ASSESSING MUTUAL FUNDS PERFORMANCE USING DATA ENVELOPMENT ANALYSIS

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ABSTRACT

This study illustrates the use of data envelopment analysis to benchmark mutual funds on the basis of risk-adjusted performance, load, 12b-1 plan, and expense ratios. Using the DEA methodology, we calculate an efficiency score for 189 funds on a scale of 1 to 100 by maximizing twelve month total return and minimizing beta, standard deviation, load, 12b-1 charges, and expense ratios. This study benchmarks a mutual fund on the basis of risk-adjusted performance, load, 12b-1 plan, and expense ratio so that investor can select best performing funds on a broader basis rather than just the performance.

Keywords: Mutual Funds, Efficiency, Data Envelopment Analysis

INTRODUCTION

Usually, in the selection of a mutual fund, investors consider historic performance, risk, the investment objective of the fund, and/or the investment manager's style. However, there is no evidence to support positive performance persistence as being more useful than prior performance as a fund selection tool. Studies by Jensen (1968), McDonald (1974), and Crenshaw (1977) do not find evidence of superior performance by open-end mutual funds. Kon and Jen (1979), Chang and Lewellen (1984), and Lee and Rahman (1990) find limited success by fund managers who practice market timing and selectivity.
In recent years, academic studies and the popular press have stressed the importance of examining a fund's expense structure, because expenses directly affect fund returns. Studies by Malkiel (1995), Malhotra and McLeod (1997), and Livingston and O'Neal (1996, 1998) highlight the significance of expenses in selecting an open-end fund. However, we cannot simply select funds on the basis of expense ratios alone, because academic studies also show that there is no relation between expense ratios and performance of a fund.

Therefore, there is need to select efficient mutual funds based on investment objective, performance, risk, and expense ratio of a fund. In this study, we use data envelopment analysis (DEA) models to separate efficient mutual funds from the inefficient funds on the basis of performance, risk, 12b-plan fees, load, and expense ratio. DEA approach will help us benchmark a mutual fund on a relative basis instead of absolute performance measurement as given by traditional performance measurement measures. Also, we will be able to include the cost of owning a mutual fund share in the form of a fund's expense ratio, load charges, 12b-1 charges as an input variable in addition to fund's objective, return and risk as measured by beta of the fund and standard deviation of the fund.
Mutual funds have of course been popular investment vehicles. The Investment Company Institute publishes historical statistics about mutual funds. According to these statistics, the first U. S. mutual

fund was established in 1924. Since that time, the number of mutual funds increased to 8,545 at the end of 2010 with assets under management of $13.1 trillion. These numbers includes equity, bond, money market, and hybrid funds. The number of U.S. households owning mutual fund shares reached 51.6 million in 2010, which is nearly one-half the total (44% of the U.S. households). Therefore, it is extremely important that investors should be able to distinguish between efficient and inefficient mutual funds. Our study will also help mutual fund manager benchmark their funds against other funds in the same fund family as well as against the competition and help improve performance of the fund.

The rest of the study is organized along the following lines. In section II, we discuss previous studies on fund performance as well as on the use of data envelopment analysis models in financial analysis. Section III provides the model used in this study. Section IV discusses the data source and methodology used in this study. In section V, we provide an empirical analysis of our results. Section VI summarizes and concludes our study.

