Journal of Applied Finance & Banking, vol.2, no.5, 2012, 97-112
ISSN: 1792-6580 (print version), 1792-6599 (online)
Scienpress Ltd, 2012

Mutual Fund Performance Evaluation using Data Envelopment Analysis with Higher Moments

Konstantina Pendaraki[1]

Abstract

The mutual fund industry has experienced huge growth internationally, becoming one of the primary vehicles through which individuals and most institutions invest in capital markets. Thus, the evaluation of the performance of mutual funds has become a very interesting research topic both for academic researchers for managers of financial, banking and investment institutions. This paper proposes Data Envelopment Analysis, a nonparametric approach, for the evaluation of mutual fund performance. This method is applied in both mean-variance and higher moment's framework on data of Greek mutual funds over the period 2007-2010 with encouraging results.

JEL classification numbers: C61, G11, G23
Keywords: Mutual funds, Performance Evaluation, Kurtosis, Skewness, Data Envelopment Analysis

1 Introduction

The traditional portfolio theory developed by Markowitz ([1], [2]), accommodates the portfolio selection problem on the basis of the existing trade-offs of risk and return in the mean-variance context through two basic assumptions: asset returns are normally distributed, and utility function of

[1] Department of Business Administration in Food and Agricultural Enterprises, University of Western Greece, Agrinio, Greece, e-mail: dpendara@cc.uoi.gr

Article Info: *Received* : June 2, 2012. *Revised* : August 8, 2012
Published online : October 15, 2012

expected returns depends only on first two central moments of return's distribution. When both these assumptions are valid, the optimal portfolio for the investor is selected from the set of portfolios which lies on the mean–variance efficient frontier. However, in international literature of the mutual fund performance assessment, there are studies that maintain arguably that portfolio returns are not always normally distributed (see e.g. [3], [4]). Besides, return distributions have the leptokurtic problem, which also has to be taken into account in mutual funds performance evaluation under the risk-return framework [5]. Moreover, other studies prove that investors prefer skewness, or in other words, the utility functions of investors are not quadratic (see e.g. [6], [7]). According to the empirical results of Scott and Horvath [8], the expected utility depends positively on expected return and skewness and negatively on variance and kurtosis.

Despite these problems, on the same mean-variance basis several other approaches for the evaluation of funds portfolios have been developed, including the Capital Asset Pricing Model-CAPM ([9], [10], [11]), the Arbitrage Pricing Theory-APT [12], etc. Additionally, in the empirical literature for the evaluation of the performance of MF portfolios several indices regarding the performance of fund per unit of risk have been proposed. The most well known indices are those of Treynor [13], Sharpe [14], and Jensen [15] which are based on the CAPM.

To solve these problems, a nonparametric approach namely Data Envelopment Analysis (DEA) began to be applied in mutual fund evaluation problem. This approach doesn't need the hypothesis of validity of the capital market while it gives the opportunity to a fund manager to appraise and rank mutual funds in a risk-return framework without using indices. It has also the ability to deal with several inputs and outputs without demanding the precise relation between input and output variables. The usual variables in DEA are such that "more is better for outputs, and less is better for inputs" [16]. Thus, the rule of the Markowitz portfolio selection theory [1] that "the expected return is a desirable thing and the variance of return an undesirable thing" is fully justified through DEA employment.

Studies on Greek mutual funds performance evaluation based on traditional risk returns approaches have been applied by Milonas [17], Philipas [18], Artikis [19], Sorros [20], etc. Moreover, Pendaraki et al. ([21], [22]) and Babalos et al. [23] evaluate Greek MF's performance through multicriteria analysis, while Spanoudakis et al., [24] through argumentation-based decision making theory.

In the present study, DEA, in both mean-variance (MV) and higher moments (HM) framework on data of Greek funds over the period 2007-2010 is applied. The higher moments of fund returns (skewness and kurtosis) used can overcome the aforementioned theoretical difficulties, reflect the preference of investors and are consistent with the distribution of portfolio returns. The main scope of this paper is to analyze the effect of higher moments on DEA efficiency upon the performance of mutual funds.

Studies on Greek mutual fund performance evaluation using DEA are only two, which are based on risk-return measures and expense ratios. Both studies, applied the input minimization analysis through the BCC DEA model [25], for the evaluation of Greek equity mutual funds. Precisely, in 2011, Alexakis and Tsolas [26], incorporated in their models, one input (fund returns) and five outputs (standard deviation, beta coefficient, assets and front-end and back-end loads) over the period 2001-2004. Babalos et al., [27] evaluated the funds total productivity change using the DEA-based Malmquit Index [28] over the period 2003 -2009 and employ the Carhart's [29] risk adjusted return as an output measure and the total expense ratio, the fund's age, the assets, and the standard deviation as inputs. None of them take into account higher moments characteristics of returns in their empirical applications.

