Mutual fund performance evaluation: a value efficiency analysis approach

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Abstract: Data envelopment analysis (DEA) is an efficient tool for evaluating mutual fund performance. It is important for investors to select the best funds for investment. In evaluation of mutual fund performance, besides quantitative elements, there are many qualitative elements that are of importance to the investors. In this paper, value efficiency analysis (VEA) was used in mutual funds performance evaluation to incorporate the investor’s judgements about qualitative elements into the evaluation. Also, the results of this approach were compared with those of general DEA models. This approach is based on choosing convenient variables (inputs and outputs) by reviewing the past studies. Then the input/output data are analysed using the concept of value efficiency, a novel procedure for incorporating the decision maker’s preferences into DEA via the most preferred solution (MPS).

Keywords: DEA; data envelopment analysis; value efficiency; mutual fund.


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1 Introduction

The first question the investor will want to address is the question of performance. What is good and what is poor performance. With a lot of Mutual Funds now available, investors need efficient tools to select the best funds to invest in. Performance measurement and comparison of funds have become an important issue for both managers and investors in the finance industry, and hence there is a pressing need for a credible measure for assessing and ranking the performance of these funds.

Since the seminal works of Sharpe (1964, 1966), Treynor (1965) and Jensen (1968), numerous studies have been concerned with measuring performance in two dimensions, risk and return, mainly using the capital asset pricing model (CAPM). In capital assets pricing models, the boundary of the attainable set of portfolios gives a benchmark relative to which the efficiency of a portfolio can be measured.

There is a growing body of studies that apply efficiency and productivity techniques for evaluating the performance of mutual funds. Studies applying the parametric approach in frontier analysis to mutual funds include Briec and Lesourd (2000), where an application of the stochastic parametric approach is provided, and Annaert et al. (2003) which apply the stochastic Bayesian approach (Van den Broeck et al., 1994).

Among the non-parametric approaches, studies have recently adopted data envelopment analysis (DEA) developed by Charnes et al. (1978, 1979), which is a methodology extensively used to estimate production frontiers for assessing mutual fund performance; this methodology is discussed in the next sections. Contrary to other performance measures, the DEA technique has the ability to incorporate many factors that are associated with fund performance in addition to the usual risk and return measures. Also DEA can offer investors a useful instrument for ranking mutual funds by self-appraisal and peer group appraisal.
The original DEA models are value-free. Efficiency evaluation is based on the data available without taking the decision-maker’s (DM) preferences into account. All efficient DMUs are considered equally ‘good’. However, if the efficient units are not equally preferred by the DM, it is necessary to somehow incorporate the DM’s judgements or a priori knowledge into the analysis. Halme et al. (1999) introduces value efficiency analysis (VEA), a way to incorporate preference information into DEA. In this paper, the use of VEA in mutual funds performance evaluation is proposed to incorporate the decision maker’s judgements (preferences) or a priori knowledge into the evaluation (decision maker, in this paper, can be investors, specialists, managers or any person or group but our focus are investors). Also the results of this approach are compared with those of general DEA models.

This paper consists of four sections. Section two describes DEA methodology, its applications in the performance evaluation of funds and VEA. In Section 3, VEA is applied to the evaluation of mutual funds performance. In this section, basic DEA models are also ran and their results are compared with the VEA result. A discussion of the data set used and the variables considered in this study is provided in this section. Section 4 concludes the paper.

2 Literature review

2.1 Data envelopment analysis

DEA is a standard non-parametric approach to productivity analysis, especially to relative efficiency analysis of decision-making units (DMUs). Since the introduction of the first DEA model CCR in 1978, it has been widely used in efficiency analysis of many business and industry evaluation procedures. The most well-known DEA models are the CCR model (Charnes et al., 1978), the BCC model (Banker et al., 1984) and the Super Efficiency model (Andersen and Petersen, 1993). The CCR and BCC models require choosing the orientation which directs movement to the efficient surface. An input orientation focuses on proportional decrease in the input vector while the output orientation seeks to maximise the proportional increase in the output vector. For more details about these models, you can see Appendix. In this Appendix, CCR-input oriented (I) and super efficiency (CCR-I base) models are illustrated. Furthermore, in this Appendix, DEA models introduced by Morey and Morey (1999), and Joro and Na (2006) are also presented. They used this model in mutual fund performance evaluation. In Section 3, these DEA models are used and their results are compared with the result of our VEA.

