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AN ENSEMBLE APPROACH FOR PORTFOLIO SELECTION IN A MULTI-CRITERIA DECISION MAKING FRAMEWORK

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Abstract: *Investment in Mutual Funds (MF) has generated increasing interest among the investors over last few decades as it provides an opportunity for flexible and transparent choice of funds to diversify risk while having return potential. MF are essentially a portfolio wherein investors' funds are invested in the securities traded in the capital market while sharing a common objective. However, selection and management of different asset classes pertaining to a particular MF are done by an active fund manager under regulatory supervision. Hence, for an individual investor, it is important to assess the performances of the MF before investment. Performances of MF depend on several criteria based on risk-return measures. Hence, selection of MF is subject to satisfying multiple criteria. In this paper, we have adopted an ensemble approach based on a two-stage framework. Our sample consists of the open ended equity large cap funds (direct plan) in India. In the first stage, the efficiencies of the funds are analyzed using DEA for primary selection of the funds. In order to rank the funds based on risk and return parameters for investment portfolio formulation, we have used MABAC approach in the second stage wherein criteria weights have been calculated using the Entropy method.*

Keywords: *Mutual Fund, Portfolio Selection, Multi-Criteria Decision Making, Data Envelopment Analysis (DEA), Entropy, Multi-Attribute Border Approximation Area Comparisons (MABAC).*

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1. Introduction

The aftermath of the economic liberalization, Indian Capital Market (ICM) has witnessed significant changes in investment pattern. With the development of Information and Communication Technology (ICT), there is no dearth of information regarding available investment opportunities. Moreover, with increasing efforts from the Govt. of India (GOI), MF have emerged as a preferred choice for common investors because of many reasons. First, it provides reportedly high return as compared to other popular investment options like Fixed Deposits (FD), National Savings Certificates (NSC), Public Provident Funds (PPF), and other postal savings. Alongside, with increasing awareness and available information, risk can also be brought down to an affordable level by carefully evaluating the performances of the MF for the prudent selection of funds to invest. The concept of MF resembles the selection of portfolio wherein the active fund managers invest the total amount invested in other asset classes such as stocks. The objective is to generate sizeable return out of the investment made in the portfolio while minimizing the risk through diversification i.e. by appropriate selection of the securities and allocating optimum weights dynamically (Gupta et al., 2019). MF in India have a long stint with ICM since the inception of Unit Trust of India (UTI) in 1963. Recent reports (AMFI, 2018) indicate a significant growth in the asset base of the Indian MF Industry (IMI) from INR 5.05 trillion (31st March, 2008) to INR 22.20 trillion (February, 2018) despite the event of bankruptcy of the renowned US bank Lehman Brothers in September, 2008. Therefore, a large number of investors have been attracted by the promising nature of IMI. However, in order to ensure the possibility of considerable return at an affordable risk, one has to select the funds apt to his/her risk appetite and financial goal.

With this preamble, in this study, we have focused on open ended equity MF(direct plans) in India belonging to the large cap segment. The equity MF segment accounts for around 50.7% share of the total asset base of the industry in February, 2018 as reported by AMFI (2018). Unlike the close ended funds (CF), open ended funds (OF) allow the investors to buy and sell the units of the funds on a continuous basis, which means the new investors are allowed to enter at convenience and so as the existing investors can exit whenever needed. Moreover, for CF the unit capital is fixed and also there is a limit on sales. In other words, OF allow greater flexibility for the investors than CF. Large cap funds show relatively stable movements in the return as compared to the mid-cap and small cap funds. We have considered direct plans only since, unlike regular plans, they impose less pressure on expense ratio as no intermediate commission is involved. In essence, we like to perceive the performance of MFs from a common investors' point of view without imposing significant burden on Net Assets Value (NAV). In our approach, we have used Non-Parametric Methods (NPM). Literatures manifest comparatively less evidence of such methods than their traditional parametric counterparts (Babalos et al., 2011). Selection of MF needs to satisfy the objectives pertaining to several criteria based on risk and return and time horizon, etc. Therefore, among NPM, DEA has been a popular method, though, moderate evidences of the use of MCDM techniques have been found in the state-of-the art. The reason lies in the fundamental use of DEA to assess and differentiate between the efficient and non-efficient Decision Making Units (DMU). MCDM techniques allow to rank the DMU based on a number of criteria. Hence, for identifying efficient DMU or MF while ranking them based on performance parameters, we propose a two-stage assessment framework. The rest of the paper proceeds as follows. Section 2 highlights some of the related work while in the section 3 we discuss the research methodology. Section 4 summarizes the results and put forward necessary discussions on the same. Finally, section 5 concludes the paper and posits some future scope of research.