LITERATURE REVIEW

Numerous studies have analyzed the operating efficiency of firms using data envelopment analysis models. Hung, Lu, and Wang (2010) explore the operating efficiency, the scale efficiency targets, and the variability of DEA efficiency estimates of Asian container ports. Joo, Min, Kwon, and Kwon (2010) use data envelopment analysis to assess the operating efficiency of specialty coffee retailers from the perspective of socially responsible global sourcing. They evaluate the impact of socially responsible sourcing on the operating efficiencies of specialty coffee retailers before and after implementing fair-trade practices. Their study also compares the operating efficiencies of fair-trade coffee retailers to those of non-fair-trade coffee retailers. Hung and Lu (2008) study applies the Data Envelopment Analysis (DEA) approach with the classical radial measure, non-radial efficiency measure and efficiency achievement measure, respectively, combining multiple outputs and inputs to measure the magnitude of performance differences between the IC firms. Shimshak and Lenard (2007) present a Two-Model approach for including quality measures in DEA studies. This approach allows decision-makers to evaluate two models simultaneously, one measuring operational efficiency and the second measuring quality efficiency. This new method selects only DMUs that are efficient in both operational and quality measures to be members of the benchmark set. Their study demonstrates the Two-Model DEA approach using data from the nursing home industry. Lu, Yang, Hsiao, and Lin (2007) study uses the CCR model of Data Envelopment Analysis (DEA) and the slack variable analysis to evaluate the operating efficiency of the domestic banks in Taiwan from 1998 to 2004. Using data from the Annual Survey of Hospitals compiled by the Department of Health in Taiwan for years 1994 through 1997, Chang, Chang, Das, and Li (2004) use Data Envelopment Analysis (DEA) to evaluate the impact of a National Health Insurance (NHI) Program on the operating efficiency of district hospitals in Taiwan. Anderson, Fok, Springer, and Webb (2002) measure the technical efficiency and economies of scale for real estate investment trusts (REIT) by employing data envelopment analysis (DEA). Using data from the National Association of Real Estate Investment Trusts (NAREITs) for the years 1992-1996, they report that REITs are technically inefficient, and the inefficiencies are a result of both poor input utilization and failure to operate at constant returns to scale. Golany, Roll, and Ryback (1994) study applies data envelopment analysis (DEA) for measuring and evaluating the operating efficiency of power plants in the Israeli Electric Corporation is discussed.

A large number of studies have examined mutual fund performance using data envelopment analysis approach. Chehade (1998) uses production models based on DEA methodology to evaluate the performance of Canadian mutual funds by computing efficiency scores. Basso and Funari (2001, 2003) use DEA methodology to develop mutual fund performance index. Anderson, Brockman, Giannikos, and McLeod. (2004) apply DEA models to evaluate real estate mutual funds.

In this paper, we extend previous studies by illustrating the use of DEA models to benchmark the performance of mutual funds in terms of risk-adjusted performance as well as expenses. No previous study has benchmarked mutual funds in terms of return and expenses.

MODEL

The Data Envelopment Analysis Model:
The Data Envelopment Analysis (DEA) (Charnes et al., 1978) is a widely used optimization-based technique that measures the relative performance of decision making units that are characterized by a multiple objectives and/or multiple inputs structure. Data envelopment analysis is a technique used to assess the comparative efficiency of homogenous operating units such as schools, hospitals, utility companies, sales outlets, prisons, and military operations. More recently, it has been applied to banks (Haslem, Scheraga, & Bedingfield, 1999) and mutual funds (Haslem & Scheraga, 2003; Galagedera & Silvapulle, 2002; McMullen & Strong, 1998; Murthi, Choi, & Desai, 1997). It is a powerful technique for measuring performance because of its objectivity and ability to handle multiple inputs and outputs that can be measured in different units. The DEA approach does not require specification of any functional relationship between inputs and outputs, or a priori specification of weights of inputs and outputs. DEA provides gross efficiency scores based on the effect of controllable and uncontrollable factors.

The DEA methodology measures the performance efficiency of organization units called Decision-Making Units (DMUs). This technique aims to measure how efficiently a DMU uses the resources available to generate a set of outputs. The performance of DMUs is assessed in DEA using the concept of efficiency or productivity defined as a ratio of total outputs to total inputs. Efficiencies estimated using DEA are relative, that is, relative to the best performing DMU or DMUs (if multiple DMUs are the most efficient). The most efficient DMU is assigned an efficiency score of unity or 100 percent, and the performance of other DMUs vary between 0 and 100 percent relative to the best performance.

Consider a set of n observations on the DMUs. Let us define the following:

$j = 1,2,\ldots\ldots,n$ DMU.
$i = 1,2,\ldots\ldots,m$ inputs
$r = 1,2,\ldots\ldots,s$ outputs

Each observation, DMU_j, $j = 1,2,\ldots..,n$, uses:

x_{ij} – amount of input i for unit j, $i =1,2,\ldots\ldots,m$ and $j =1,2,\ldots.,n$.
y_{rj} – amount of output r for unit j, $r = 1,2,\ldots..,s$ and $j = 1,2,\ldots.,n$.
u_r – weight assigned to output r, $r = 1,2,\ldots..,s$
v_i – weight assigned to input i, $i =1,2,\ldots\ldots,m$.