In this paper, output-oriented BCC models are only addressed. In BCC models, the efficiency of a DMU is determined by maximising outputs subject to given input levels. It is believed that in our context the BCC model is more suitable than the CCR model, because it allows variable returns to scale. The output oriented BCC-model is given in equation (1).
\[
\begin{align*}
\text{Max } Z_\phi &= \phi_p + \epsilon \left[ \sum_{j=1}^n \lambda_j x_{ij}^{+} + \sum_{j=1}^n S_j^{+} \right] \\
\text{S.t.: } & \quad \sum_{j=1}^n \lambda_j x_{ij}^{+} + S_j^{+} = x_{ij} \quad i = 1, 2, \ldots, m \\
& \quad \sum_{j=1}^n \lambda_j y_{ir}^{+} - S_r^{+} = \phi_p y_{ir} \quad r = 1, 2, \ldots, s \\
& \quad \sum_{j=1}^n \lambda_j = 1 \quad \forall \lambda_j \geq 0 \quad j = 1, 2, \ldots, n \\
& \quad S_j^{+}, S_r^{+}, \epsilon \geq 0 \quad \phi_p \quad \text{free} \\
\end{align*}
\]

(1)

where, \(m\) is the number of inputs, \(s\) is the number of outputs, \(n\) is the number of DMUs, \(x_{ij}\) is the input \(i\) in DMU \(j\), \(y_{ir}\) is the output \(r\) in DMU \(j\), \(p\) is the DMU under evaluation, \(\lambda_j\) is the weight of DMU \(j\) in the projection point.

2.2 DEA and funds

A fund is a company that collects people and companies’ financial resources and invests in a portfolio of securities. People who buy shares of a fund are the owners or shareholders. Their investments provide the capital for a fund to buy securities such as stocks and bonds (Hanafizadeh et al., 2009).

In Table 1, you can see studies which apply DEA models to empirically evaluate the performance of mutual funds, exchange traded funds (ETF), ethical funds and more recently hedge funds. In this table, model name and variables of each study are presented. The common point of these works lies in supposing that fund performance is a combination of multiple fund attributes (inputs and outputs). By reviewing these studies, we can see that they generally follow two main goals;

- improving the DEA model which is used evaluating the efficiency of funds
- developing the used variables (input and output) in DEA models for having a complete evaluation of fund’s efficiency.

Here, we describe some of these studies: Basso and Funari (2001) use DEA to evaluate the performance of mutual funds. In this study, The DEA performance indexes for mutual funds proposed represent a generalisation of various traditional numerical indexes and permit to take into account several inputs as well as several outputs.

Joro and Na (2006) have developed a portfolio performance measure based on mean–variance–skewness (MVS) framework by utilising DEA, as a non-parametric efficiency analysis tool. They conclude from their study that the efficiency measures in the MVS case are always as good as or better than in the mean–variance case. This results from the fact that mathematically the MVS model is more constrained.

Lozano and Gutierrez (2008) have combined DEA with stochastic dominance criteria. In this study, six distinct DEA-like linear programming (LP) models are proposed for computing relative efficiency scores consistent (in the sense of necessity) with second
order stochastic dominance (SSD). Their aim is that, being SSD efficient, the obtained target portfolio should be an optimal benchmark for any rational risk-averse investor. Their proposed models are also compared with several related approaches from the literature.

Zhao et al. (2011) propose two quadratic-constrained DEA models for evaluation of mutual funds performance, from a perspective of evaluation based on endogenous benchmarks. In comparison to previous studies, this paper decomposes two vital factors for mutual funds performance, i.e., Risk and return, to define mutual funds’ endogenous benchmarks and give insights and suggestions for managements. The most important conclusion of their study is that the ranking of mutual funds in China depends mostly on system risk control.

Zhao and Yue (2012) investigate a multi-subsystem fuzzy data envelopment analysis (MFDEA) model to evaluate mutual funds management companies’ core competence which is apparently characterised with both qualitative factors and quantitative factors. Their results are based on empirical study of 32 mutual funds management companies in China leads to a meaningful analysis and some management insights. They believed this approach can also be applied to many other hard assessment and evaluation problems.

