of *Table 4* reports the results of changes in pure technological efficiency. Since the fund market experienced technological efficiency greater than one over the periods 2000–2001, 2004–2005, 2005–2006, 2010–2011 and 2011–2012, it is apparent that technological progress occurred in the market during the said periods. The sixth column of *Table 4* also shows significant growth greater than one over the periods 2004–2005, 2010–2011 and 2011–2012, thus implying overall productivity growth of our funds. Of great interest are the scores of technological efficiency and total productivity, which show the worst magnitude among all periods during the crisis.

The total productivity reduction is chiefly driven by the incompatible technological changes imposed by the majority of our sample funds. Specifically, the average annual technological change is 0.944 while the average technical efficiency change is relatively high and equal to 1.035 in each period. For the period of our analysis, five out of 12 periods show a positive technical efficiency change. This indicates an improvement in technical efficiency over the period of interest. The scale efficiency is equal to one for all of the periods, except three surrounding periods of 2006–2009, indicating that there is no growth in the technical efficiency of scale.

6.3. Determinants of Efficiency

In this section, we investigate the potential factors responsible for mutual funds' efficiency using the two-step approach as proposed by Coelli et al. (1998). This approach is a conditional logit probability model which forms a relationship between the possibility of a fund to be efficient and productive and different funds' operational attributes including the management fee, age, asset and incentive fee. A logistic regression coefficient shows the changes (reduction when $\beta_i < 0$, increase when $\beta_i > 0$) in the predicted logged odds of having an attribute of interest for a one-

Table 5 Conditional Logit Panel Regression

Determinants of efficiency		Determinants of productivity	
Period	2000–2012 (11,522 US funds)	Period	2000–2012 11,522 US funds)
β_0	-3.01	β'_0	-2.22
t-statistic	-13.46***	t-statistic	-9.71
β_1	-0.028	β'_1	-0.023
t-statistic	-4.18*	t-statistic	-3.97
β_2	0.14	β'_2	0.16
t-statistic	3.67	t-statistic	3.84
β_3	-0.032	β'_3	-0.015
t-statistic	-4.21	t-statistic	-4.56
β_4	0.15	β'_4	0.17
t-statistic	8.23	t-statistic	8.77

Notes: The table reports our estimated regression coefficients from the random impacts and conditional logit model over the period 2000–2012. *** (*) denotes statistical significance at the level of 1% (10%).

unit change in the independent variables. Thus, we estimate the following balanced panel regressions by assuming the random impacts:

$$Eff_{it} = \beta_0 + \beta_1 Assets_{it} + \beta_2 Age_{it} + \beta_3 MFEE_i + \beta_4 IFEE + \varepsilon_{it} \quad (14)$$

where $i = 1, \dots, N; t = 1, \dots, T$

$$TFPG_{it} = \beta'_0 + \beta'_1 Assets_{it} + \beta'_2 Age_{it} + \beta'_3 MFEE_i + \beta'_4 IFEE + \varepsilon_{it} \quad (15)$$

where $i = 1, \dots, N; t = 1, \dots, T$

where Eff is a binary variable that has the value of 1 if mutual fund i is efficient and 0 if it becomes inefficient; $TFPG$ is the changes in total productivity (or total productivity growth), $Assets$ is the mutual fund's i total assets at the end of the period considered in millions of dollars, and Age is the mutual fund's i age assessed in years from its inception, $MFEE$ is the management fee, and $IFEE$ is the incentive fee.

The initial finding is that a fund's size contributes negatively to the possibility of being efficient. More specifically, a larger size leads to lower efficiency of a mutual fund. This is a significant finding which is probably related to the US stock market's microstructure, showing that size is a constraint for US mutual funds, in particular for a stock market that is characterized by big and liquidity capitalization. The latter is reinforced by the statistics of US stock exchanges, which are reported in *Table 6*. The age variable has a positive and significant influence on the possibility of being efficient. It implies that older mutual funds develop an effective organizational structure, more management techniques or even better knowledge of financial markets in general. Similarly, the management fee has a negative influence on the possibility of being efficient. It implies that managers who are higher paid are not necessarily more motivated or more able to manage the performance of funds. In contrast, the incen-

