Benchmarking of Indian Sectoral Mutual Funds - A Non-Separable Undesirable Output Model

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Abstract

Performance analysis of mutual funds is usually made on the basis of return-risk framework where return is considered an output indicator and risk is considered as an input indicator. However, portfolio risk in actuality is a non-separable undesirable output and any effort to reduce it also causes a reduction in portfolio return. In view of this, the present paper uses a non-parametric non-separable undesirable output model to evaluate the performance of 27 sectoral mutual fund schemes based on observations for the period July 2010 to June 2013. The USP of the present study is that return and risk are considered as both non-separable outcome of the process of investment. The results exhibit stability of mean efficiency scores across the observed years. Further, fund inefficiency mostly emerged from the input side and not from the output side.

JEL Classification: C-61, D-21, G-23.

Keywords: Mutual Fund, Endogenous Benchmarking, DEA, Non-separability, Undesirable Output

1. Introduction

Mutual fund performance in financial markets is subject to market risks. This performance benchmarking of mutual funds requires the design of a return-risk framework against the backdrop of which fund performance is evaluated. Traditionally, such evaluation was done in terms of excess return to risk/volatility ratios. In recent times, however, sophisticated frontier methods have been used for the purpose of mutual fund performance evaluation.

The mutual fund industry in India started in 1963 with the formation of Unit Trust of India, at the initiative of the Government of India and Reserve Bank. Up to 1987, Unit Trust of India, the government promoted institution had monopoly over the mutual fund market. There after competition was allowed in the industry to a limited extent as the Government of India allowed the operation of public sector commercial bank (and insurance company) sponsored funds to operate in the mutual fund market. In 1987, two large public sector banks, namely, the State Bank of India and the Canara Bank floated mutual funds. They were followed by Life Insurance Corporation of India (June 1989), Punjab National Bank Mutual Fund (Aug 89), Indian Bank Mutual Fund (Nov 89), Bank of India (Jun 90), General Insurance Corporation of India (engaged in non-life business) and Bank of Baroda Mutual Fund (Oct 92).

In 1993, the mutual fund market was truly deregulated by allowing private and foreign competition. At the same time, the mutual funds came under the control of Securities and Exchange Board of India- the capital market regulator. The permission granted to the private sector to operate in the Industry led to the introduction of a significant number of new players. Currently there are 40+ players in the market with Asset Under management exceeding Rs 1,18,80,000 Millions.

In the recent years, sectoral funds have gained popularity among investors because of high returns generated by them during bullish periods. Sectoral mutual fund schemes restrict their investment in specific high growth sectors of the economy and consequently are more risky than diversified equity funds.

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Against this backdrop, the present study discusses the application of non-parametric frontier method for benchmarking the performance of 27 major sectoral mutual fund schemes operating in the Indian market. The study shows how by using data envelopment analysis, it is possible to generate performance frontier of mutual funds without requiring any knowledge about exogenous benchmark returns. Another distinguishing feature of the present study is that it uses the concept of undesirable output for the purpose of performance evaluation. The paper is organized into five sections and proceeds as follows: Section 1 provides an introduction to modern portfolio theory of benchmarking. Section 2 provides a brief discussion of the received literature on mutual fund benchmarking. Section 3 is devoted to the research methods. Section 4 is for results and discussions and finally, section 5 provides the concluding observations.

Table 1: Mutual Fund Business in India: Growth in Asset Under Management

Particulars	*December 1988*	*December 1993*	*September 2004*	*September 2012*	*March 2015*
Total Asset Under Management (Rs Million)	67000	4,70,004	15,31,080	74,03,017	1,18,80,000

2. Modern Portfolio Theory of Benchmarking

(i) The Mean-Variance Criteria:

One of the earliest attempts towards portfolio benchmarking was by Markowitz (1952) and Tobin (1958) in the form of the mean-variance criterion. The basic idea behind the mean-variance approach is that the optimal portfolio for an investor is not simply any collection of securities but a balanced portfolio which provides the investor with the best combination of return and risk where return is measured by the expected value and risk is measured by the variance of the probability distribution of portfolio return. The decision rule which emanates from the M-V efficiency criteria is as follows: Given two discrete return distributions f(x) and g(x), investors will prefer F(x) over F(G) if $\mu_F \geq \mu_G$ and $Var_F \leq Var_G$ (not both equalities holding simultaneously).