### Table 1: Studies on measurement fund performance within DEA frameworks

<table>
<thead>
<tr>
<th>R</th>
<th>Studies</th>
<th>Year</th>
<th>Fund Model(s)</th>
<th>Input(s)</th>
<th>Output(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Murthi et al.</td>
<td>1997</td>
<td>MF CCR</td>
<td>SD, expense ratio, turnover, loads</td>
<td>M (gross) return</td>
</tr>
<tr>
<td>2</td>
<td>McMullen and Strong</td>
<td>1998</td>
<td>MF CCR with restricted weights</td>
<td>SD, min investment, expense ratio, loads</td>
<td>M return</td>
</tr>
<tr>
<td>3</td>
<td>Morey and Morey</td>
<td>1999</td>
<td>Quadratic constrained DEA</td>
<td>V</td>
<td>M return</td>
</tr>
<tr>
<td>4</td>
<td>Wilkens and Zhu</td>
<td>2001</td>
<td>HF BCC</td>
<td>SD, percentage of periods with negative returns</td>
<td>M return, S, min return</td>
</tr>
<tr>
<td>5</td>
<td>Basso and Funari</td>
<td>2001</td>
<td>MF CCR</td>
<td>beta, lower semi-V, loads</td>
<td>M return, $d_j$</td>
</tr>
<tr>
<td>6</td>
<td>Tarim and Karan</td>
<td>2001</td>
<td>MF CCR with restricted weights</td>
<td>SD, expense ratio, loads</td>
<td>M return</td>
</tr>
<tr>
<td>7</td>
<td>Choi and Murthi</td>
<td>2001</td>
<td>MF CCR et BCC</td>
<td>SD, expense ratio, turnover, loads</td>
<td>M return</td>
</tr>
<tr>
<td>8</td>
<td>Galagedera and Silvapulle</td>
<td>2002</td>
<td>MF BCC</td>
<td>SD of 1,2,3,5 gross performance, sales charges, operating expenses, min initial investment</td>
<td>1,2,3,5 year gross performance</td>
</tr>
<tr>
<td>9</td>
<td>Haslem and Scheraga</td>
<td>2003</td>
<td>MF CCR(IDEAS[2000] system)</td>
<td>Cash percentage, price Sharpe index to earnings ratio, price to book ratio, total fund assets</td>
<td></td>
</tr>
<tr>
<td>R</td>
<td>Studies</td>
<td>Year</td>
<td>Fund</td>
<td>Model(s)</td>
<td>Input(s)</td>
</tr>
<tr>
<td>----</td>
<td>-------------------------------</td>
<td>------</td>
<td>------</td>
<td>------------------</td>
<td>--------------------------------------------------------------------------</td>
</tr>
<tr>
<td>10</td>
<td>Basso and Funari</td>
<td>2003</td>
<td>MF</td>
<td>CCR</td>
<td>Three brackets of subscription costs, three brackets of redemption cost, two measure of risk</td>
</tr>
<tr>
<td>11</td>
<td>Sengupta</td>
<td>2003</td>
<td>MF</td>
<td>BCC</td>
<td>Beta, expense ratio, turnover, load</td>
</tr>
<tr>
<td>12</td>
<td>Gregoriou et al.</td>
<td>2003</td>
<td>HF</td>
<td>BCC, CE, SE</td>
<td>Lower M, lower semi-V, lower semi-S</td>
</tr>
<tr>
<td>13</td>
<td>Anderson et al.</td>
<td>2004</td>
<td>MF</td>
<td>CCR</td>
<td>SD, sales charge, management expense ratio, minimum initial investment</td>
</tr>
<tr>
<td>14</td>
<td>Chang</td>
<td>2004</td>
<td>MF</td>
<td>Non-standard DEA</td>
<td>SD, Beta, total assets, load</td>
</tr>
<tr>
<td>15</td>
<td>Briec et al.</td>
<td>2004</td>
<td>MF</td>
<td>Quadratic constrained DEA (extended)</td>
<td>V</td>
</tr>
<tr>
<td>17</td>
<td>Kooli et al.</td>
<td>2005</td>
<td>HF</td>
<td>SE</td>
<td>Lower M, lower semi-V, lower semi-S</td>
</tr>
<tr>
<td>18</td>
<td>Joro and Na</td>
<td>2006</td>
<td>MF</td>
<td>Cubic constrained DEA, CCR</td>
<td>V</td>
</tr>
<tr>
<td>19</td>
<td>Nguyen-Thi-Thanh</td>
<td>2006</td>
<td>HF</td>
<td>CCR</td>
<td>SD, excess K</td>
</tr>
<tr>
<td>20</td>
<td>Daraio and Simar</td>
<td>2006</td>
<td>MF</td>
<td>A robust nonparametric approach compared with DEA, FDH</td>
<td>SD, expense ratio, turnover, fund size</td>
</tr>
<tr>
<td>21</td>
<td>Gregoriou</td>
<td>2006</td>
<td>MF</td>
<td>CCR, CE, SE</td>
<td>monthly average SD, small SD</td>
</tr>
<tr>
<td>22</td>
<td>Briec et al.</td>
<td>2007</td>
<td>MF</td>
<td>Cubic constrained DEA</td>
<td>V</td>
</tr>
<tr>
<td>23</td>
<td>lozano and Gutierrez</td>
<td>2008</td>
<td>MF</td>
<td>DEA-like linear programming with second-order stochastic dominance</td>
<td>Six DEA-like model with risk, return and safety</td>
</tr>
<tr>
<td>24</td>
<td>Chu et al.</td>
<td>2010</td>
<td>ETF</td>
<td>Range Directional Measure (RDM)</td>
<td>Downside risk, expense ratio</td>
</tr>
<tr>
<td>25</td>
<td>Tsolas</td>
<td>2011</td>
<td>ETF</td>
<td>A two-stage procedure: 1- GPDF in DEA, 2- Tobit model</td>
<td>Portfolio P/CF ratio, portfolio P/B ratio, total expense ratio</td>
</tr>
</tbody>
</table>
Table 1  Studies on measurement fund performance within DEA frameworks (continued)