Table 6 Summary Statistics of US Stock Exchanges

Period	Capitalization			Average Number of trades			Average trade spread	
	Large capitalization	Medium & small capitalization	Other	Total	Large capitalization	Medium & small capitalization		Other
2000–2001	743.14	60.73	31.12	834.99	228 602.44	56 144.11	321.00	1.67
2001–2002	755.11	65.32	43.21	863.64	296 341.11	64 219.21	21.01	1.16
2002–2003	766.22	64.29	59.22	889.73	216 167.02	70 016.01	124.00	1.34
2003–2004	780.44	55.24	64.32	900.00	298 244.12	69 256.15	216.00	1.29
2004–2005	802.21	61.28	44.12	907.61	215 221.01	73 211.19	301.00	1.17
2005–2006	803.24	60.19	45.14	908.57	226 114.22	74 122.45	219.00	1.44
2006–2007	800.01	59.97	41.22	901.20	201 594.31	52 987.32	54.00	1.03
2007–2008	769.21	52.23	16.17	837.61	187 452.21	51 244.15	39.00	1.01
2008–2009	859.11	60.05	29.22	948.38	231 329.22	59 144.16	18.02	1.44
2009–2010	920.22	63.12	32.13	1015.47	264 144.11	67 244.17	54.00	1.76
2010–2011	954.21	60.19	29.01	1043.41	279 516.29	69 014.34	16.00	1.78
2011–2012	1,032.02	70.21	38.18	1140.41	281 116.54	72 256.54	91.00	1.91

Notes: The table reports capitalization (billions of USD), volume of trades (millions of shares) and average daily number of trades on US stock exchange. Trading volume comprises trades recorded in December of each year while the average daily average trading volume is without block trades. Data are gathered from different sources including US stock exchanges and the Bloomberg database. The last column of Table 6 shows the average trading spread for the whole market over the period 2000–2012. The spread is the ratio of the difference between the best bid price and the best ask over the average of the sum of two prices. The average trading spread is weighted by the traded values. The spread that corresponds to a trade is the one experienced before the trade. Data are gathered from US stock exchanges.

Table 7 Predictive Ability of a Mutual Fund's Performance Measure

Period	2000–2001	2001–2002	2002–2003	2003–2004	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009	2009–2010	2010–2011	2011–2012
Spearman correlation coefficient	0.029 (0.15)	0.27 (0.14)	0.49 (0.24)	0.66 (0.32)	0.73 (0.39)	0.82 (0.42)	0.011 (0.07)	0.007 (0.04)	0.144 (0.92)	0.215 (1.11)	0.224 (1.14)	0.253 (1.29)

Notes: The table shows the Spearman rank correlation coefficient for mutual fund rankings over the period 2000–2012. The brackets report our estimated t-statistic.

tive fee has a positive and significant influence on the likelihood of being efficient. This implies that funds with higher incentive fees may manage to attract the best managers and that funds pursue the absolute returns to deliver higher efficiency and performance.

An interesting finding is that the results of our sensitivity analysis of total productivity growth are similar to the findings of our efficiency analysis, in which a fund's size and management style have a negative impact on the likelihood of being productive. In contrast, a fund's age and incentive fee have a positive impact on the likelihood of being productive.

6.4 Predictive Ability of the Suggested Performance Measure

To date, there have been numerous studies to examine the predictive ability of performance measures such as the works developed by Jensen (1968), Grinblatt and Titman (1992), Carhart (1997) and, more recently, Fama and French (2010). However, the findings pertaining to fund performance persistence, particularly of mutual funds, are still inconclusive. Recently, a series of studies investigated the predictive ability of various performance measures on international fund markets—see, for example, Cortez et al. (1999) on Portuguese funds, Fletcher and Forbes (2002) on the UK fund industry, Otten and Bams (2002) on five European markets, and Ferruz et al. (2007) on German and Spanish equity-based funds. Following Babalos et al. (2008) on mutual funds, they find weak evidence of performance persistence that is sensitive to the choice of desirable performance measures. However, despite the different studies on the predictive ability of traditional performance measures including regression-based measures and raw returns, there is limited literature on estimating the practical relationship of relative performance measures. This study uses the Spearman rank correlation coefficient to test the degree of dependency among the funds ranked by our suggested measure during a one-year horizon over the period 2000–2012. The findings, which show the absence of significant dependency among the mutual fund rankings, are reported in *Table 7*. More specifically, the suggested measure has no predictive ability over time. Even so, further study on the robustness of these results would be useful.

7. Conclusion

We focused on two key purposes. Firstly, we evaluated the operational efficiency of a large sample of US mutual funds with the non-parametric DEA method over the period 2000–2012. As for efficiency evaluation, we used original data spanning the cost and risk attributes of mutual funds so that a common risk-adjusted return model, namely the revised Carhart's alpha (1997), is used as the output variable. The empirical results report some important aspects of the US mutual fund industry. The findings show that only a small percentage of mutual funds (or periods) in our sample operate on the efficiency frontier. Another interesting finding reached by investigating the slacks is the negative impact that expenses impose on mutual funds' operational efficiency. Specifically, our result does not support the notion of MV efficiency for the mutual funds in our sample.