Markowitz pointed out that in the context of risk aversion, a quadratic of the form $a+bR+cR^2$ provides a close approximation of a smooth and concave utility function. In this case, maximization of expected utility implies:

$$\text{Max } E[U(R)] = \text{Max } [a + b\mu + c\, E(R^2)] = \text{Max } [a + b\mu + c(\mu^2+\sigma^2)]$$

Where μ =expected value of R and σ^2 = variance of R. Therefore, this investor will choose his portfolio solely on the basis of the mean and variance of R.

(ii) Efficiency Criteria Based on Stochastic Dominance

Roy (1952) argued that an investor would be driven by the safety of principal first when dealing with risk. He stated that the investor would prefer the investment with the lowest probability of going below the target return. By maximizing an excess return to variability ratio, $(R_e - R_t)/S$, the investor would select the portfolio with the lowest probability of going below the target level R_t, given an average return, R_e, and a standard deviation, S. Subsequently, Hadar and Russell (1969) pointed out that barring some special cases (like the quadratic utility function), the specification of distributions in terms of their moments is unlikely to provide strong results as information about the moments cannot be used efficiently for the purpose of ranking uncertain prospects in the case of unknown utility function. In this context, Hadar and Russell (1969) and Whitmore (1970) proposed three decision rules based on stochastic dominance (ordering) which are stronger than the moment method (see Appendix 1 for the decision rules).

In the seventies, many researchers challenged the methods of portfolio performance evaluation based on Mean-Variance-CAPM framework since they depended on normal distribution. Klemkosky (1973) and Ang and Chua (1979) showed that these measures could provide incorrect rankings and suggested the use of reward to semi-variability (R/SV) ratio as an alternative. However, path-breaking development in the field of downside risk measures occurred with the development of the Lower Partial Moment (LPM) risk measure by Bawa (1975) and Fishburn (1977). Bawa (1975) was the first to define lower partial moment (LPM) as a general family of below-target risk measures that provided a proof that the LPM measure is mathematically related to stochastic dominance for risk tolerance values of 0, 1, and 2.This model was later further generalised by Fishburn.

3. Mutual Fund Benchmarking-the Received Literature

At the international level there are quite few research studies which employed non-parametric methods to evaluate efficiency performance in the mutual fund sector. A few of them are now discussed in brief.

Murthi, Choi, and Desai (1997) put forward a portfolio performance measurement method based on DEA portfolio efficiency index (DPEI) using two inputs (standard deviation and transaction loads) and one output (excess return as output). They investigated the performance of 2083 mutual funds for the period of July-September 1993. Their analysis is spread over two phases. In the first phase, they compared the DPEI measure with traditional measures of performance for 731 mutual funds which were classified in to seven categories: income, balanced, equity-income, asset allocation, growth, growth-income and aggressive growth. In the next phase, they used all the in-sample (2083) mutual fund for computing DPEI for each fund. They also used a regression estimate for the identification of the sources of variation in efficiency.

Basso and Funari (2001) used several risk measures (standard deviation, standard semi-deviation and beta) and subscription and redemption costs as inputs, and the mean return and the fraction of periods in which the mutual fund was non-dominated as outputs. They proposed two DEA measures for the evaluation of performance. In the first measure, mutual fund return has been taken as the output and the standard deviation and transaction cost have been taken as the inputs. In the second DEA measure, they built a stochastic dominance indicator that reflects both the investors' preference structure and the time occurrence of returns assigning a higher score to mutual funds which are not dominated by other mutual funds in the higher number of sub-periods. The study was based on weekly return data corresponding to the Italian financial market for the period January 1997 to June 1999. In a later study (2003), Basso and Funari used an ethical score of mutual funds in place of the stochastic dominance indicator.

Gregoriou, Sedzro, Zhu (2005) used DEA to evaluate the performance of 168 hedge funds for the span 1997–2001. They initially used the radial Banker-Charnes-Cooper model to classify the hedge funds into efficient and inefficient categories. Then, they used cross efficiency and super-efficiency models to further analyse the efficiency of funds.

Using the Morningstar database of mutual funds, Daraio and Simar (2006) evaluated the performance of six categories of mutual funds (growth and growth income, asset allocation, aggressive growth, balanced and equity income) in terms of the conditional input oriented order-m efficiency estimator, Free Disposal Hull (FDH) method and DEA, Jensen's α and Sharpe Index. Total return has been considered as the output in the study while Expense Ratio, Loads and Turnover Ratio have been chosen as the inputs. The study also compared the traditional CAPM based indicators (Jensen's α and Sharpe Index) with their non-parametric counterparts (order m efficiency, DEA and FDH) using several measures of correlation (Pearson, Spearman and Kendall's tau-b). The results indicate that the non-parametric efficiency indicators (DEA, FDH, order-m) are highly positively correlated. However, they are weakly correlated with the traditional ratio based indicators (Sharpe ratio and Jensen's alpha).