<table>
<thead>
<tr>
<th>R</th>
<th>Studies</th>
<th>Year</th>
<th>Fund</th>
<th>Model(s)</th>
<th>Input(s)</th>
<th>Output(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>Zhao et al.</td>
<td>2011</td>
<td>MF</td>
<td>Two quadratic-constrained DEA models</td>
<td>Return deviation V</td>
<td>total return</td>
</tr>
<tr>
<td>27</td>
<td>Zhao and Yue</td>
<td>2012</td>
<td>MF</td>
<td>MFDEA model</td>
<td>1- Subsystem of investment and research: weighted VAR during term 1,</td>
<td>1- number of funds in charge, number of types covered, products innovation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>weighted VAR during term 2, the reverse of fund managers’ average tenure.</td>
<td>speed, weighted return during term 1, weighted return during term 2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2- Subsystem of marketing and service: cost of marketing service</td>
<td>2- scale growth, average initial subscription scale, information service</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>quality, total shares</td>
</tr>
<tr>
<td>28</td>
<td>Rubio et al.</td>
<td>2012</td>
<td>Islamic MF</td>
<td>BCC and input-oriented non-radial model (Russell)</td>
<td>MCG, lower partial momentum0, lower partial momentum4</td>
<td>Max drawdown period, upper partial momentum0, upper partial momentum4</td>
</tr>
<tr>
<td>29</td>
<td>Carlos Matallin et al.</td>
<td>2014</td>
<td>MF</td>
<td>Non-convex counterpart of DEA(FDH) and order-m and order-α partial frontiers</td>
<td>SD daily returns, K daily returns, expense ratio, Beta</td>
<td>Gross return, S daily returns</td>
</tr>
</tbody>
</table>

M = Mean, SD = Standard Deviation, V = Variance, S = Skewness, K = Kurtosis, CE = Cross Efficiency, SE = Super Efficiency.

2.3 Value efficiency analysis

As mentioned before, the original DEA models are value-free. Efficiency evaluation is based on the data available without taking the decision-maker’s (DM) preferences into account. All efficient DMUs are considered equally ‘good’. However, if the efficient units are not equally preferred by the DM, it is necessary to somehow incorporate the DM’s judgements or a priori knowledge into the analysis.

The idea of VEA is to incorporate the DM’s preference information regarding a desirable combination of inputs and outputs into the analysis. VEA is an approach which applies the ideas developed for multiple objective linear programming (MOLP) to DEA. VEA is based on the following assumptions:

- the decision-maker (DM) has a pseudoconcave utility function, which is not known explicitly
- the DM is able to state his or her most preferred solution (MPS) from the technically efficient surface.

The MPS on the efficient frontier is assumed to be the point maximising his or her implicitly known value function. This is in contrast with traditional DEA, which assumes that no output or input is more important than another. As explained in Halme
et al. (1999), in our scheme the preference information is incorporated via the MPS, i.e., a (virtual or existing) DMU on the efficient frontier having the most desirable values of inputs and outputs. Besides weights restrictions, other schemes for incorporating preference information into DEA include target setting (Golany, 1988; Thanassoulis and Dyson, 1992), and adding dummy (artificial) DMUs into the analysis (Thanassoulis and Allen, 1998), (see also Thompson et al., 1986; Allen et al., 1997; Pedraja-Chaparro et al., 1997; Joro et al., 1998; Soleimani-damanek et al., 2012).

The basic idea of VEA is illustrated in Figure 1. There are five units (A, B, C, D and E), which produce two outputs and use the same amount of one input. In Figure 1, the problem has been described in the output space. The efficiency measure for unit D in standard DEA is the ratio: OD/OD. It is desired to evaluate the ratio: OD/OD, but because the value function is unknown, it is not possible. If it is possible to approximate the indifference contour by a tangent, the ratio: OD/OD could be used. As it is not assumed that this is possible in practice, all possible tangents of the contour have to be considered. This leads to the use of the ratio: OD/OD as an approximation to the (true) value efficiency score because this approximation is the best that can be got, this score will be simply called value efficiency score. Note that DD2/OD = 0 for a value efficient unit.

**Figure 1**  Illustration of value efficiency analysis (see online version for colours)

Theoretically the DM is assumed to have a (unknown) pseudoconcave value function \( v(u, u = [y, -x] \in \mathbb{R}^{n+r} \), which is strictly increasing (i.e., strictly increasing in \( y \) and strictly decreasing in \( x \)) and with a (local) maximal value \( v(u^*), u^* = [y^*, -x^*] \in T \), at the MPS \( u^* \), where \( T \) stands for the feasible set.
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VEA can be carried out as easily as standard DEA using linear programming. A DMU is inefficient with respect to any strictly increasing pseudo concave value function \( v(u), u = [y_j - x_i] \) with a maximum at point \( u^* \), if the optimum value \( Z^* \) of the following problem is greater than one:

Note that model (2) is the same as model (1) with one exception. Non-negative constraints referring to the basic \( \lambda \)- and \( z \)-variables with positive values corresponding to the MPS are relaxed. It is important that the MPS really lies on the efficient frontier. Otherwise the solution is unbounded (for a more detailed discussion, see Halme et al., 1999).

\[
\begin{align*}
\text{Max } & \quad Z = \phi_p + \epsilon \left[ \sum_{i=1}^{n} S_i^- + \sum_{s=1}^{m} S_s^+ \right] \\
\text{S.t.: } & \quad \sum_{i=1}^{n} \lambda_i x_i - S_i^+ = x_{op} \quad i = 1, 2, \ldots, m \\
& \quad \sum_{j=1}^{s} \lambda_j y_{op} - S_s^+ = \phi_p \quad r = 1, 2, \ldots, s \\
& \quad \sum_{j=1}^{s} \lambda_j + z \leq 1 \\
& \quad S_i^+, S_s^+, z \geq 0, \phi_p \text{ free} \\
& \quad \lambda_j \geq 0 \quad \text{if } \lambda_j^* = 0 \quad j = 1, 2, \ldots, n \\
& \quad z_j \geq 0 \quad \text{if } z_j^* = 0 \\
\end{align*}
\]

Then \( \text{Efficiency} = \theta_p = \frac{1}{\phi_p} \),

where \( \lambda^* \in \Lambda, z^* \) correspond to the MPS

\[
\begin{align*}
y^* &= \sum_{j=1}^{n} y_{op} \lambda_j^* \\
x^* &= \sum_{j=1}^{n} x_{op} \lambda_j^* \\
\end{align*}
\]

3 Application of VEA in mutual funds

Our approach is illustrated using a data set of 22 mutual funds. Our initial selection criteria for the funds were 5-star Morningstar star rating, Morningstar’s highest category rating, and large market capitalisation as defined by Morningstar. Of the funds meeting the above-mentioned criteria, 19 funds were chosen for which there were dividend-adjusted monthly return data available from January 2005 to December 2007 in the Morningstar. In addition, three larger, well-known funds were added as benchmarks (Fidelity Magellan, Janus, and Vanguard Windsor). A list of funds used is provided in Table 2. Furthermore, it is assumed that the return statistics from the past are a reasonably good predictor of future returns (see www.Morningstar.com).
Table 2