The proposed methodological framework incorporates higher moments as variables in DEA to fill a gap in the Greek literature in evaluating the domestic equity funds performance. In the mutual fund evaluation scholarly literature, the high moments are widely used with DEA in order to measure the hedge fund performance ([30], [31], [32], [33], etc.), although, they are not so common on the mutual fund evaluation ([34], [35]).

The rest of the paper is organized as follows. Section two describes the data set and methodology used. Section three presents the obtained results and finally, section four concludes the paper and points out some future directions.

2 Data and Methodology

The industry of collective investments in Greece has been growing rapidly. Today, in Greece, there are 22 mutual funds management companies that manage 310 MFs, with assets rising to 5229.1 million EURO (data as of 31/12/2011; Association of Greek Institutional Investors data).

The sample used in the present study is provided from the Association of Greek Institutional Investors and consists of daily data of domestic equity mutual funds over the period January 2007 to December 2010. In order to eliminate the effect that could be caused by the fact that not all MFs were in operation the whole sample period, daily returns for only 43 domestic equity mutual funds are examined for four different one year periods (the funds for which complete data are available for all sub-periods).

Data Envelopment Analysis introduced by Charnes, Cooper and Rhodes [36], based on the assumption of Constant Returns to Scale, has been proven an effective tool in performance evaluation of entities by indentifying the piecewise linear approximation of their empirical efficient frontier. In the preset study, the BCC (Banker, Charnes and Cooper, 1984 [25]) extension, based to the assumption of Variable Returns to Scale, of the first DEA formulation [36] is applied. Input orientation of BCC-DEA model, whose objective is to minimize the inputs while outputs are kept at least at their current levels, is employed. The DEA model under consideration is specified as follows:

Suppose there are n DMUs (Decision Making Units) with common *m* inputs and *s* outputs. Given these data the efficiency of each DMU_j $(j=1,\ldots,n)$ is part of the optimal solution of the following linear programming problem.

$$
\begin{aligned}
&\min \theta + \varepsilon\left(\sum_{r=1}^{s} s_r^+ + \sum_{i=1}^{m} s_i^-\right) \\
&s.t. \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{rj_0} \qquad r=1,\ldots,s \\
&\sum_{j=1}^{n} x_{ij}\lambda_j - s_i^- = \theta x_{ij_0} \quad i=1,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0, s_r^+ \geq 0, s_i^- \geq 0,\ \varepsilon > 0, \quad \forall j,r,i
\end{aligned}
\tag{1}
$$

where

DMU_{j0} is one of the *n* DMUs under evaluation,

x_{ij_0} and y_{rj_0} are the i_{th} input and the r_{th} output of unit DMU_{jo}, respectively,

λ_j $(j=1,\ldots,n)$ are nonnegative scalars such that $\sum_{j=1}^{n}\lambda_j = 1$ (VRS) and,

s_i^- and s_r^+ represents input and output slack variables, respectively.

The θ^* represents the input-oriented efficiency score of DMU_{jo}. A DMU is efficient if $\theta^*=1$ and all slacks equal zero; otherwise it is inefficient. The presence of the non-Archimedean ε (a very small positive number) in the objective function of (1) allows the minimization over θ to preempt the optimization involving the slacks, during a two-stage process calculation of programme solution. With the value of θ fixed, in a second stage, the slacks are maximized, substituting the θ with the solution of the first stage of the problem [37]. The left hand sides in the constraints define an efficient portfolio (reference set) which is the benchmark for the inefficient fund under evaluation. The scalars in right-hand sides are the inputs and the outputs of the fund under evaluation. Thus the output constrain fix the output level of the efficient portfolio to be the same as those of the fund under evaluation. The theta is a multiplier that indicates the distance from the efficient frontier. For the inefficient funds, a projection point into the efficient frontier is defined. The distance between the evaluated fund and its projection point is the efficiency measure. The slacks variables are used to ensure that the projection point is truly efficient as opposed to weakly efficient. In case there is no truly efficient portfolio in the same output level as the unit under evaluation, the slacks indentify the closest efficient portfolio.

The variables used to evaluate mutual fund performance through DEA model are: (1) the cumulative return; the return on a mutual fund investment includes both income and capital gains or losses, (2) the standard deviation; the variability of daily returns (3) the year-end asset of the examined funds; a proxy of fund's size, mobility and popularity, (4) the skewness of returns; a measure of the symmetry of the distribution of the data (investors prefer positive skewness), and

(5) the kurtosis of returns; a measure of the degree of their peakness (investors oppose excess kurtosis). A more detailed description of the variables used is presented in Appendix.