2. Related Work

A plethora of research has been conducted on MF for understanding the nature and setting performance measurement framework with an objective to inflate the expected utility while reducing the risk level. In one of the seminal works in the stated field, Markowitz postulated the mean-variance model related to efficiently diversified portfolio (Markowitz, 1952). In the following works, the researchers (Tobin, 1958; Markowitz, 1959; Sharpe, 1966; Jensen, 1968; Treynor, 1965) further explained and extended the framework by introducing new risk measures such as semi-variance and risk adjusted performance metrics such as reward to volatility ratio, alpha and reward to variability ratio based on the Capital Assets Pricing Model (CAPM). The objective was to assess portfolio performance with respect to the benchmark with an objective to minimize the systematic risk which is represented by beta. The authors exhibited that unsystematic risk can be reduced through diversification of the portfolio. Based on these measures, several researchers and practitioners worked on evaluating the performances of the MF (Kacperczyk et al., 2005; Pedersen &Rudholm-Alfvin, 2003; Eling & Schuhmacher, 2007; Plantinga & de Groot, 2002; Redman et al., 2000). In the Indian context also, across different periods, many researchers (Barua & Verma, 1991; Jayadev, 1996; Gupta, 2000; Sehgal & Jhanwar, 2008; Tripathy, 2004; Anand & Murugaiah, 2006; Anitha et al., 2011; Arora, 2015; Kundu, 2009) worked on selection of funds based the criteria like Sharpe ratio, Jensen ratio, and Sortino ratio, alpha, beta, NAV, timing to market, and selectivity skill following traditional statistical approaches.

Over the years apart from the traditional parametric approaches, applied operations research techniques have also been adopted by the researchers. The authors (Pendaraki et al., 2004; Sharma & Sharma, 2006) have applied goal programming to evaluate the performances of MF for formulating the portfolio. DEA has been a widely accepted method by the researchers and practitioners (Murthi& Choi, 2001; Murthi et al., 1997; Anderson et al., 2004; Sengupta, 2003; Daraio & Simar, 2006; Babalos et al., 2015; McMullen & Strong, 1998; Wilkens & Zhu, 2001; Tarim & Karan, 2001; Galagedera & Silvapulle, 2002; Chang, 2004; Carlos Matallín et al., 2014; Nguyen-Thi-Thanh, 2006; Chu et al., 2010; Tsolas, 2011; Morey & Morey, 1999; Basso & Funari, 2001; Briec et al., 2004; Zhao et al., 2011; Joro & Na, 2006; Kooli et al., 2005; Haslem & Scheraga, 2003) among the non-parametric applied operations research techniques. The researchers have considered the variables like standard deviation, expense ratio, loads, turnover, beta, costs, fund size, variance, percentage of periods with negative return, lower semi-variance, sales charges, operating expenses, cash percentage, P/E ratio, P/B ratio, total assets, lower mean, lower semi-skewness, and excess kurtosis as input while considering the variables like return, deviations from median return, capital flow, skewness, Sharpe ratio, upper semi-variance, upper semi-skewness, and Jensen's α as output in assessing the performances of the funds under study. There has been another string of the literature in which MCDM techniques are applied for selection of MF (Pendaraki et al., 2005; Lin et al., 2007; Gladish et al., 2007; Chang et al., 2010; Babalos et al., 2011; Alptekin, 2009; Karmakar et al., 2018; Pendaraki & Zopounidis, 2003; Sielska, 2010). Attribute based classification approaches like UTADIS (UTilités Additives DIScriminantes) (Pendaraki et al., 2005; Lin et al., 2007), fuzzy MCDM techniques (Gladish et al., 2007), distance based MCDM methods like TOPSIS (Lin et al., 2007; Chang et al., 2010; Alptekin, 2009; Karmakar et al., 2018; Sielska, 2010) and EDAS (Karmakar et al., 2018), outranking methods such as PROMETHEE (Sielska, 2010) and PROMETHEE II (Pendaraki & Zopounidis, 2003) have been selected for portfolio selection issue based on the parameters like Sharpe ratio, Sortinoratio, Treynorratio, Jensen's α, AUM, beta, standard deviation, NAV, annualized return, average return, Information ratio, and R-squared. In this context, in paper (Babalos et al., 2011) the authors used Stochastic Multi-criteria Acceptability Analysis (SMAA-2) framework for assessing performances of MF. Predominantly, objective weight method using Euclidean Distance has been applied for calculating criteria weight. However, some authors like Chang et al. (2010) experimented with different distance measures for examining performances of the MF.