The total productivity changes using the DEA-based Tornqvist index provide some interesting results based on the diffusion of best-practice technology in the US mutual fund industry. Specifically, we found a substantial productivity loss for

the US mutual funds over the sample period. The shortage of investment in management techniques and leading technologies by fund management firms seems to impose a significant technological regression. As for determinants of mutual funds' operational inadequacies and as a part of our sensitivity analysis, we used a second-stage panel logit regression to investigate the existence of a negative relationship between the possibility of being efficient and productive and the assets under management and the management fee. This adverse impact can be attributed to the micro-structure features of the US stock market characterized by big market and liquidity capitalization.

These findings have practical dependency for US mutual fund shareholders because investors may consider some fund characteristics investigated in the mutual funds' selection process. Specifically, investors prefer a fund that provides maximum returns (benefits) at minimum cost in the form of front-end loads, charges, etc. In addition, investors must consider funds' size and expenses when choosing a fund in the US stock market because these variables can be the source of significant operational inefficiencies. Another analysis focuses on the lack of predictive ability of our suggested measure for performance evaluation. However, further study on the robustness of this finding would be useful.

However, there are two potential ways to upgrade mutual funds' operational efficiency and productivity. Firstly, mutual fund management firms representing the weakest performance should adopt a more efficient, incentive-oriented managerial policy that allows them to improve and move toward the efficiency frontier. More specifically, mutual fund firms should minimize the expenses charged to shareholders by using more effective channels to achieve economies of scale. The purpose of attaining better levels of diversification in managed portfolios must be kept at higher levels in managers' agendas. Secondly, their attempt toward modification should focus on technological innovations such as techniques, methods, launching new products, etc. In addition, modifications in the efficiency of US mutual funds depend on the actions of market regulatory authorities, which involves four recommendations: (1) improve the implementation of their regulatory obligations, (2) require disclosure of mutual funds' detailed operational information in order to bring greater larger transparency into the market, (3) provide favorable tax behavior for mutual fund management firms and investors, and (4) implement the best practices proposed by other regulatory authorities in keeping with the investors' best interest.

Finally, inefficient and unproductive measures may be applied for competitive benchmarking, in that management fees have dependency on the same costs as well as more efficient and productive mutual funds. Such a framework can (1) improve mutual fund managers' motivation to achieve further efficiency and productivity and (2) decrease informational asymmetry between mutual fund managers, investors and regulators.

Our findings support the first hypothesis in which the total productivity of US mutual funds is enhanced by a series of institutional variations. In responding to our second research hypothesis, we observed that the majority of funds show significant operational inefficiency and unproductiveness over the sample period. This inefficiency and unproductiveness were chiefly derived from mutual funds' expenses, which inevitably decrease investors' wealth. With respect to portfolio diversification,

US funds showed not to have effectively omitted non-systematic factors of their portfolio riskiness because the risk variables showed significant inefficiencies (slacks). As for total productivity change, we reported a remarkable productivity loss due mainly to the lack of technological advances. In responding to our fourth and fifth hypotheses, the second-stage measurement of the DEA efficiency scores showed interesting dimensions of funds' inadequacies. A higher probability of efficiency and productivity is related to smaller fund size and management fees, and higher age and incentive fees. A big asset appears to be a limitation in the context of the micro-structure attributes of the US stock market: big mutual funds are frequently forced to invest disproportionately in special stocks, particularly in the case of liquid stock markets, which lead to erosion of fund performance (see, for example, Chen et al. 2004).