Descriptive statistics and efficiency measures of the mutual funds

<table>
<thead>
<tr>
<th>Ticker</th>
<th>Name</th>
<th>Excess return$^{(i)}$</th>
<th>Variance$^{(i)}$</th>
<th>Skewness$^{(i)}$</th>
<th>CCR</th>
<th>SE</th>
<th>MM</th>
<th>JN</th>
<th>BCC</th>
<th>SE</th>
<th>BCC</th>
<th>SE</th>
<th>VEA</th>
<th>BCC</th>
<th>BCC</th>
<th>BCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALARX</td>
<td>Alger Capital Appreciation Inst I</td>
<td>5.037</td>
<td>12.278</td>
<td>-75.817</td>
<td>0.660</td>
<td>0.660</td>
<td>0.856</td>
<td>0.861</td>
<td>0.713</td>
<td>0.713</td>
<td>0.889</td>
<td>0.889</td>
<td>0.640</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BREAX</td>
<td>BlackRock International Opp A</td>
<td>6.327</td>
<td>36.265</td>
<td>32.075</td>
<td>0.558</td>
<td>0.558</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.604</td>
<td>1.000</td>
<td>2.114</td>
<td>1.000</td>
<td></td>
<td></td>
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<tr>
<td>CHASX</td>
<td>Chase Growth</td>
<td>2.613</td>
<td>9.194</td>
<td>15.640</td>
<td>1.000</td>
<td>1.353</td>
<td>0.453</td>
<td>0.792</td>
<td>1.000</td>
<td>1.000</td>
<td>1.667</td>
<td>1.000</td>
<td>1.419</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EVTMX</td>
<td>Eaton Vance Dividend Builder A</td>
<td>5.554</td>
<td>13.547</td>
<td>2.307</td>
<td>0.907</td>
<td>0.907</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.514</td>
<td>1.000</td>
<td>1.220</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ENIDX</td>
<td>Endowments Growth and Income</td>
<td>2.097</td>
<td>7.530</td>
<td>-13.461</td>
<td>0.596</td>
<td>0.596</td>
<td>0.547</td>
<td>0.738</td>
<td>0.762</td>
<td>0.596</td>
<td>0.599</td>
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<td>0.596</td>
<td>0.529</td>
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<tr>
<td>FNIAX</td>
<td>Fidelity Advisor New Insights A</td>
<td>3.986</td>
<td>8.591</td>
<td>2.749</td>
<td>0.910</td>
<td>0.910</td>
<td>0.877</td>
<td>0.907</td>
<td>0.981</td>
<td>0.981</td>
<td>0.992</td>
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<td>Fidelity Contrafund</td>
<td>3.776</td>
<td>7.614</td>
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<td>1.101</td>
<td>0.921</td>
<td>0.969</td>
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<td>1.107</td>
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<td>Fidelity Magellan</td>
<td>2.628</td>
<td>9.421</td>
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<td>0.505</td>
<td>0.505</td>
<td>0.372</td>
<td>0.410</td>
<td>0.551</td>
<td>0.505</td>
<td>0.541</td>
<td>0.541</td>
<td>0.459</td>
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<td>FMI Large Cap</td>
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<td>0.717</td>
<td>0.717</td>
<td>0.513</td>
<td>0.565</td>
<td>0.827</td>
<td>0.717</td>
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<td>0.717</td>
<td>0.472</td>
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<td>HIADX</td>
<td>Hartford Dividend &amp; Growth HLS IA</td>
<td>2.782</td>
<td>10.110</td>
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<td>0.609</td>
<td>0.609</td>
<td>0.398</td>
<td>0.647</td>
<td>0.632</td>
<td>0.609</td>
<td>0.691</td>
<td>0.691</td>
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<td>JANSX</td>
<td>Janus</td>
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<td>9.171</td>
<td>-30.122</td>
<td>0.481</td>
<td>0.481</td>
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<td>Ticker</td>
<td>Name</td>
<td>Excess return(1)</td>
<td>Variance(2)</td>
<td>Skewness(3)</td>
<td>CCR</td>
<td>SE</td>
<td>MM</td>
<td>JN</td>
<td>BCC</td>
<td>SE</td>
<td>BCC</td>
<td>SE</td>
<td>VEA</td>
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<td>Jensen J</td>
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<td>0.609</td>
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<td>LKCM Equity</td>
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<td>6.294</td>
<td>5.179</td>
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<td>0.717</td>
<td>0.534</td>
<td>0.591</td>
<td>0.863</td>
<td>0.717</td>
<td>0.751</td>
<td>0.717</td>
<td>0.459</td>
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<td>LDFVX</td>
<td>Lord Abbott All Value A</td>
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<td>8.003</td>
<td>-5.030</td>
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<td>0.592</td>
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<td>0.601</td>
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<tr>
<td>MFGFX</td>
<td>Mairs &amp; Power Growth</td>
<td>1.638</td>
<td>10.214</td>
<td>-7.648</td>
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<td>0.323</td>
<td>0.635</td>
<td>0.635</td>
<td>0.635</td>
<td>0.323</td>
<td>0.345</td>
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<td>OARDX</td>
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<td>2.798</td>
<td>8.946</td>
<td>8.775</td>
<td>0.843</td>
<td>0.843</td>
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<td>PRBLX</td>
<td>Parnassus Equity Income – Inv</td>
<td>2.523</td>
<td>4.959</td>
<td>2.833</td>
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<td>0.943</td>
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<td>TGVX</td>
<td>Thornburg International Value A</td>
<td>5.537</td>
<td>18.158</td>
<td>12.079</td>
<td>0.699</td>
<td>0.699</td>
<td>0.917</td>
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<td>1.085</td>
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</tr>
</tbody>
</table>

In this case slacks of efficient funds in all models are zero.

I = Input oriented, O = Output oriented, SE = Super Efficiency, JN = Joro and Na model, MM = Mory and Mory model.

\[
(1) = \mathbb{E}[r(\lambda)], (2) = \mathbb{E}[(r(\lambda) - \mu(\lambda))^2], (3) = \mathbb{E}[(r(\lambda) - \mu(\lambda))^3].
\]
It seems reasonable to conclude from the literature that there is no agreement as to which measures should be used as inputs and outputs for a DEA-based performance measurement of funds (see Table 1). Because investors might have positive preferences for odd moments and negative preferences for even moments, Nguyen-Thi-Thanh (2006) chooses standard deviation and excess kurtosis as inputs and average return and skewness as outputs, and Briec et al. (2007) choose variance as input and mean return and skewness as outputs. Also, Joro and Na (2006) in their MVS framework use variance as input and mean return and skewness as outputs. According to the above-mentioned points, here, variance is chosen as input and mean return and skewness are chosen as outputs (for more detail see Joro and Na, 2006).