The DEA methodology gives a measure of efficiency that is defined as the ratio of weighted outputs to weighted inputs. The most important issue in this method is the assessment of the weights. Charnes et. al. define the efficiency measure by assigning to each unit the most favorable weights. In general, the weights will not be the same for different units. Further, if a unit happens to be inefficient, relative to the others, when most favorable weights are chosen, then it is inefficient, independent of the choice of weights. Given these weights, the efficiency of a DMU in converting the inputs to outputs can be defined as the ratio of weighted sum of output to weighted sum of inputs.

$$\text{Efficiency} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \qquad (3.1)$$

The weights for a DMU are determined using mathematical programming as those that will maximize the efficiency of a DMU subject to the condition that the efficiency of other DMUs (calculated using the same set of weights) is restricted to values between 0 and 1. The weights are chosen that only most efficient units will reach the upper bound of the efficiency measure, chosen as 1. Let us take one of the DMUs, say the o^{th} DMU as the reference DMU under evaluation whose efficiency (E_o) is to be maximized. Therefore, to compute the DEA efficiency measure for the oth DMU, we have to solve the following fractional linear programming model:

$$\max E_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \qquad (3.2)$$

Subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \; j = 1,..,n \qquad (3.3)$$

$u_r \ge \varepsilon$, r = 1,…,s
$v_i \ge \varepsilon$, i = 1,….,m

Where ε is an infinitesimal or non-Archimedean constant that prevents the weights from vanishing (Charnes, et. al., 1994). When we solve the above mathematical program, we get the optimal objective function (3.2) that represents the efficiency of DMU_o. If the efficiency is unity, then the firm is said to be efficient, and will lie on the efficiency frontier. Otherwise, the firm is said to be relatively inefficient. To find the efficiency measure of other DMUs, we have to solve the above mathematical program by considering each of the DMUs as the reference DMU. Therefore, we obtain a Pareto efficiency measure where the efficient units lie on the efficiency frontier (Thanassoulis, 2001). The fractional mathematical programs are generally difficult to solve. To simplify them, we should convert them to a linear program format. The fractional program (3.2), (3.3) can be conveniently converted into an equivalent linear program by normalizing the denominator using the constraint $\sum_{i=1}^{m} v_i x_{io} = 1$. As the weighted sum of inputs is constrained to be unity and the objective function is the weighted sum of outputs that has to be maximized.

$$\max \sum_{r=1}^{s} u_r y_{ro} \qquad (3.4)$$

Subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1, \qquad (3.5)$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \ j = 1,..,n,$$

$$u_r \geq \varepsilon, \ r = 1,\ldots,s$$

$$v_i \geq \varepsilon, \ i = 1,\ldots.,m$$

This model is the CCR (Charnes, Cooper, and Rhodes) model. Similarly, a general input minimization CCR model can be represented as

$$\min \sum_{i=1}^{m} v'_i x_{io} \qquad (3.6)$$

Subject to

$$\sum_{r=1}^{s} u'_r y_{ro} = 1$$

$$\sum_{r=1}^{s} u'_r y_{rj} - \sum_{i=1}^{m} v'_i x_{ij} \leq 0, \ j = 1,..,n, \qquad (3.7)$$

$$u_r \geq \varepsilon, \ r = 1,\ldots,s$$

$$v_i \geq \varepsilon, \ i = 1,\ldots.,m$$

According to the basic linear programming, every linear programming problem (usually called the primal problem) has another closely related linear program, called its dual. Therefore, the dual of the output maximizing DEA program is as follows:

$$\theta^* = \min \theta \qquad (3.8)$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \ i = 1,\ldots.,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \ r = 1,\ldots,s \qquad (3.9)$$

$$\lambda_j \geq 0,$$

$$\theta \text{ unrestricted.}$$

If $\theta^* = 1$, then the current input levels cannot be reduced, indicating that DMU_o is on the frontier. Otherwise, if $\theta^* < 1$, then DMU_o is dominated by the frontier. θ^* represents the input-oriented efficiency score of DMU_o. The individual input reduction is called slack. In fact, both input and output slack values may exist in model (3.8)

$$s_i^- = \theta^* x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \quad i = 1,\ldots.,m$$

$$s_r^+ = \sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro}, \quad r = 1,\ldots,s \qquad (3.10)$$