Zhao, Wang and Lai (2011) put forward two quadratic-constrained DEA models for evaluating mutual funds performance on the basis of endogenous benchmarks. They decomposed two vital factors for mutual funds performance, i.e. risk and return, in order to define mutual funds' endogenous benchmarks and give insights and suggestions for managements. Of the two quadratic-constrained DEA models used by them, one is a partly controllable quadratic-constrained programming. The glide path is illustrated by a sample of twenty-five mutual funds operating in the Chinese Market corresponding to the years 2005 and 2006. The outcomes indicate that although the market environment in the year 2006 was much better than that in 2005, average efficiency score declined in the year 2006 due to relaxing of system risk control. The majority of mutual funds do not show persistence in efficiency ranking. The answers indicate that mutual fund ranking in China depends mostly on system risk controls.

While there are several research studies which applied non-parametric DEA or quadratic constrained programming models for assessing mutual fund performance, none of them considered portfolio return and risk as a non-separable good and bad outputs. The present study seeks to fill this gap in literature and evaluate mutual fund portfolios in this new framework.

4. Methods of Portfolio Benchmarking

The traditional approach to portfolio benchmarking relied on the ratio analysis using excess return on the numerator and a criterion of risk/volatility on the denominator. Nevertheless, since we are interested in multi-criteria performance evaluation, the ratio analysis is not suited.

In such cases, Shephard's (1953, 1970) concept of distance function provides a solid theoretical foundation for the development of evaluation standards. The estimate is based on a multi-input-end product output/price/revenue system in the context of which a frontier is constructed and the efficiency of a production system is evaluated in terms of its propinquity to the frontier. Importantly, distance function provides a functional characterization of the structure of production technology. The input set of the production technology is characterized by the input distance function while the output set is characterized by the output distance function.

In order to elaborate the concept of distance function, we consider a technology T using a nonnegative vector of inputs $X=(x_1,x_2,......,x_n)\in R^n_+$ to produce a nonnegative vector of outputs $Y=(y_1,y_2,......,y_m)\in R^m_+$. In operational terms, they can be related as: Y=P (X) and X=L (Y)

Given this, an input distance function can be defined as D_{input}= Max [λ: $X/\lambda \in L(Y)$]. Intuitively speaking, an input distance function gives the maximum amount by which the producer's input vector can be reduced and yet remains feasible for the output vector it produces. The reciprocal of the input distance function can be considered as the radial measure of input oriented technical efficiency.

In an analogous fashion, the output distance function is defined as: D_{output}= Min [μ:$Y/\mu \in P(X)$]. Intuitively speaking, an output distance function gives the minimum amount by which the producer's output vector can be deflated and yet remains feasible for a given input vector. The radial measure of output oriented technical efficiency coincides with the output distance function.

4.1 Comparison of Performance using DEA:

The performance of a mutual fund can be evaluated using Data Envelopment Analysis (DEA) in the context of a return-risk framework without requiring knowledge about either the risk free rate or return on the market portfolio. Data Envelopment Analysis is a non-parametric mathematical programming tool often used for comparing the relative performances of economic units with minimal prior assumption on the input-output relation. The DEA method is a generalization of Farrell's Single input single output technical efficiency measure to the multiple output- multiple input case. The methodology was originally developed by Charnes, Cooper and Rhodes (1978) and later was further extended by Banker, Charnes and Cooper (1984).

The DEA approach constructs the efficiency frontier of mutual funds out of piecewise linear stretches, thereby forming a convex production possibility set. On DEA frontier, efficient observations are those for which no other decision making unit or linear combination of units has as much or more of every output (given inputs) or as little or less of every input (given outputs). It envelops data sets and therefore makes no room for noise. In the present paper, we make use of two variants of DEA: the output expanding approach and the input conserving approach.

4.2 Accommodation of Undesirable Outputs for the Computation of Technical Efficiency:

In the efficiency studies, one finds several approaches for accommodating undesirable outputs in data envelopment analysis. In the present context a few may be cited. One of the earliest attempts to incorporate undesirable outputs was by Pittman (1981). Pittman provided an asymmetric treatment of the undesirable and desirable outputs in the process of performance measurement of 30 paper mills in the United States.