REFERENCES

- Ali AI (1990): Translation invariance in data envelopment analysis. *Operations Research Letters*, 9(6):403–5.
- Anderson R, Brockman C, Giannikos C, McLeod R (2004): A non-parametric examination of Real Estate mutual fund efficiency. *International Journal of Business and Economics*, 3(3):225–38.
- Babalos V, Caporale GM, Philippas N (2012): Efficiency evaluation of Greek equity funds. *Research in International Business and Finance*, 26(2):317–33.
- Babalos V, Caporale GM, Kostakis A, Philippas N (2008): Testing for persistence in mutual fund performance and the ex-post verification problem: evidence from the Greek market. *The European Journal of Finance*, 14(8):735–53.
- Babalos V, Kostakis A, Philippas N (2009): Managing mutual funds or managing expense ratios? Evidence from the Greek fund industry. *Journal of Multinational Financial Management*, 19(4): 256–72.
- Basso A, Funari S (2001): A data envelopment analysis approach to measure the mutual fund performance. *European Journal of Operational Research*, 135(3):477–92.
- Berk JB, Green RC (2004): Mutual fund flows and performance in rational markets. *Journal of Political Economy*, 112(6):1269–95.
- Carhart M (1997): On persistence in mutual fund performance. *The Journal of Finance*, 52(1):52–82.
- Caves DW, Christensen LR, Diewert WE (1982b): The economic theory of index numbers and the measurement of input, output and productivity. *Econometrica*, 50(6):1393–1414.
- Charnes A, Cooper W, Lewin AY, Seiford LM (1994): *Data envelopment analysis: Theory, methodology and application*. Springer, Boston.
- Charnes A, Cooper W, Rhodes E (1978): Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6):429–44.
- Chen J, Hong H, Huang M, Kubik J (2004): Does fund size erode performance? The role of liquidity and organization. *American Economic Review*, 94(5):1276–1302.
- Coelli TJ, Rao P, Battese GE (1998): *An Introduction to Efficiency and Productivity Analysis*. Springer, Kluwer Academic Press.
- Cortez R, Paxson DA, Rocha MJ (1999): Persistence in Portuguese mutual fund performance. *The European Journal of Finance*, 5(4):342–65.
- Dahlquist M, Engström S, Söderlind P (2000): Performance and Characteristics of Swedish Mutual Funds. *Journal of Financial and Quantitative Analysis*, 35(3):409–23.
- Daraio C, Simar L (2006): A robust nonparametric approach to evaluate and explain the performance of mutual funds. *European Journal of Operational Research*, 175(1):516–42.

- Del Guercio D, Dann LY, Partch MM (2003): Governance and boards of directors in closed-end investment companies. *Journal of Financial Economics*, 69(1):111–52.
- Del Guercio D, Tkac P (2002): The determinants of the flows of funds of managed portfolios: Mutual funds vs. pension funds. *The Journal of Financial and Quantitative Analysis*, 37(4):523–57.
- Edwards FR, Caglayan MO (2001): Hedge Fund Performance and Manager Skill. *Journal of Futures Markets*, 21(11):1003–28.
- Fama E, French K (2010): Luck versus Skill in the Cross Section of Mutual Fund Returns. *The Journal of Finance*, 65(5):1725–54.
- Farrell MJ (1957): The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society*, 120(3):253–81.
- Feng G, Serletis A (2010): Efficiency, technical change, and returns to scale in large US banks: Panel data evidence from an output distance function satisfying theoretical regularity. *Journal of Banking & Finance*, 34(1):127–38.
- Ferris S, Chance D (1987): The Effects of 12b-1 Plans on Mutual Fund Expense Ratios: A Note. *Journal of Finance*, 42(4):1077–82.
- Ferruz L, Sarto JL, Andreu L (2007): A comparison between German and Spanish equity fund markets. *Journal of Asset Management*, 8(3):147–51.
- Fletcher J, Forbes D (2002): An exploration of the persistence of UK unit trust performance. *Journal of Empirical Finance*, 9(5):475–93.
- Galagedera D, Silvapulle P (2002): Australian mutual fund performance appraisal using data envelopment analysis. *Managerial Finance*, 28(9):60–73.
- Garcia MTM (2010): Efficiency evaluation of the Portuguese pension funds management companies. *Journal of International Financial Markets, Institutions and Money*, 20(3):259–66.
- Geranio M, Zanotti G (2005): Can mutual funds characteristics explain fees? *Journal of Multi-national Financial Management*, 15(4-5):354–76.
- Golec JH (1996): The effects of mutual fund managers' characteristics on their portfolio performance, risk, and fees. *Financial Services Review*, 5(2):133–48.
- Grinblatt M, Titman S (1989): Mutual fund performance: An analysis of quarterly portfolio holdings. *The Journal of Business*, 62(3):393–416.
- Grinblatt M, Titman S (1992): The Persistence of mutual fund performance. *The Journal of Finance*, 47(5):1977–84.
- Grinblatt M, Titman S (1994): A Study of Monthly Mutual Fund Returns and Performance Evaluation Techniques. *The Journal of Financial and Quantitative Analysis*, 29(3):419–44.
- Grossman S, Stiglitz S (1980): On the impossibility of informational efficient markets. *The American Economic Review*, 70(3):393–408.
- Ippolito RA (1989): Efficiency with costly information: A study of mutual fund performance 1965–1984. *The Quarterly Journal of Economics*, 104(1):1–22.
- Jensen M (1968): The performance of mutual funds in the period 1945–64. *The Journal of Finance*, 23(2):389–416.
- Koh F, Koh W, Teo M (2003): Asian hedge funds: Return persistence, style, and fund characteristics. *Singapore Management University, School of Business, Working Paper*.
- Koopmans TC (1951): An analysis of Production as Efficient Combination of Activities. In: Koopmans TC (Ed.): *Activity Analysis of Production and Allocation*. Cowles Commission for Research in Economics, Monograph no. 13. New York.
- Korkeamaki T, Smythe T (2004): An empirical analysis of Finnish mutual fund expenses and returns. *European Financial Management*, 10(2):413–38.
- Lehman B, Modest D (1987): Mutual fund performance evaluation: A comparison of benchmarks and benchmark comparisons. *The Journal of Finance*, 42(2):233–26.
- Lintner J (1965): The Valuation of risky assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, 47(1):13–37.