At first, it is tried to assess the efficiency of mutual funds using the previous applied models to compare with VEA results, then the application of VEA in efficiency assessing on mutual funds is presented. For this aim, The BCC (input and output oriented), CCR (input oriented), Super Efficiency (CCR and BCC base), Morey and Morey (MM) and Joro and Na (JN) models were used. The results of applying these models in are shown Table 2. The five points below about these results can be interesting: First, all efficiency values of BCC models are more than efficiency values of similar CCR models. Secondly, owing to one added constrain related to skewness, all of efficiency values of JN model is greater than MM model. For example, consider the efficiency values and skewness in CHASX. Thirdly, supper efficiency models are used to rank efficient funds (Considering values greater than 1). Fourthly, in comparing linear model BCC-I with non-linear model JN, in normal situation, all BCC values must be greater than the values of JN. But it is seen that because of creating one or multi Non-convex part in frontier of non-linear model, this action does not appear in several funds (for more details see Joro and Na (2006)). Fifthly, considering the results of our basic model for VEA, namely BCC-O, one can see that seven funds are efficient and two funds have values >0.9. On the basis of Morningstar data and considering investment style, four efficient funds belong to growth funds and three of them belong to blend funds. Besides, two of these seven funds, namely TGVAX and BREAX, belonged to foreign funds.

In evaluation of mutual funds by decision makers, in addition to elements used in DEA as the first three moments of the return distribution, there are many qualitative elements that are important. Samples of These qualitative elements are information asymmetries such as investor’s private information set, types of stocks held by the fund, portfolio management style, domestic or foreign investor, prudency constraints such as overrate risk against return by decision maker or responsibility of fund manager to investors, received money by fund, fund size, fund age, liquidity of fund, fame of fund and many elements that are discussed in behavioural finance approach (for more details, see Badrinath et al., 1989; Gorman, 1991; Zheng, 1999; Lakonishok et al., 1994; Shefrin and Statman, 1995; Del Guercio, 1996; Falkenstein, 1996; Dahlquist et al., 2000; Gompers and Metrik, 2001; Shefrin, 2001; Chan et al., 2002; Drew et al., 2002). Behaviour of decision makers (investors) towards these elements is not same (similar). These qualitative elements cannot be accommodated without incorporating value judgements in the assessment of performance. Thus value function of decision maker must be incorporate in performance evaluation. In DEA, one way to do it, is VEA.

A corresponding VEA of the mutual funds has been performed. As discussed in the body of this paper, the DM’s preferences are incorporated in the efficiency analysis via his or her MPS. Hence, the DM’s MPS must be first identified over the set consisting of all convex combinations of existing mutual funds. We begin by formulating model (3) as
a bi-criteria problem, where we wish to maximise all output variables (mean, skewness) and minimise the input variable (variance):

\[
\begin{align*}
\text{Max} & \quad \sum_{j=1}^{n} \mu_j \lambda_j \\
\text{Min} & \quad \sum_{j=1}^{n} \sigma_j^2 \lambda_j \\
\text{Max} & \quad \sum_{j=1}^{n} \kappa_j \lambda_j \\
\text{S.t.:} & \quad \sum_{j=1}^{n} \lambda_j = 1 \quad \forall \lambda_j \geq 0 \quad j = 1, 2, \ldots, n.
\end{align*}
\]

Model (3) like any multiple objectives linear programming model, has no unique solution. Several MOLP methods can be used to solve the above model. For this purpose, the VIG software is used (Korhonen, 1987). VIG implements Pareto Race, a dynamic and visual free search type of interactive procedure for multiple objective linear programming (for a more detailed discussion, see Korhonen, 1987; Korhonen and Wallenius, 1988).

Figure 2 shows the Pareto Race interface and the final solution at which the search was terminated. This point, which is a convex combination of fund TGVAX and BREAX, was taken as the MPS. The corresponding values of the basic variables are TGVAX (0.2311) and BREAX (0.7689). Both values are positive, and thus the non-negative constraints corresponding to these variables are relaxed in the VEA. Taking this MPS can show that decision maker have a good concept about foreign funds. The results of the VEA are given in the last column of Table 2.

As seen in Table 2, considering these MPS and applying VEA model, decision maker (investor) can affect his value judgements in a manner that are interpreted as special positive attention to foreign funds for ranking of funds.

In VEA result, only four of the seven previously BCC-efficient units remained value efficient. It is also worth noting that all value efficiency scores are at least as good as the corresponding scores of BCC-O. This is intuitively understandable, because the value efficient frontier in a sense covers the BCC-O efficient frontier.
If we consider the values of efficient funds in the supper efficiency (BCC-O) model, we can observe that four efficient funds in VEA, are the same as 4 funds that have been ranked from 1 to 4 in the supper efficiency model (In order: BREAX, CHASX, EVTMX, And TGVAX).

4 Conclusion

The problem addressed in this paper was how value judgement of decision maker (his or her qualitative consideration) can be incorporated into the performance evaluation of mutual funds using DEA models. To this aim, the use of VEA is proposed in this study.

Our approach in based on choosing convenient variables (inputs and outputs) by reviewing the past studies. Then the input/output data are analysed using the concept of value efficiency, a novel procedure for incorporating the DM’s preferences into DEA via the MPS. We have used real data for testing this approach. (Monthly return of 22 US Mutual funds from 2005 to 2007). Results show that VEA have a good performance in cooperating DM’s preferences and judgements into mutual funds performance evaluation.