Fare et al. (1989) extended the Farrell measure of technical efficiency to accommodate both desirable and undesirable factors where they are treated differently. The modification allowed asymmetric treatment of the inputs, desirable outputs and undesirable outputs and consequently they were able to generate several hyperbolic efficiency measures.

Golany and Roll (1989) recommended the multiplicative inverse method. This method was later applied by Lovell et al. (1995) and Athanassopoulos and Thanassoulis (1995). As per this approach, each undesirable output is incorporated as desirable output through the following transformation: f_i^k (U) =1/UK.

Berg et al. (1992) advanced a different way of incorporating undesirable outputs in the model: they treated undesirable outputs as desirable outputs. This was achieved by using a transformation: f (U) =-U where U stands for undesirable output.

Scheel (2000) proposed efficiency measures which are oriented towards desirable and undesirable outputs respectively. The technical efficiency measures suggested by Scheel are based on the assumption that any change in output levels involves both desirable and undesirable outputs. He found that this non-separable output measure assigns technical efficiency scores to decision making units which are significantly lower than those applicable to separable output efficiency measures.

Seiford and Zhu (2002) used data translation as a means of integrating undesirable inputs/outputs into DEA. In case of undesirable outputs, they suggested the multiplication of each such output by -1 and thereafter finding out an appropriate translation vector so that all negative undesirable outputs can be converted into positive desirable output. Maximization of the modified output will tantamount to minimization of 'undesirable output'.

4.3 The Slacks Based Measure of Technical Efficiency

The Slacks Based Measure model was introduced by Tone (2001). The SBM methodology is now introduced in brief:

Suppose there are n DMUs (decision making units) each having three factors: inputs, good outputs and bad (undesirable) outputs, as represented by three vectors $x\epsilon R^m$,$y^g =R^{s1}$,$y^b= R^{s2}$ respectively. We define the matrices $X = [x_1, x_2,...., x_n] \epsilon R^{pxq}$ $=[y_1^g,.......]$, $[y_q^g]\in R^{s_1 xn}$ and $Y_b =[y_1^b,........, y_q^b]\in R^{s_2 xq}$. We assume that X>0, Y_b>0, Y_g>0.

We define the production possibility set as P= {(x, Yb, y^g) $\vert x\geq X\lambda$, $y^g\leq Y^g\lambda$, $y^b\geq Y^b\lambda$, $\lambda\geq 0$} where $\lambda\in R+$ is the intensity vector. The efficiency scores are computed from the following linear program:

$$\text{Min } \beta = (1-1/m\sum s^-_l/x_{l0})/\ (1+1/n\sum s^+_k/y_{k0}) \qquad (1)$$

$$\text{S.t. } x_0= X (+s^-$$

$$y_0 =Y (- s^+$$

$$l\geq 0, \sum l=1, s^- \geq 0, s^+ \geq 0$$

Technical Efficiency = 1/ β

The Slacks Based Measure of Efficiency has some very nice properties: (i) The SBM efficiency remains unaffected by the units of data chosen; (ii) The measure is monotone decreasing for the input and output slacks; (iii) The slacks-based measure possess an additive structure. Thus SBM gets rid of input and output slacks by way of addition and subtraction from the relative inequality constraints.

4.4 Introduction of Undesirable Output

For accommodating undesirable outputs, Tone (2003) modified the fractional linear program as follows:

$$\text{Min } \beta =(1-1/m\sum s^-_l/x_{l0})/\ \{1+(1/n_1+n_2)(\sum s^+_{gk}/y_{gk0} +\sum s^+_{bl}/ y_{bl0})\} \quad (2)$$

$$\text{S.t. } x_0= Xl +s^-,\quad y^g_0 =Y^g l - s^g,\ y^b_0 =Y^b l + s^b, l\geq 0,\sum l=1, s^- \geq 0, s^+ \geq 0$$

Technical Efficiency=1/β

Non-separable Inputs and Outputs

When the good and bad outputs and inputs are non-separable, the aforementioned program needs modification.

$$\text{Min } \beta_{NS} =[1-1/m\sum s^-_l/x^{NS}_{l0}-(1- \alpha)]/\ \{1+(1/n_1+n_2)[\ s^+_{bl}/ y^{NSb}_{l0} +(n_1+n_2)(1-\alpha)]\}\ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

$$\text{S.t. } x^{NS}_0= X^{NS}l +s^-,\quad \alpha\, y^{NSg}_0 =Y^{NSg}l - s^g,\ y^{NSb}_0 =Y^{NSb}l + s^b, l \geq 0,\sum l=1, s^- \geq 0, s^+ \geq 0$$

Technical Efficiency=1/β_{NS}

Where y^{NSg} and y^{NSb} indicate good and bad outputs respectively, and X^{NS} represents the input.