To analyze the effect of inclusion of higher moments as variables in DEA performance risk – return framework the input oriented DEA model is ran twice. Firstly, standard deviation is considered as input, and returns and assets as outputs (mean-variance framework). In a second run, the kurtosis is added as a second input and skewness as the third output variable (high moment framework). These two measures are very useful for describing the asymmetry, the fat-taildness and the peakdness of funds' return distributions, which make it possible to compute a reasonable and robust risk adjusted indicator of the overall performance of the examined mutual funds.

Except of the consideration of higher central moments of returns, this study is differentiated from the existing Greek literature in two more aspects. Firstly, the variable of net assets is incorporated in the output side of the model, while in the existing Greek literature assets are in the input side of DEA models. But the inclusion of fund's assets as input has drawbacks since penalizes a larger fund relative to a smaller one. Secondly, since the aim of the present study is to examine the effect of higher moments on the DEA performance scores, these scores are calculated net of management expenses, in order to give a clear picture of fund's performance.

3 Empirical Results

To prove if the incorporation of high moments as variables in DEA model is justified, it is applied the Kolmogorov-Smirnov test of normality at the 5% significance level. According to the results of this test, in all the examined periods, return distributions are significantly deviate from normality. In 2007 and 2008, return distributions are not normal (100%) for none of the examined mutual funds, while in 2009 and 2010 there is 32.56% and 62.79% deviation from normality, respectively.

Table 1 reports some useful descriptive statistics of the variables used in the analysis over the period 2007-2010. According to the findings of this Table, the last years, the Greek market has been characterized by major fluctuations, a considerably decline in all stock prices and high liquidity conditions. More precisely, the examined period contain both bull and bear market sub-periods due to the 2008 worldwide financial crisis and 2010 Greek sovereign crisis. Thus, negative returns are presented in 2008 and 2010. Due to the negative returns of these two years, the values of the two traditional indexes, Sharpe and Treynor are also negative and, above all, meaningless, thus they are not incorporated in the present study. Additionally, the volatility of returns, presented by standard deviation, is high over whole period. Furthermore, net asset value (NAV) has a major decrease from 86.409 million euro in 2007 to 30.231 million euro in 2010.

As far as higher moments are concerned, it is obvious that while in 2007 return distributions are skewed on the left, 2010 are skewed on the right. In 2008 and 2009, the examined funds have mixed skewness values. Finally, out of the four years under consideration only 2008 presents, on mean, excessive kurtosis. These findings are due to the general market conditions during the time period of this analysis.

Table 1: Descriptive Statistics of Variables Used

Year		Returns (%)	St. Dev.	Skew	Kurt	NAV (mil. €)
2007	Mean	16.24	15.00	-0.76	2.12	86.409
	Std. dev	3.79	0.94	0.11	0.44	116.218
	Min	7.68	12.13	-1.00	1.39	0.884
	Max	24.15	17.10	-0.53	3.23	474.256
2008	Mean	-58.00	31.28	-0.06	3.02	32.529
	Std. dev	5.11	4.41	0.18	0.70	42.349
	Min	-66.05	21.69	-0.44	1.88	0.282
	Max	-43.30	42.79	0.30	4.71	172.540
2009	Mean	22.30	26.93	-0.21	1.04	41.013
	Std. dev	5.96	3.68	0.11	0.44	51.661
	Min	8.84	19.52	-0.46	0.50	0.219
	Max	36.58	37.54	0.01	3.13	204.894
2010	Mean	-30.51	28.69	0.29	2.22	30.231
	Std. dev	3.38	3.65	0.10	1.08	46.510
	Min	-38.86	22.85	0.09	0.64	0.138
	Max	-22.91	39.71	0.58	5.34	257.645

In order to satisfy the nonnegative requirement of DEA on variables used, it is utilized the translation invariance property of input BCC model, normalizing returns and skewness through the addition of a constant [37].

The detailed results of DEA implementation are presented in Table 2. The traditional two-moment (MV-Mean Variance) and four-moment (HM-High Moment) results are quite different. Moreover, within each year, adding the higher moment's variables in the standard mean-variance framework, the number of efficient funds and the average efficiency are increasing significantly. On average, the mean efficiency score for all years is 80.6 and 90.2, in the MV and HM framework respectively. Finally, on average, the number of efficient funds for all years is 4.8 and 11.3 and the number of inefficient funds is 38.3 and 31.8 in the MV and HM framework respectively. Finally, at least in one of the four years under examination, eighteen inefficient funds in the mean variance framework, find themselves in the high moments efficient frontier (e.g. # 1, 2, 3).