It may be of interest for decision makers that how the value efficient DMUs (funds) resulting from VEA can be ranked. As future research, we propose to find a DEA-base model which can do this action.

References


Mutual fund performance evaluation: a value efficiency analysis approach


Appendix: Information of DEA models that are used in this paper

<table>
<thead>
<tr>
<th>Model name</th>
<th>CCR (input oriented-primal)</th>
<th>Super efficiency (CCR-I-P base)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Author</td>
<td>Charnes et al. (1978)</td>
<td>Andersen and Petersen (1993)</td>
</tr>
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Assumption Concerning Returns to Scale

<table>
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<tr>
<th>Linear/Non-Linear</th>
<th>Range of EfficiencyScore</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>between 0 and 1</td>
<td>starts with 0, but larger than 1 is possible</td>
</tr>
<tr>
<td>Weakly</td>
<td>0 = 1, S1 = 0 &amp; S2 = 0</td>
<td>Super</td>
</tr>
<tr>
<td>Strong</td>
<td>0 = 1</td>
<td>Efficiency</td>
</tr>
<tr>
<td>i = 1, ..., m</td>
<td>0 = 1, S1 or S2 = 0</td>
<td>0 = 1</td>
</tr>
<tr>
<td>r = 1, ..., s</td>
<td>0 = 1, S1 = 0 or S2 = 0</td>
<td>0 = 1</td>
</tr>
</tbody>
</table>

Model Formulation

\[
\begin{align*}
\text{Max} \quad & \theta_y = \frac{s^+ + s^-}{\sum_{i=1}^n s_i + \sum_{j=1}^m s_j} \\
\text{St:} & \quad \sum_{j=1}^m \lambda_j y_j - s^- = y_y, \quad r = 1, 2, \ldots, s \\
& \quad \sum_{j=1}^m \lambda_j y_j + s^+ = \theta_x y_y, \quad i = 1, 2, \ldots, m \\
& \quad \lambda_j \geq 0, \quad j = 1, 2, \ldots, n \\
& \quad s^+, s^- \geq 0, \quad \theta_x \text{ free}
\end{align*}
\]

Model name | Quadratic constrained DEA | Cubic constrained DEA


Assumption Concerning Returns to Scale

Linear/Non-Linear | Range of EfficiencyScore | Efficiency |
<table>
<thead>
<tr>
<th></th>
<th></th>
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</tr>
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<tbody>
<tr>
<td>Non-Linear</td>
<td>between 0 and 1</td>
<td>starts with 0, but larger than 1 is possible</td>
</tr>
<tr>
<td>Weakly</td>
<td>0 = 1, S1 = 0 or S2 = 0</td>
<td>Super</td>
</tr>
<tr>
<td>Strong</td>
<td>0 = 1, S1 = 0, S2 = 0</td>
<td>Efficiency</td>
</tr>
<tr>
<td>i = 1, ..., m</td>
<td>0 = 1, S1 or S2 = 0</td>
<td>0 = 1</td>
</tr>
<tr>
<td>r = 1, ..., s</td>
<td>0 = 1, S1 = 0 or S2 = 0</td>
<td>0 = 1</td>
</tr>
</tbody>
</table>

Model Formulation

\[
\begin{align*}
\text{MinZ} = & \quad \theta_y = \frac{s^+ + s^-}{\sum_{i=1}^n s_i + \sum_{j=1}^m s_j} \\
\text{St:} & \quad \sum_{j=1}^m \lambda_j r_j - s^+ = \mu_y \\
& \quad \left( \sum_{j=1}^m \lambda_j (r_j - \mu_j) \right) + s_1 = 0, \beta^2_x \\
& \quad \sum_{j=1}^m \lambda_j \geq 0, \quad j = 1, 2, \ldots, n \\
& \quad s_1, s_2 \geq 0, \quad \theta_x \text{ free}
\end{align*}
\]

\[
\begin{align*}
\text{MinZ} = & \quad 0 = \frac{s^+ + s^-}{\sum_{i=1}^n s_i + S_2 + S_3} \\
\text{St:} & \quad \sum_{j=1}^m \lambda_j r_j - s^+ = \mu_y \\
& \quad \left( \sum_{j=1}^m \lambda_j (r_j - \mu_j) \right) + S_1 = 0, \beta^2_x \\
& \quad \sum_{j=1}^m \lambda_j \geq 0, \quad j = 1, 2, \ldots, n \\
& \quad S_1, S_2, S_3 \geq 0, \quad \theta_x \text{ free}
\end{align*}
\]

m: number of inputs, s: number of outputs, n: number of DMUs, s, r_j: input i in DMU, y: output r in DMU, p: DMU and er evaluation, \lambda_j: weight of DMU j in the projection point r_j, \mu_y: excess return of assets, \beta_x: variance of asset under evaluation, \kappa: skewness of asset under evaluation.