To determine the possible non-zero slacks after solving the linear program (3.8), we should solve the following linear program:

$$\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$

subject to

$$\begin{aligned} &\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta^* x_{io},\ i = 1,\ldots,m \\ &\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro},\ r = 1,\ldots,s \qquad (3.11) \\ &\lambda_j \geq 0, \\ &\theta \text{ unrestricted.} \end{aligned}$$

DMU_o is efficient if and only if $\theta^* = 1$ and $s_i^{-*} = s_r^{+*} = 0$ for all i and r. DMU_o is weakly efficient if and only if $\theta^* = 1$ and $s_i^{-*} \neq 0$ and (or) $s_r^{+*} \neq 0$ for some i and r. In fact models (3.8) and (3.9) represent a two-stage DEA process that can be summarized in the following DEA model:

$$\min\ \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

subject to

$$\begin{aligned} &\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io},\ i = 1,\ldots,m \\ &\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro},\ r = 1,\ldots,s \qquad (3.12) \\ &\lambda_j \geq 0, \\ &\theta \text{ unrestricted.} \end{aligned}$$

Table 1: Generalized DEA Models

Frontier	Type	Input-Oriented	Output-Oriented
		$\text{Min } \theta - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)$	$\text{Max } \phi - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)$
Subject to		$\sum_{i=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}\ i=1,2,\ldots,m$	$\sum_{i=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}\ i=1,2,\ldots,m$
CRS		$\sum_{j=1}^{n} \lambda_j x_{rj} + s_r^+ = y_{ro}\ r=1, 2,\ldots,s$;	$\sum_{j=1}^{n} \lambda_j y_{rj} + s_r^+ = \phi y_{ro}\ r=1,2,\ldots,s;$
		$\lambda_j \geq 0 \quad j=1,2,\ldots n$	$\lambda_j \geq 0 \quad j=1,2,\ldots n;$
		VRS: Add $\sum_{j=1}^{n} \lambda_j = 1$; NIRS: Add $\sum_{j=1}^{n} \lambda_j \leq 1$;	NDRS: Add $\sum_{j=1}^{n} \lambda_j \geq 1$

Where s are the slack variables; x represents input variables; y represent output variables; λ is a scalar factor, and θ and ϕ represent efficiency score of a DMU.

DATA AND METHODOLOGY

The data for this study is from Morningstar Principia. The data set is for March 2011. Our annual data for each fund includes investment objective, twelve month total return, fund's beta, fund's three-year annualized standard deviation, front-end load, deferred load (percent), 12b-1 plans cost (percent), and fund's audited expense ratio (percent). We choose mutual funds with prospectus objective of aggressive growth. There are a total of 189 mutual funds for which the data is available. Table 1 provides a summary statistics of the data used in this study.

Besides the mathematical and computational requirements of the DEA model, there are many other factors that affect the specifications of the DEA model. These factors relate to the choice of the DMUs for a given DEA application, selection of inputs and outputs, choice of a particular DEA model (e.g. CRS, VRS, etc.) for a given application, and choice of an appropriate sensitivity analysis procedure (Ramanathan, 2003). Due to DEA's non parametric nature, there is no clear specification search strategy. However, the results of the analysis depend on the inputs/outputs included in the DEA model. There are two main factors that influence the selection of DMUs – homogeneity and the number of DMUs. To successfully apply the DEA methodology, we should consider homogenous units that perform similar tasks, and accomplish similar objectives. In our study, the mutual funds being of the same objective are homogenous. Furthermore, the number of DMUs is also an important consideration. In addition, the number of DMUs should be reasonable so as to capture high performance units, and sharply identify the relation between inputs and outputs. The selection of input and output variables is the most important aspect of performance analysis using DEA. In general, the inputs should reflect the level of resources used or a factor that should be minimized. The outputs reflect the level of the economic variable factor, and the degree to which an economic variable contributes to the overall strength (efficiency) of a company.