The technical efficiency so derived can be decomposed into input and output efficiencies. For details, see Cooper, Seiford and Tone (2007).

5. Framework of the Study, Results and Discussions:

(a) Inputs and Outputs

In the present study, we make use of three output indicators (including two good and one bad outputs) and one input indicators. The two good outputs are: mean return and the probability of excess return over mean. The value at risk is taken as the bad output. Standard deviation of mutual fund return is taken as the input indicator. Thus the input-output corresponding to the two models are:

Output [Mean Return, Probability of Excess Return Over Mean, Value at Risk (bad output)] = f (Standard Deviation)

(b) Period of Study

The present study is based on observations relating to 27 sectoral mutual fund schemes for the period July 2010 to June 2013. The period of analysis has been decomposed in to three sub-periods: July 2010 to June 2011, July 2011 to June 2012 and July 2012 to June 2013. The data have been collected from the AMFI (Association of Mutual Funds in India) website. Estimation has been made under the assumption that the funds operate under variable returns to scale. DEA Solver Pro 7.0 has been used for efficiency computation.

(c) Results:

(i) Summary and Fund Wise Statistics of Technical Efficiency Results:

Table 2 presents the descriptive statistics of technical efficiency scores for the three years under observation. The fund wise efficiency scores are available in appendix table A1. Table A2 provides the ranking of the in-sample funds on the basis of three year averages.

The results show that the mean technical efficiency scores exhibit stability over the period of observation- mean efficiency score varied between 0.8877 and 0.8675. However, out of the 27 in-sample funds, the number of efficient funds is 6 for 2010-11, 8 for 2011-12 and 5 for 2012-13. In fact, the dispersion of performance is quite high between the best performing funds (belonging to the frontier) and the worst performing ones and the dispersion itself fluctuates widely across the observed years. For example, for the first year (July 2010 to June 2011), the minimum efficiency score is only 0.3348 returned by IDFC Strategic Sector Equity Fund. In the next period under observation (July 2011 to June 2012) the minimum efficiency score (0.7053) improved significantly in relation to the previous year but declined again (0.4491) in the subsequent year (2012-13).

Table 2: Summary (Descriptive) Statistics of Efficiency Scores

Particulars	*July 2010 to June 2011*	*July 2011 to June 2012*	*July 2012 to June 2013*
Number of in-sample funds	27	27	27
Number of efficient funds	6	8	5
Mean Technical Efficiency	0.8877	0.8675	0.8704
Standard Deviation	0.1392	0.1064	0.1223
Maximum	1	1	1
Minimum	0.3348	0.7053	0.4491

Source: Calculated

(ii) Decomposition of Inefficiency in to Input and Output Specific Inefficiencies:

Table 3 shows the mean input and output specific inefficiencies corresponding to the input and outputs for the three years (2010-11, 2011-12 and 2012-13). Table 3 shows that the main reason for inefficiency among the projected funds (those funds exhibiting an efficiency score less than 1) is because of input side inefficiency. The fund wise input and output inefficiencies are presented in appendix tables A3 through A5.

Table 3: Mean Input and Output Specific Inefficiencies

Particulars	July 2010 to June 2011	July 2011 to June 2012	July 2012 to June 2013
Mean Input inefficiency	0.1062	0.1283	0.1132
Mean Output inefficiency (mean return)	0.0027	0.0018	0.0084
Mean Output inefficiency (Probability of excess return over mean)	0.0027	0.0018	0.0084
Mean Bad Output inefficiency (Value at Risk)	0.0027	0.0018	0.0084

Source: Calculated

6. Conclusion

In India, the mutual fund industry has improved in terms of size and depth over the years in response to the introduction of more competition and the institution of global best practices in the matter of regulation/operation. In recent times, sectoral funds acquired a growing popularity in the Indian market in view of the superior returns provided by them relative to diversified equity funds in a bullish market. In the present study, the conventional return-risk framework has been extended firstly by including stochastic dominance indicator and secondly by incorporating undesirable output which is non-separable from the good output. The analysis facilitates broad based ranking of the funds and also to explore the major sources of fund inefficiency that can facilitate the initiation of appropriate corrective measure so that fund performance can be improved in future.