3. Data and Methodology

3.1. Development of the framework

In this study, we have followed a non-parametric two stage framework wherein we have ranked the funds under study. In the first stage, we have applied DEA to appraise the efficiencies of the funds for a primary level selection. For a refined selection in a common setting for investment choice among the relatively efficient portfolios, at stage two the MCDM technique like MABAC has been used. The entropy method has been employed for calculation of criteria weight in this regard. Figure 1 depicts the framework followed in this study. We have started our analysis with total 48 number of open ended equity large cap funds under direct plan.

In the seminal works of Markowitz (1952, 1959), the underline assumption considered first two central moments of the utility function of the return which is treated as a normal distribution. However, the studies (Lau et al., 1990; Cambell & Hentsche, 1992) arguably reported that portfolio returns are always not normally distributed in practice. Hence, it is imperative to consider higher moments. Average investors prefer lower value of Kurtosis (Scott & Horvath, 1980) as it entails a higher degree of sensitivity of the funds with respect to non-favorable market condition. In view of this, for filling the gap in the literature in Indian context, this study considers Kurtosis as one of the inputs. Expense ratio puts load on the profitability as it covers the management fees and operating expense.

The third quartile return has a typical significance in the sense that it indicates relative closeness to the highest value than the average return. The ratio PSV to NSV signifies inclination of the deviation of the return from the mean towards the higher side which essentially acts as a favorable proposition for the investors. We have used standard Variable Returns to Scale (VRS) model as it resembles real life situation compared to Constant Returns to Scale (CRS) which reflects the proportionate change in the output with respect to the input (Ali & Seiford, 1990). Further, we have calculated super efficiency in order to discriminate the funds to a considerable extent.