To study the efficiency of the mutual funds, we consider four factors to develop the DEA model: a mutual fund's twelve month total return, load, 12b-1 plan charges, and expense ratios. Out of these four factors, we specify a mutual fund's load, 12b-1 plan charges, and expense ratios as input, because for a given fund the lower these variables are the better the performance of the fund is. Similarly, a high mutual fund's twelve month total return implies a better-performing fund. Thus, we consider this variable as output variables. Finally, the choice of the DEA model is also an important consideration. We should select the appropriate DEA model with options such as input maximizing or output minimizing, multiplier or envelopment, and constant or variable returns to scale. DEA applications that involve inflexible inputs or not fully under control inputs should use output-based formulations. On the contrary, an application with outputs that are an outcome of managerial goals, input-based DEA formulations are more appropriate. In addition, for an application that emphasizes inputs and outputs, we should use multiplier version. Similarly, for an application that considers relations among DMUs, envelopment models are more suitable. Furthermore, the characteristics of the application dictate the use of constant or variable returns to scale. If the performance of DMUs depends heavily on the scale of operation, constant returns to scale (CRS) is more applicable, otherwise variable returns to scale is a more appropriate assumption.

In our study, the coparative evaluation among the mutual funds is an important consideration. Therefore, we select the envelopment models for our analysis. In addition, the outputs are an outcome of managerial goals. Therefore, output-based formulation is recommended for our study. The objective of the analysis is to suggest a benchmark for the mutual funds, to investigate the effect of scale of operations, if any, among the 189 funds. Therefore, we consider variable returns to scale DEA model. Also, the structure of the DEA model (in envelopment form) uses an equation and separate calculation for every input and output. Therefore, all the input and output variables can be used simultaneously and measured in their own units. In this study, we use the Output-Oriented Variables Return to Scale (VRS) to evaluate the efficiency of mutual funds under study.

EMPIRICAL ANALYSIS

Each of the mutual funds is a homogenous unit, and we can apply the DEA methodology to asses a comparative performance of these funds. The study evaluates the efficiency of the funds that maximize the twelve month total return and minimize a mutual fund's load, 12b-1 plan charges, and expense ratios. Using the DEA methodology, we calculate an efficiency score for 189 funds on a scale of 1 to 100. We analyzed and computed the efficiency of the funds with data for the March, 2011. Table 1 illustrates the efficiency scores and the rankings of the 189 funds as of March, 2011. As illustrated in table 1, VALIC Company II Agrsv Growth Lifestyle, Transamerica Asset Allc Interm Horizon, Delaware Pooled Core Focus Fixed Income, First Investors Special Situations A LW, BlackRock Aggressive Gr Prepared Instl, Wasatch Long/Short, Invesco Dynamics Y, and Perkins Discovery are 100% efficient., and rest of the funds are less than 100% efficient. JPMorgan Growth Advantage Sel, MassMutual Select Aggressive Growth Y, American Century Vista A, American Century Vista A Load Waived, First Investors Special Situations B, MFS Aggressive Growth Allocation 529A, MFS Aggressive Growth Allocation 529A LW, Maxim Aggressive Profile II, and Alger Growth Opportunities C are 99% efficient, and so on. Similarly, SunAmerica Focused Gr B and SunAmerica Focused Gr C are 72% efficient. Midas Special is least efficient at 68% efficiency level at 182nd rank.

Figure 1 illustrates the efficiency factor of 189 funds. The pareto-efficient funds on the efficiency frontier are 100% efficient, and the inefficient funds, below the efficiency frontier, are less than 100% efficient. We present the score in percentage value varying between 0% and 100%. We find that efficiency of VALIC Company II Agrsv Growth Lifestyle, Transamerica Asset Allc Interm Horizon, Delaware Pooled Core Focus Fixed Income, First Investors Special Situations A LW, BlackRock Aggressive Gr Prepared Instl, Wasatch Long/Short, Invesco Dynamics Y, and Perkins Discovery is 100%. On the other hand, rest of the funds rank from 2 to 182 in the order of decreasing efficiency. Figure 2 illustrates the efficiency frontier formed by 100% efficient mutual funds. All the less efficient funds lie below the efficiency frontier. This means that the observed level of total 12 month return of JP Morgan Growth Advantage is .99 times the maximum output level that JP Morgan Growth Advantage can secure with its current beta (3 year), standard deviation (3 year), audited expense ratio, front load, deferred load, and 12b-1 current value. The same rationale applies to the rest of the funds.

As 180 funds are inefficient relative to VALIC Company II Agrsv Growth Lifestyle, Transamerica Asset Allc Interm Horizon, Delaware Pooled Core Focus Fixed Income, First Investors Special Situations A LW, BlackRock Aggressive Gr Prepared Instl, Wasatch Long/Short, Invesco Dynamics Y, and Perkins Discovery in Mrach, 2011; the next step is to identify the efficient peer group or funds whose operating practices can serve as a benchmark to improve the performance of these funds.
Table 2 illustrates the peer group for the inefficient countries.