The present study, however, has two limitations. First, the number of indicators can either be increased or several models with alternative indicators can be considered and compared for more robust assessment of performance. Second, it did not identify the environmental/contextual variables which influence the performance of the funds. These points can surely be taken in to account in any future research work.

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Appendix 1: The Concept of Stochastic Dominance

In order to provide a very brief introduction to the concept of stochastic dominance, let us consider a random variable x taking the values x_i. Let f and g denote the probability functions of x and F* (x_i). Let G* (x_i) be the respective cumulative distribution. We now introduce the concept of First, Second and Third Order Stochastic Dominance.

(i) First Order Stochastic Dominance (FSD):

In our example, elaborated above, f (x) dominates g (x) if F* (x) ≤G* (x) for all $x_i \in$ X. Hadar and Russell proved that under this rule, distributions may be ordered according to preference under any utility functions.

(ii) Second Order Stochastic Dominance (SSD):

The second rule is weaker than the first rule. In the discrete case second order stochastic dominance implies that f (x) dominates g (x) if $\sum_r G(xi)\,\Delta x_i \leq \sum_r F(xi)\,\Delta x_i$ for all r<n where x_n is the largest value taken by the random variable and $\Delta x_i = x_{i+1} - x_i$. Under SSD, distributions may be ordered for any utility function which exhibits non-increasing marginal utility everywhere.

(iii) Third….

Appendix 2: Fund Wise Efficiency Scores and Decomposition of Inefficiency

Table A 1: Fund Wise Efficiency Scores

Fund Name	*July 2010 to June 2011*	*July 2011 to June 2012*	*July 2012 to June 2013*	*3 Year Average*
Baroda Pioneer Infrastructure Fund	0.9889	0.7469	0.8481	0.8613
BOI AXA Focused Infrastructure Fund	0.9401	0.8121	0.8405	0.8642
Canara Robeco Infrastructure	0.9593	0.8921	1.0000	0.9505
DSP Black Rock World Energy Fund	0.9759	1	0.9076	0.9612
DSP Black Rock World Gold Fund	0.9017	1	1	0.9672
DSP Black Rock World Mining Fund	1	0.7759	0.8224	0.8661
DWS Global Agribusiness offshore Fund	0.8498	1	0.9792	0.9430
Fidelity Global Real Assets Fund	0.8355	0.8419	0.6752	0.7842
HDFC Core and Satellite Fund	1	0.9391	0.9481	0.9624
HDFC Infrastructure Fund	0.8070	0.7778	0.8498	0.8115
ICICI Prudential Banking & Financial Services Fund	0.7969	0.8495	0.7872	0.8112
ICICI Prudential Exports and Other Services Fund	0.7330	0.8060	1	0.8463
ICICI Prudential Technology Fund	0.8756	1	0.7749	0.8835
IDFC Strategic Sector (50-50) Equity Fund	0.3348	0.8101	0.8514	0.6654
ING Global Commodities Fund	1	1	0.4491	0.8164
JPMorgan India Smaller Companies Fund	0.9859	1	1	0.9953
Kotak PSU Bank ETF	1.0000	0.7181	0.8598	0.8593
L&T Infrastructure Fund	0.9392	0.8613	0.9137	0.9047
LIC NOMURA MF Infrastructure Fund	1	0.7450	0.8070	0.8507
Mirae Asset Global Commodity Stocks Fund	0.6886	0.8753	0.9673	0.8437
Pine Bridge Infrastructure & Economic Reform Fund	1	1	0.9600	0.9867
Pine Bridge World Gold Fund	0.8220	0.7515	1	0.8578
Reliance Banking Fund	0.8753	0.7286	0.7757	0.7932
SBI Infrastructure Fund	0.8574	0.7930	0.8582	0.8362
Sundaram Energy Opportunities Fund	0.9334	0.9918	0.8787	0.9346
Tata Growing Economies Infrastructure Fund	1	1	1	1.0000
UTI Banking Sector Fund	0.8675	0.7053	0.7474	0.7734

Source: Calculated.