Table 2: Efficiency Results of DEA Models

Mutual Fund	MV – BCC Efficiency				HM– BCC Efficiency			
	2007	2008	2009	2010	2007	2008	2009	2010
MF01	81.31	63.94	85.33	69.66	90.59	74.17	100	90.92
MF02	73.46	52.46	54.96	57.77	95.75	95.72	100	97.03
MF03	80.76	66.64	100	77.85	84.29	66.64	100	100
MF04	76.01	71.02	78.24	100	78.96	81.67	79.3	100
MF05	76.97	73.92	77.03	77.05	79.16	94.18	85.63	93.58
MF06	76.31	56.51	64.38	67.97	100	74.54	100	81.98
MF07	100	89	100	100	100	89	100	100
MF08	100	100	100	89.61	100	100	100	100
MF09	88.79	97.27	94.89	100	88.79	97.27	94.89	100
MF10	83.52	62.23	69.85	76.65	83.52	68.04	71.59	88.44
MF11	83.15	67.38	82.8	71.02	91.53	72.98	99.46	96.24
MF12	82.54	56.89	68.85	74.97	95.84	69.91	80.98	82.7
MF13	75.64	51.71	64.98	87.25	100	100	76.1	96.6
MF14	82.66	57.8	70.24	76.67	99.21	65.87	79.65	86.37
MF15	100	100	100	85.14	100	100	100	98.59
MF16	90.16	75.15	78.22	93.11	91.88	77.01	78.26	93.11
MF17	81.19	65.96	73.22	75.33	93.02	79.42	88.78	84.89
MF18	82.92	74.53	100	100	85.47	75.54	100	100
MF19	100	100	100	94.31	100	100	100	100
MF20	76.41	65.03	71.48	75.87	83.29	80.91	71.48	99.75
MF21	85.06	79.69	76.02	82.12	89.32	97.28	76.02	97.73
MF22	100	72.6	88.6	97.19	100	72.6	95.12	97.19
MF23	84.37	69.29	72.44	84.84	92.64	85.1	84.73	95.42
MF24	74.99	68.72	76.88	67.87	91.39	74.1	100	96.2
MF25	76.04	73.2	100	87.66	82.86	73.2	100	91.16
MF26	83.12	66.88	69.15	72.58	90.99	78.78	90.65	83.58
MF27	83.12	66.88	69.18	72.58	91.03	78.78	90.68	83.57
MF28	81.95	67.04	76.84	87.34	100	80.83	100	100
MF29	88.81	76.8	82.43	78.36	91.07	93.39	83.86	100
MF30	80.07	69.68	75.75	75.87	100	87.7	75.75	93.04
MF31	79.17	76.99	99.2	96.9	86.32	76.99	100	100
MF32	88.77	81.7	88.55	88.47	100	87.83	100	100
MF33	86.39	87.44	94.38	83.24	92.66	98.51	100	95.64
MF34	99	99.31	94.01	81.13	99	99.31	94.54	99.6
MF35	90	79.63	94.35	89.66	90	79.9	95.67	95.19
MF36	85.66	68.28	72.87	65.31	88.14	82.5	100	100
MF37	88.84	76.3	83.68	79.01	92.48	94.7	85.02	91.84
MF38	86.12	89.54	84.14	81.51	93.82	100	92.44	90.43
MF39	77.83	63.05	72.67	78.44	87.32	74.27	81.98	84.73

MF40	78.64	79.5	88.42	97.51	79.98	94.21	88.76	100
MF41	79.19	78.78	78.78	85.81	85.76	100	81.77	93.73
MF42	82.65	70.08	82.75	86.14	84.19	70.08	91.88	87.47
MF43	84.47	61.45	63.08	66.35	92.27	75.19	82.65	89.45

Four funds (# 7, 8, 15, 19) are efficient (in at least three out of four years) under both DEA runs. This persistency characterizes them as the best performers of the research's 43 funds sample. On the contrary, eighteen funds are inefficient in both evaluation contexts for all years, though they are the worst performers of the sample. These funds have low skewness and high kurtosis, thus adding these variables does not make a difference for them.

One may argue that the larger portion of funds being identified as efficient under the incorporation of additional inputs and outputs in higher moment framework is due to a decrease in the number of degrees of freedom. The inclusion of any additional input or output in the analysis imposes another constraint, thus the set of feasible solutions tends to become smaller and more and more funds tend to lie on or close to the frontier.

In this context, in order to assess the net effect of skewness and kurtosis dimensions on efficiency scores, the whole sample of funds is split out twice. It is split into two groups each time, according to the size of their skewness and kurtosis values. The results for each year under examination are presented in Table 3.