- Lozano S, Gutierrez E (2008): Data envelopment analysis of mutual funds based on second-order stochastic dominance. *European Journal of Operational Research*, 189(1):230–44.
- Markowitz H (1952): Portfolio selection. *The Journal of Finance*, 7(1):77–91.
- Murthi BPS, Choi Y (2001): Relative performance evaluation of mutual funds: A non-parametric approach. *Journal of Business Finance & Accounting*, 28(7-8):853–76.
- Murthi BPS, Yoon K, Choi DP (1997): Efficiency of mutual funds and portfolio performance measurement: A non-parametric approach. *European Journal of Operational Research*, 98(2): 408–18.
- Nemoto J, Goto M (2005): Productivity, efficiency, scale economies and technical change: A new decomposition analysis of TFP applied to the Japanese prefectures. *Journal of the Japanese and International Economies*, 19(4):617–34.
- Otten R, Bams D (2002): European mutual fund performance. *European Financial Management Journal*, 8(2):75–101.
- Prather L, Bertin WJ, Henker T (2004): Mutual fund characteristics, managerial attributes, and fund performance. *Review of Financial Economics*, 13(4):305–26.
- Perold AF, Salomon RS (1991): The Right Amount of Assets under Management. *Financial Analysts Journal*, 47(3):31–39.
- Renneboog L, Horst JK, Zhang C (2008): The price of ethics and stakeholder governance: The performance of socially responsible mutual funds. *Journal of Corporate Finance*, 14(3): 302–322
- Romacho JC, Cortez MC (2006): Timing and selectivity in Portuguese mutual fund performance. *Research in International Business and Finance*, 20(3):348–68.
- Sengupta J (2003): Efficiency tests for mutual fund portfolios. *Applied Financial Economics*, 13(12): 869–76.
- Sharpe WF (1964): Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–42.
- Sharpe WF (1966): Mutual fund performance. *Journal of Business*, 39(S1):119–38.
- Solow R (1957): Technical Change and the Aggregate Production Function. *Review of Economics and Statistics*, 39(3):312–20.
- Steri R, Giorgino M, Viviani D (2009): The Italian hedge funds industry: An empirical analysis of performance and persistence. *Journal of Multinational Financial Management*, 19(1):75–91.
- Tavakoli Baghdadabad MR (2013): The effects of drawdown risk reduction on the US hedge funds. *Journal of Derivatives & Hedge Funds*, 19(1):50–73.
- Tavakoli Baghdadabad MR, Habibi Tanha F, Halid N (2013): The Efficiency Evaluation of Mutual Fund Managers based on DARA, CARA, IARA. *Journal of Business Economics and Management*, 14(4):677–95.
- Tobin J (1958): Liquidity preference as behavior towards risk. *Review of Economic Studies*, 25(2): 65–86.
- Tornqvist L (1936): The Bank of Finland's Consumption Price Index. *Bank of Finland Monthly Bulletin*, 10(1):1–8.
- Treynor J (1965): How to rate management of investment funds. *Harvard Business Review*, 43(1): 63–75.
- Treynor JL, Mazuy K (1966): Can mutual funds Outguess the market? *Harvard Business Review*, 44(4):131–6.
- Tufano P, Sevick M (1997): Board structure and fee-setting in the U.S. mutual fund industry. *Journal of Financial Economics*, 46(3):321–355.
- Yuan R, Xiao JZ, Zou H (2008): Mutual funds' ownership and firm performance: Evidence from China. *Journal of Banking & Finance*, 32(8):1552–65.