As shown in the table, Delaware Pooled Core Focus Fixed Income, Wasatch Long/Short, and First Investors Special Situations A LW serve as peer for Western Asset Absolute Return I. In addition, Western Asset Absolute Return I is more comparable to Delaware Pooled Core Focus Fixed Income (weight 72%), less comparable to its distant peer First Investors Special Situations A LW (27%), and even less comparable to Wasatch Long/Short (1%). Thus, Delaware Pooled Core Focus Fixed Income should scale up its current beta (3 year), standard deviation (3 year), audited expense ratio, front load, deferred load, and 12b-1 current value factors to make them comparable with Delaware Pooled Core Focus Fixed Income. Similarly, Reaves Select Research Instl has First Investors Special Situations A LW (83%) as the closest peer that it should emulate, VALIC Company II Agrsv Growth Lifestyle (9%) as its next distant peer, Transamerica Asset Allc Interm Horizon (7%) as its far distant peer, and Wasatch Long/Short (1%) as its farthest distant peer. Similarly, we can use the most highly weighted peers of all other inefficient funds to assess their relative efficiency performance and make decisions regarding what factors to change in comparison to the closest peers. Although, we list the efficiency score of Invesco Dynamics Y and Perkins Discovery as 100%, their efficiency level is 1.00129 and 1.00191 respectively, so these funds are not exactly on the efficiency frontier but very near to the frontier and therefore have corresponding peer funds.

First Investors Special Situations A LW serves as the closest peer, and the second closest peer for all the inefficient funds. Similarly, BlackRock Aggressive Gr Prepared Instl serves as the most immediate or immediate peer for most of the inefficient funds. On the other hand, Delaware Pooled Core Focus Fixed Income is the immediate peer or the distant peer for some of the inefficient funds. Similarly, Wasatch Long/Short is the distant peer for some of the inefficient funds. VALIC Company II Agrsv Growth Lifestyle is the distant peer or the farther distant peer for a small number of the inefficient funds. Finally, Transamerica Asset Allc Interm Horizon is farthest distant peer for three of the inefficient funds. Therefore, First Investors Special Situations A LW is the most efficient fund among all the funds under study as not only is the First Investors Special Situations A LW 100% efficient, but it also serves as the role model for all funds. Similarly, BlackRock Aggressive Gr Prepared Instl is also the next most efficient fund among the group of funds under study. The efficient peer funds have a similar mix of input-output levels to that of the corresponding inefficient funds, but at more absolute levels. The efficient funds generally have lower input levels relative to the fund in question. The features of efficient peer funds make them very useful as role models inefficient funds can emulate to improve their performance. Furthermore, First Investors Special Situations A LW is used as an efficient peer to all Pareto-inefficient funds, so its frequency of use as an efficient-peer, expressed as a percentage of the number of pareto-inefficient countries, is 100%. BlackRock Aggressive Gr Prepared Instl is an efficient peer to 103 of inefficient funds with a frequency rate of 58%. Wasatch Long/Short and Delaware Pooled Core Focus Fixed Income is an efficient peer to 30 funds with net percentage of 16%. In addition, VALIC Company II Agrsv Growth Lifestyle has the peer efficiency frequencies of 13%. Finally, Transamerica Asset Allc Interm Horizon has a benchmarking factor of 2%. Thus, we have enhanced confidence that First Investors Special Situations A LW is the most outperforming mutual fund followed by BlackRock Aggressive Gr Prepared Instl as they outperform all the other funds. Furthermore, these funds are more likely to be a better role model for less efficient funds to emulate because their operating practices and environment match more closely those of the bulk of inefficient funds. Table 3 displays the benchmarking factor and the hit percentage of efficient fund.