Table 3: Average MV & HM Efficiencies by Higher Moments Dimension

Size	2007			2008			2009			2010		
Skewness	Skew	HM	MV	Skew	HM	MV	Skew	HM	MV	Skew	HM	MV
High[a]	-0.69	93.93	83.59	0.07	87.57	71.87	-0.12	93.49	78.16	0.39	96.33	77.39
Low	-0.86	88.26	86.04	-0.20	80.20	75.86	-0.29	87.66	85.67	0.22	92.74	86.07
Average	-0.76	91.69	84.56	-0.06	84.14	73.73	-0.21	90.64	81.83	0.29	94.33	82.24
Kurtosis	Ku	HM	MV	Ku	HM	MV	Ku	HM	MV	Ku	HM	MV
High	2.50	88.31	85.96	3.68	78.92	75.51	1.41	88.87	86.23	3.25	96.24	85.73
Low	1.79	94.62	83.34	2.50	88.28	72.31	0.82	91.69	79.22	1.48	92.96	79.72
Average	2.12	91.69	84.56	3.02	84.14	73.73	1.04	90.64	81.83	2.22	94.33	82.24

a. High (low) = above (below) sample average, MV: mean- variance DEA score, HM: higher moment DEA score

Indeed, it is concluded that the skewness and kurtosis dimension influence funds efficiency scores. Comparing average efficiencies under two scenarios one concludes that they are always bigger in higher moment framework, independently of the size of skewness and kurtosis. But clearly this improvement is relative better in high skewness or low kurtosis groups. For example, in 2007, higher skewness group has approximately 10 units (93.93% - 83.59%) higher average efficiency in higher-moment than in mean-variance framework. On the other hand, the incorporation of skewness variable in low skewness group causes only a slight improvement in efficiency by 2 units (88.26%-86.04%).

Furthermore, always, the mean-variance model gives higher performance scores in low skewness (high kurtosis) group compared to high skewness (low kurtosis) group. This is due to the fact that the mean-variance criterion is based only on large returns and small standard deviation, failing to account for either their small skewness or large kurtosis values. For example, in 2007, average MV efficiency is 86.04 % in low skewness group compared to 83.59 % in high skewness group.

In high moment framework, group with high skewness (low kurtosis) is more efficient than the one with low skewness (high kurtosis) in all years except 2010. In 2010, funds with lower kurtosis values do not have higher efficiency scores due to the fact that this group has also too low skewness values.

Conclusively, skewness values of HM-efficient funds are higher than those of MV-efficient funds and also kurtosis values of HM-efficient funds are lower than those of MV-efficient funds. Clearly, these results demonstrate that the higher moment DEA scores are sensitive to skewness and kurtosis values of returns' distributions. These results are consistent with the findings of Guo et al., [35].

The reference sets (benchmarking portfolios) of inefficient funds and the frequencies of efficient funds (how often each belongs to a benchmarking portfolio) as benchmarks of inefficient ones are reported in Table 4. As the frequency of a mutual fund appearing in a reference set increases, the likelihood of the fund being a good performer increases [38]. The efficient funds appearing in the most reference sets can be considered as the best performers and can give to inefficient funds insights from their superior management and investment practices. For example, mutual fund 8 is in the benchmark portfolio for more than 25 funds in both mean variance and higher moment framework in all examined years, except 2010. Additionally, based on the aforementioned frequencies one can provide a full ranking of efficient funds in both evaluation perspectives for all years under examination.

The existence of non-normality in funds leads to the choice of different efficient portfolios compared to the ones under the normality assumption. More specifically, in higher moment framework the optimal portfolios are more diversified since they are combinations of more funds than the ones under the standard mean variance framework, during all time horizons. For example, in 2010, the efficient portfolio for mutual fund 13 is consisted of only two funds (# 04, 18) under mean variance framework while in higher moment framework it is constructed by five funds (# 07, 08, 09, 28, 32). The higher grade of diversification of efficient portfolios under higher moment framework allows