Table A2: Ranking of In-sample Schemes based on Three Year Efficiency Scores

Fund Name	Efficiency Average	Rank
Tata Growing Economies Infrastructure Fund	1.0000	1
JPMorgan India Smaller Companies Fund	0.9953	2
Pine Bridge Infrastructure & Economic Reform Fund	0.9867	3
DSP Black Rock World Gold Fund	0.9672	4
HDFC Core and Satellite Fund	0.9624	5
DSP Black Rock World Energy Fund	0.9612	6
Canara Robeco Infrastructure	0.9505	7
DWS Global Agribusiness offshore Fund	0.9430	8
Sundaram Energy Opportunities Fund	0.9346	9
L&T Infrastructure Fund	0.9047	10
ICICI Prudential Technology Fund	0.8835	11
DSP Black Rock World Mining Fund	0.8661	12
BOI AXA Focused Infrastructure Fund	0.8642	13
Baroda Pioneer Infrastructure Fund	0.8613	14
Kotak PSU Bank ETF	0.8593	15
Pine Bridge World Gold Fund	0.8578	16
LIC NOMURA MF Infrastructure Fund	0.8507	17
ICICI Prudential Exports and Other Services Fund	0.8463	18
Mirae Asset Global Commodity Stocks Fund	0.8437	19
SBI Infrastructure Fund	0.8362	20
ING Global Commodities Fund	0.8164	21
HDFC Infrastructure Fund	0.8115	22
ICICI Prudential Banking & Financial Services Fund	0.8112	23
Reliance Banking Fund	0.7932	24
Fidelity Global Real Assets Fund	0.7842	25
UTI Banking Sector Fund	0.7734	26
IDFC Strategic Sector (50-50) Equity Fund	0.6654	27

Source: Calculated.

Table A 3: Fund wise decomposition of inefficiency (2010–11)

Fund Name	Standard Deviation	Probability of Excess Return	Mean Return	Value at Risk
Baroda Pioneer Infrastructure Fund	0.0111	0	0	0
BOI AXA Focused Infrastructure Fund	0.0408	0.0068	0.0068	0.0068
Canara Robeco Infrastructure	0.0388	0.0007	0.0007	0.0007
DSP Black Rock World Energy Fund	0.0231	0.0004	0.0004	0.0004
DSP Black Rock World Gold Fund	0.0983	0	0	0
DSP Black Rock World Mining Fund	0	0	0	0
DWS Global Agribusiness offshore Fund	0.1494	0.0003	0.0003	0.0003
Fidelity Global Real Assets Fund	0.1475	0.0068	0.0068	0.0068
HDFC Core and Satellite Fund	0	0	0	0
HDFC Infrastructure Fund	0.1851	0.0033	0.0033	0.0033

Fund Name	Standard Deviation	Probability of Excess Return	Mean Return	Value at Risk
ICICI Prudential Banking & Financial Services Fund	0.1801	0.0096	0.0096	0.0096
ICICI Prudential Exports and Other Services Fund	0.2546	0.0056	0.0056	0.0056
ICICI Prudential Technology Fund	0.1097	0.0056	0.0056	0.0056
IDFC Strategic Sector (50-50) Equity Fund	0.6527	0.0125	0.0125	0.0125
ING Global Commodities Fund	0	0	0	0
JPMorgan India Smaller Companies Fund	0.0115	0.0009	0.0009	0.0009
Kotak PSU Bank ETF	0	0	0	0
L&T Infrastructure Fund	0.0589	0.0007	0.0007	0.0007
LIC NOMURA MF Infrastructure Fund	0	0	0	0
Mirae Asset Global Commodity Stocks Fund	0.3003	0.0054	0.0054	0.0054
Pine Bridge Infrastructure & Economic Reform Fund	0	0	0	0
Pine Bridge World Gold Fund	0.1641	0.0056	0.0056	0.0056
Reliance Banking Fund	0.1221	0.0010	0.0010	0.0010
SBI Infrastructure Fund	0.1324	0.0040	0.0040	0.0040
Sundaram Energy Opportunities Fund	0.0650	0.0006	0.0006	0.0006
Tata Growing Economies Infrastructure Fund	0	0	0	0
UTI Banking Sector Fund	0.1215	0.0042	0.0042	0.0042

Source: Calculated.