After calculating the efficiency of a fund using DEA, and identifying the efficient peers, the next step in DEA analysis is feasible expansion of the output or contraction of the input levels of the fund within the possible set of input-output levels. The DEA efficiency measure tells us whether or not a fund can improve its performance relative to the set of funds to which it is being compared. Therefore, after maximizing the output efficiency, the next stage involves calculating the optimal set of slack values with assurance that output efficiency will not increase at the expense of slack values of the input and output factors. Once efficiency has been maximized, the model does seek the maximum sum of the input and output slacks. If any of these values is positive at the optimal solution to the DEA model that implies that the corresponding output of the fund (DMU) can improve further after its output levels have been raised by the efficiency factor, without the need for additional input. If the efficiency is 100% and the slack variables are zero, then the output levels of a fund cannot be expanded jointly or individually without raising its input level. Further, its input level cannot be lowered given its output levels. Thus, the funds are pareto-efficient with technical output efficiency of 1. If the fund is 100% efficient but one slack value is positive at the optimal solution then the DEA model has identified a point on the efficiency frontier that offers the same level on one of the outputs as fund A in question, but it offers in excess of the fund A on the output corresponding to the positive slack. Thus, fund A is not Pareto-efficient, but with radial efficiency of 1 as its output cannot be expanded jointly. Finally, if the fund A is not efficient (<100%) or the efficiency factor is greater than 1, then the fund in question is not Pareto-efficient and efficiency factor is the maximum factor by which both its observed output levels can be expanded without the need to raise its output. If at the optimal solution, we have not only output efficiency > 1, but also some positive slack, then the output of fund A corresponding to the positive slack can be raised by more than the factor output efficiency, without the need for additional input. The potential additional output at fund A is not reflected in its efficiency measure because the additional output does not apply across all output dimensions. Table 5 illustrates the slack values identified in the next stage of the DEA analysis. The slack variables for 100% efficient funds are zero. Therefore, VALIC Company II Agrsv Growth Lifestyle, Transamerica Asset All c Interm Horizon, Delaware Pooled Core Focus Fixed Income, First Investors Special Situations A LW, BlackRock Aggressive Gr Prepared Instl, Wasatch Long/Short, Invesco Dynamics Y, and Perkins Discovery is 100%. Pareto-efficient as the DEA model has been unable to identify some feasible production point which can improve on some other input or output level. On the other hand, for Western Asset Absolute Return I, decreasing the input level of Audited Expense Ratio by 0.2010 units, will enable the fund to outperform.. Western Asset Absolute Return I can follow Delaware Pooled Core Focus Fixed Income and First Investors Special Situations A LW as its role model and emulate their policies. Similarly, Western Asset Absolute Return FI can reduce its Audited Expense Ratio level by 0.3113 units and 12b-1 Current value by 0.1676 units while maintaining efficient levels equivalent to that of its peers—Delaware Pooled Core Focus Fixed Income and First Investors Special Situations A LW. On the same lines, we can find the slack factors for the underperforming funds Table 4 illustrates the slack values of the relevant factors for inefficient firms.

SUMMARY AND CONCLUSIONS

Using data envelopment analysis approach, this study compared the relative efficiency of aggressive growth mutual funds in terms of risk-adjusted performance, load, 12b-1 plan, and expense ratios. We calculated an efficiency score for 189 funds on a scale of 1 to 100 by maximizing twelve month total return and minimizing beta, standard deviation, load, 12b-1 charges, and expense ratios. There are seven aggressive growth mutual funds that are 100 percent efficient. Other mutual funds were less than 100% efficient. The study also showed the areas in which inefficient mutual funds are lagging behind and how they can improve their performance to bring them at par with other efficient mutual funds.

The data envelopment analysis is a powerful technique for performance measurement. The major strength of DEA is its objectivity. DEA identifies efficiency ratings based on numeric data as opposed to subjective human judgment and opinion. In addition, DEA can handle multiple input and outputs measured in different units. Also, unlike statistical methods of performance analysis, DEA is non-parametric, and does not assume a functional form relating inputs and outputs.

However, as with any other study, this study using DEA has certain limitations (Ramanathan, 2003). The application of DEA involves solving a separate linear program for each DMU. Thus, the use of DEA can be computationally intensive. In addition, as DMU is an extreme point technique, errors in measurement can cause significant problems. DEA efficiencies are very sensitive to even small errors, thus making sensitivity analysis an important component of post-DEA procedure. Also, as DEA is a non-parametric technique, statistical hypothesis tests are difficult to apply. Therefore, further extension of this study would be to perform principal component analysis of the all the DEA model combinations. Furthermore, we can also use logistic regression to test the validity of the results.

TABLES, FIGURES, & REFERENCES

Tables, figures, references, and full paper available upon request from the authors.