Table 4: References Funds and Benchmarks

Fund	MV				HM			
	2007	2008	2009	2010	2007	2008	2009	2010
MF01	07, 08	08	03, 18	04, 18	08, 15, 32	08, 38, 41	(11)	03, 32, 36
MF02	08	08	08, 25	04, 18	06, 30	13, 38, 41	(6)	07, 28, 36
MF03	08, 15	08	(5)	04	08, 15, 32	08	(4)	(10)
MF04	08	08	08, 25	(34)	08,32	08, 15, 41	01, 08, 31, 32	(5)
MF05	08	08	08, 25	04, 18	08,32	38, 41	01, 03, 31, 32	28, 32, 36
MF06	08	08	08, 25	04, 18	(3)	19, 41	(3)	28, 32, 36
MF07	(12)	15, 19	(3)	(7)	(6)	15, 19	(4)	(5)
MF08	(39)	(38)	(29)	04	(30)	(31)	(25)	(10)
MF09	07, 08	08	08, 15	(2)	07,08	08, 15	08, 15	(9)
MF10	08, 15	08	08, 25	04, 18	08,15	08, 41	08, 19, 25, 31	28, 32, 36
MF11	08	08	18, 25	04	08,32	08, 41	01, 03, 19, 32	03, 32, 36
MF12	08	08	08, 25	04	08, 15, 32	08, 41	01, 08, 31, 32	08, 09, 28
MF13	07, 08	08, 15	08, 15	04, 18	(1)	(2)	02, 08, 32	07, 08, 09, 28, 32
MF14	08	08	08, 25	04	15, 30, 32	08, 15, 41	01, 08, 31, 32	08, 09, 28
MF15	(4)	(11)	(9)		(17)	(11)	(4)	03, 19, 40
MF16	08, 15	08	08, 25	04	06, 15	08, 41	08, 25, 31	04
MF17	07, 08	08, 15	15, 19, 25	04, 18	08, 15, 32	08, 38, 41	01, 06, 07, 08	08, 09, 32
MF18	07, 08	08, 15	(4)	(21)	07, 08, 32	08, 15, 19	(1)	(1)
MF19	(1)	(4)	(3)		(1)	(7)	(7)	(5)
MF20	08	08	08	04	08, 15, 32	08, 41	08	03, 32, 36
MF21	08	08	08	04	08, 32	08, 41	08	03, 32, 36
MF22	(1)	08	03, 25	04	(1)	08	01, 03, 19, 31	04
MF23	07, 08	08, 15	08, 15, 25	04, 18	08, 15, 32	15, 38, 41	01, 06, 07, 08	08, 09, 32
MF24	08	08	08	04, 18	15, 32	08, 15,	(1)	28, 32,

						41		36
MF25	08	08	25	04, 18	08, 15, 32	08	(5)	03, 19, 40
MF26	08	08	08, 25	04	08, 15, 32	08, 41	02, 08, 28, 32	08, 28, 32
MF27	08	08	08, 25	04	08, 15, 32	08, 41	02, 08, 28, 32	08, 28, 32
MF28	08	08	08, 25	04	(1)	08, 41	(4)	(15)
MF29	08	08	08, 25	04	08, 32	08, 41	08, 31, 32	(1)
MF30	08	08	08	04	(4)	15, 41	08	03, 32, 36
MF31	08	08	08, 25	04	08, 32	08	(13)	(1)
MF32	07, 08	08, 15	08, 15	07, 18	(28)	08, 19, 38	(14)	(22)
MF33	08	08	08	04	08, 32	08, 41	(1)	08, 09, 28, 32
MF34	07, 08	15, 19	07, 15	07, 18	07, 08, 32	15, 19	07, 08, 15, 19	03, 07, 19, 36
MF35	07, 08, 15	08, 15	15, 19, 25	07, 18	07, 08, 15	08, 15, 19	08, 15, 19, 25	04, 19, 32, 40
MF36	08	08	03, 18, 25	04	08, 32	08, 41	(3)	(14)
MF37	08	08	08, 25	04	08, 32	08, 41	08, 31, 32	03, 32, 40
MF38	07, 08	15, 19	07, 15		08, 08, 15, 32	(8)	02, 08, 19, 32	07, 28, 32, 36
MF39	08	08	08, 25	04	08, 32	08, 41	01, 08, 36	08, 09, 32
MF40	08, 15	08	08, 25	04	08, 15, 32	08, 41	08, 25, 31	(6)
MF41	08	08	08, 25	04, 18	08, 32	(27)	08, 31, 32	09, 28
MF42	08	08	08, 25	04	08, 32	08	01, 08, 31	04, 32, 40
MF43	07, 08	08	08, 25	04, 18	08, 32	08, 38, 41	02, 08, 28, 32, 36	28, 32, 36

Note: for inefficient funds: the reference funds are referred without the prefix “MF” (e.g. 07 means MF07), for efficient funds: the number of inefficient funds which have chosen the fund as benchmark is referred in parenthesis.

investors to participate in a variety of investment opportunities while reducing the risk of large losses. Thus, the proposed approach could be a very useful tool for the Greek fund managers, in order to outperform the market, leaving room for developing successful portfolio diversification strategies.

5 Conclusion

The present study, demonstrates the potential for using higher moments measures in a DEA framework in order to assist investors, mutual fund managers and individuals in selecting mutual funds. As mutual fund returns are not normally distributed, the DEA higher moment framework gives a better measure of performance as it accounts not only for standard deviation but also for skewness and kurtosis characteristics of returns. A fund with high sensitivity (i.e. high kurtosis or/and negative skewness) to negative market conditions will be penalized by the model with lower efficiency score.

The higher moment framework, as it is presented, is a valuable complement to standard risk measures. This is because it presents a more comprehensive picture of mutual funds performance appraisal, since it incorporates with a more sophisticated manner the peak and tail behavior of fund returns. It also captures better, with robustness and sensitivity, the preferences of an investor.