Table A 4: Fund wise decomposition of inefficiency (2011–12)

Fund Name	Standard Deviation	Probability of Excess Return	Mean Return	Value at Risk
Baroda Pioneer Infrastructure Fund	0.2483	0.0022	0.0022	0.0022
BOI AXA Focused Infrastructure Fund	0.1815	0.0026	0.0026	0.0026
Canara Robeco Infrastructure	0.1079	0	0	0
DSP Black Rock World Energy Fund	0	0	0	0
DSP Black Rock World Gold Fund	0	0	0	0
DSP Black Rock World Mining Fund	0.2195	0.0020	0.0020	0.0020
DWS Global Agribusiness offshore Fund	0	0	0	0
Fidelity Global Real Assets Fund	0.1428	0.0061	0.0061	0.0061
HDFC Core and Satellite Fund	0.0609	0	0	0
HDFC Infrastructure Fund	0.2217	0.0002	0.0002	0.0002
ICICI Prudential Banking & Financial Services Fund	0.1505	0	0	0
ICICI Prudential Exports and Other Services Fund	0.1940	0	0	0
ICICI Prudential Technology Fund	0	0	0	0
IDFC Strategic Sector (50-50) Equity Fund	0.1782	0.0048	0.0048	0.0048
ING Global Commodities Fund	0	0	0	0
JPMorgan India Smaller Companies Fund	0	0	0	0
Kotak PSU Bank ETF	0.2819	0	0	0
L&T Infrastructure Fund	0.1387	0	0	0
LIC NOMURA MF Infrastructure Fund	0.2353	0.0088	0.0088	0.0088

Fund Name	*Standard Deviation*	*Probability of Excess Return*	*Mean Return*	*Value at Risk*
Mirae Asset Global Commodity Stocks Fund	0.1094	0.0058	0.0058	0.0058
Pine Bridge Infrastructure & Economic Reform Fund	0	0	0	0
Pine Bridge World Gold Fund	0.2341	0.0064	0.0064	0.0064
Reliance Banking Fund	0.2688	0.0012	0.0012	0.0012
SBI Infrastructure Fund	0.1928	0.0059	0.0059	0.0059
Sundaram Energy Opportunities Fund	0.0082	0	0	0
Tata Growing Economies Infrastructure Fund	0	0	0	0
UTI Banking Sector Fund	0.2884	0.0029	0.0029	0.0029

Source: Calculated.

Table A 5: Fund Wise Decomposition of Inefficiency (2012–13)

Fund Name	*Standard Deviation*	*Probability of Excess Return*	*Mean Return*	*Value at Risk*
Baroda Pioneer Infrastructure Fund	0.1278	0.0095	0.0095	0.0095
BOI AXA Focused Infrastructure Fund	0.1447	0.0059	0.0059	0.0059
Canara Robeco Infrastructure	0	0	0	0
DSP Black Rock World Energy Fund	0.0907	0.0006	0.0006	0.0006
DSP Black Rock World Gold Fund	0	0	0	0
DSP Black Rock World Mining Fund	0.1440	0.0136	0.0136	0.0136
DWS Global Agribusiness offshore Fund	0.0121	0.0030	0.0030	0.0030
Fidelity Global Real Assets Fund	0.3244	0.0002	0.0002	0.0002
HDFC Core and Satellite Fund	0.0447	0.0025	0.0025	0.0025
HDFC Infrastructure Fund	0.1304	0.0078	0.0078	0.0078
ICICI Prudential Banking & Financial Services Fund	0.1915	0.0090	0.0090	0.0090
ICICI Prudential Exports and Other Services Fund	0	0	0	0
ICICI Prudential Technology Fund	0.2104	0.0063	0.0063	0.0063
IDFC Strategic Sector (50-50) Equity Fund	0.1233	0.0099	0.0099	0.0099
ING Global Commodities Fund	0.4079	0.1061	0.1061	0.1061
JPMorgan India Smaller Companies Fund	0	0	0	0
Kotak PSU Bank ETF	0.1140	0.0101	0.0101	0.0101
L&T Infrastructure Fund	0.0831	0.0012	0.0012	0.0012
LIC NOMURA MF Infrastructure Fund	0.1755	0.0072	0.0072	0.0072
Mirae Asset Global Commodity Stocks Fund	0.0323	0.0001	0.0001	0.0001
Pine Bridge Infrastructure & Economic Reform Fund	0.0262	0.0048	0.0048	0.0048
Pine Bridge World Gold Fund	0	0	0	0
Reliance Banking Fund	0.2053	0.0082	0.0082	0.0082
SBI Infrastructure Fund	0.1330	0.0034	0.0034	0.0034
Sundaram Energy Opportunities Fund	0.1143	0.0026	0.0026	0.0026
Tata Growing Economies Infrastructure Fund	0	0	0	0
UTI Banking Sector Fund	0.2193	0.0149	0.0149	0.0149

Source: Calculated.