Although the analysis conducted in this paper focused only on equity mutual funds and two higher central moments characteristics, kurtosis and skewness, the proposed methodology can be easily extended to consider other types of mutual funds (e.g. value and bond funds) as well as more other characteristics of return’s distribution (e.g. coskewness and cokurtosis).

Appendix

The return on a mutual fund investment includes both income (in form of dividends or interest payments) and capital gains or losses (the increase or decrease in the value of security). The return is calculated net of management fees and other expenses charged to the fund. Thus, a funds' return in the period t is expressed as follows:

$$R_{pt} = \frac{NAV_t + DIST - NAV_{t-1}}{NAV_{t-1}}$$

where NAV_t = net asset value per unit of the mutual fund in the period t, NAV_{t-1} = net asset value per unit of the mutual fund in the period $t-1$, and $DIST_t$ = dividend of the mutual fund in the period t. In this analysis are compouned daily returns in order to achieve longer time period returns and yearly cumulative return is calculated as follows:

$$R_{ct} = \left[\left[\left(1+\frac{R_{p1}}{100}\right)\left(1+\frac{R_{p2}}{100}\right) \text{....} \left(1+\frac{R_{pt}}{100}\right)\right]\text{-1}\right] * 100$$

The basic measure of variability is the standard deviation, also known as the volatility. For a mutual fund the standard deviation is used to measure the variability of daily returns presenting the total risk of the fund. The standard deviation of a MF is defined as follows:

$$\sigma = \sqrt{(1/T)\sum (R_{pt} - \overline{R}_{pt})^2}$$

where σ is the standard deviation of MF in period t, $\overline{R}_{pt}$ is the average return in period t, and T is the number of observation (days) in the period for which the standard deviation is being calculated.

The year-end asset of the examined MFs is recorded in millions of Euros. The assets are useful in evaluating fund's size, mobility and popularity. Furthermore, assets give a picture upon the effect of economies of scale associated with the management of larger funds and specify whether a small company fund remain in its investment-objective category while its asset reaches an ungainly size.

Skewness is a measure of the symmetry of the distribution of the data and refers to the 'third moment' of the frequency distribution and is defined as follows:

$$\text{Skewness} = \frac{T}{(T-1)(T-2)} \sum_{i=1}^{T} \left(\frac{R_i - \overline{R}}{\sigma}\right)^2$$

Normal distribution has zero skewness. When skewness is positive (skewed to the right) then the frequency distribution has a long 'right tail', while when we have negative skewness (skewed to the left), then large negative returns are more common than large positive returns and the tail distribution is heavier on the left.

Kurtosis is a measure of the degree of peakness (fourth central moment minus 3 is called excess kurtosis) and is defined as follows:

$$\text{Kurtosis} = \left(\frac{T(T+1)}{(T-1)(T-2)(T-3)}\right)\sum_{i=1}^{T}\left(\frac{R_i-\overline{R}}{\sigma}\right)^4 - \frac{3(T-1)^2}{(T-2)(T-3)}$$

When the data has more peakedness than the normal distribution (long tails), kurtosis is greater than three (leptokurtosis) while in the case we have lower peak we have platykurtosis (bounded distribution). The normal distribution has Kurtosis equal to three.

References

[1] H. Markowitz, Portfolio selection, *Journal of Finance*, **7**, (March 1952), 77-91.

[2] H. Markowitz, *Portfolio Selection: Efficient Diversification of Investments*, John Wiley, New York, 1959.

[3] A.H. L. Lau, H.S. Lau and J.R. Wingender, The distribution of stock returns: New evidence against the stable model, *Journal of Business and Economic Statistics*, **8**, (1990), 217-223.

[4] J.Y. Cambell and L. Hentschel, No news is good news: An asymmetric model of changing volatility of stock returns, *Journal of Financial Economics*, **31**, (1992), 281-318.

[5] L.C. Hsu, S.C. Ou and Y.C. Ou, How to choose mutual funds that perform well? Evidence from Taiwan, *International Journal of Economics and Finance*, **4**(1), (2012), 47-259.

[6] A. Kane, Skewness preference and portfolio choice, *Journal of Financial and Quantitative Analysis*, **17**, (1982), 15-25.

[7] Y.K. Ho and Y.L. Cheung, Behavior of intra-daily stock return on an Asian emerging market-Hong Kong, *Applied Economics*, **23**, (1991), 957-966.

[8] R.C. Scott and P.A. Horvath, On the direction of preference for moments of higher order than the variance, *Journal of Finance*, **35**, (1980), 915-919.

[9] W.F. Sharpe, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance*, **19**, (1964), 425-442.

[10] J. Lintner, The valuation of risk assets and selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics*, **47**, (1965), 13-37.

[11] J. Mossin, Optimal Multiperiod Portfolio Policies, *Journal of Business*, **41**, (1969), 215-229.

[12] S. Ross, The Arbitrage Theory of Capital Asset Pricing, *Journal of Economic Theory*, **6**, (December, 1976), 341-360.

[13] JL. Treynor, How to rate management of investment funds, *Harvard Business Review*, **43**, (1965), 63-75.
[14] W.F. Sharpe, Mutual fund performance, *The Journal of Business*, **39**(1), (Part 2), (1966), 119-138.
[15] C.M. Jensen, Risk, the pricing of capital assets, and evaluations of investment portfolio, *Journal of Business*, **42**, (1969), 67-247.
[16] W.D. Cook and L.S. Seiford, Data envelopment analysis (DEA) – Thirty years on, *European Journal of Operational Research*, **192**, (2009), 1-17.
[17] N. Milonas, *Greek Mutual Funds*, Athens: Hellenic Bank Association and Sakoulas Editions, 1999, (In Greek).
[18] N.D. Philippas, *Mutual Funds and Stock Exchange Environment*, Athens: Globus Invest, 1999, (In Greek).
[19] G.P. Artikis, Performance evaluation of the bond mutual funds operating in Greece, *Managerial Finance*, **30**(10), (2004), 1-13.
[20] J.N. Sorros, Return and risk analysis: A case study in equity mutual funds operating in the Greek financial market, *Managerial Finance*, **29**(9), (2003), 21-28.
[21] K. Pendaraki, M. Doumpos and C. Zopounidis, Assessing equity funds' performance using a multicriteria methodology: A comparative analysis, *South Eastern Europe Journal of Economics*, **1**, (2003), 85-104.
[22] K. Pendaraki, C. Zopounidis and M. Doumpos, A multicriteria methodology and an application to the Greek market of equity mutual funds, *European Journal of Operational Research*, **163**, (2005), 462-481.
[23] V. Babalos, N. Philippas, M. Doumpos and C. Zopounidis, Mutual fund perormance appraisal using stochastic multicriteria aacceptability analysis, *Applied Mathematics and Computation*, **218**, (2012), 5693-5703.
[24] N. Spanoudakis, K. Pendaraki and G. Beligiannis, Portfolio Construction Using Argumentation and Hybrid Evolutionary Forecasting Algorithms, *International Journal of Hybrid Intelligent Systems*, **6**(4), (2009), 231-243.
[25] R. Banker, A. Charnes and W. Cooper, Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science*, **30**(9), (1984), 1078-1092.
[26] P. Alexakis and I. Tsolas, Appraisal of mutual equity fund performance using Data Envelopment Analysis, *Multinational Finance Journal*, **15**(3/4), (2011), 273-296.
[27] V. Babalos, G. M. Caporale and N. Philippas, Efficiency evaluation of Greek equity funds, *Research in International Business and Finance*, **26**, (2012), 317-333.
[28] S. Malmquist, Index numbers and indifference surfaces, *Trabajos de Estadistica*, **4**, (1953), 209-242.
[29] M.M. Carhart, On Persistence in Mutual Fund Performance, *Journal of Finance*, **52**(1), (March 1997), 57-82.
[30] G.N. Gregoriou, Performance appraisal of funds of hedge funds using Data Envelopment Analysis, *J. Wealth Manage*, **5**(4), (2003), 88-95.

[31] G.N. Gregoriou, K. Sedzro and J. Zhu, Hedge fund performance appraisal using data envelopment analysis, *European Journal of Operational Research*, **164**, (2005), 555-571.

[32] K. Wilkens and J. Zhu, Classifying Hedge Funds Using Data Envelopment Analysis, in Gregoriou, G.N., F. Rouah, and V.N. Karavas (Eds.): *Hedge Funds: Strategies, Risk Assessment, and Return*s. Washington, Beard Books, 2005.

[33] M. Eling, Performance measurement of hedge funds using Data Envelopment Analysis, *Fin Mkts Portfolio Mgmt*, **20**, (2006), 442-471.

[34] T. Joro and P. Na, Portfolio performance evaluation in a mean-variance-skewness framework, *European Journal of Operational Research*, **175**, (2006), 446-461.

[35] J. Guo, M. Chaoqun and Z. Zhongbao, Performance evaluation of investment funds with DEA and higher moments characteristics: Financial Engineering perspective, *Systems Engineering Procedia*, **3**, (2012), 209-216.

[36] A. Charnes, W. Cooper and E. Rhodes, Measuring the Efficiency of Decision Making Units, *European Journal of Operational Research*, **3**(6), 1978, 429-444.

[37] W.W. Cooper, L.M. Seiford, K. Tone, *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA* –Solver Software. (2nd Ed.) Springer Publishers, 2007.

[38] D. Sherman and J. Zhu, *Service Productivity Management: Improving Service Performance Using Data Envelopment Analysis (DEA)*, Springer, Boston, 2006