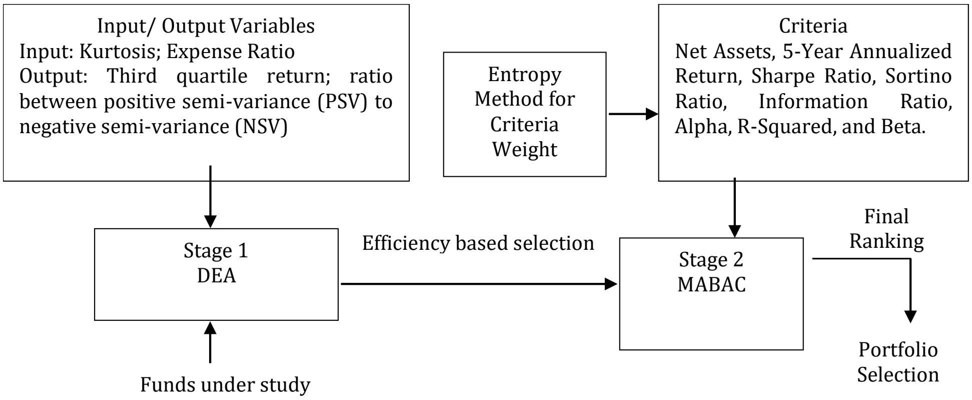

Figure 1. Research Framework

The higher value of net assets of a fund indicates the greater possibility of a good return. The Sharpe ratio, α, and Sortino ratio specify the excess return with respect to risk, i.e. risk-adjusted performance while beta captures the systematic risk. To what extent, the portfolio return with respect to the benchmark, i.e. index, adjusts the volatility of the return is reflected in the value of Information ratio which stands beneficial for the investors. The value of R-squared manifests the nature of diversification of the portfolio, which leads to reduction of unsystematic risk.

3.2. Sample

In our study, we focus on open ended and large cap equity mutual funds under direct plan. In this context, we have excluded the fixed maturity plan, and plans suspended for sales which otherwise leaves lesser chance to gain more at calculated risk. For spotting the funds, we have referred the Value research online data base and subsequently for collecting information on the performance criteria. Appendix 1 shows the descriptive statistics of the total 48 funds selected initially for the study. Returns of the last 12 quarters (i.e. Sep 2015 to Jun 2018) have been considered for calculating distribution based parameters used in DEA.

3.3. Data Envelopment Analysis (DEA)

DEA evaluates a set of peer entities (homogenous) i.e. Decision Making Units (DMUs) having multiple inputs or outputs. As introduced by Charnes et al. (1978), this technique has gained extensive importance by the researchers in measuring performance efficiency in terms of the frontiers or envelop rather than the central tendency as in the case of fitting a regression model. In DEA, the efficiency of the homogenous entities is calculated by using the linear programming method. Calculations for input oriented, constant return to scale (CRS) are as follows:

$\min \theta$

Subject to:

$$\sum_{j=1}^{n} x_{ij} \lambda_j \leq \theta x_{it} \; i = 1,2, \dots, m; \quad \text{Input Constraint} \tag{1}$$

$$\sum_{j=1}^{n} y_{rj} \lambda_j \geq y_{rt} \; r = 1,2, \dots, s; \quad \text{Output Constraint} \tag{2}$$

Where, $\lambda_j \geq 0 \; \forall \, i, j, r$

For variable return to scale (VRS) the sets of equations are:

$\min \theta$

Subject to:

$\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{it}$ $i = 1,2,\dots,m;$ Input Constraint (3)

$\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{rt}$ $r = 1,2,\dots,s;$ Output Constraint (4)

Where, $\sum_{j=1}^{n}\lambda_j = 1$; $\lambda_j \ge 0\ \forall$ i, j, r

If two or more DMUs are found to be efficient (i.e. θ = 1 or 100%) then the Super-efficiency value is calculated to discriminate them. For VRS the super efficiency is calculated as below:

$\min\theta$

Subject to

$\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{it}$ $i = 1,2,\dots,m;$ Input Constraint (5)

$\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{rt}$ $r = 1,2,\dots,s;$ Output Constraint (6)

Where, $\sum_{j=1}^{n}\lambda_j = 1; \lambda_j \ge 0\ \forall$ i, j, r ; j ≠ t.

3.4. Entropy Method

It is an objective method for calculating criteria weights based on relative information content wherein, higher value of the entropy (degree of disorder) indicates more information content for the respective criterion (Shannon, 1948). The steps are as given below where,

a_i: i^{th} alternative where i = 1,2,3,.....m;

c_j: j^{th} criterion where j = 1,2,3,.....n;

x_{ij}: j^{th} criterion value for the i^{th} alternative;

Step1. Normalization of the criteria.

For this purpose, we have used the enhanced accuracy method of normalization (Zeng et al., 2013) as mentioned in Jahan and Edwards (2015). Accordingly, the normalized matrix R = $[r_{ij}]_{m\times n}$ is given by:

$$r_{ij} = 1 - \frac{x_j^{max} - x_{ij}}{\sum_{i=1}^{m}\left(x_j^{max} - x_{ij}\right)} \quad \text{(Beneficial Criteria)} \tag{7}$$

$$r_{ij} = 1 - \frac{x_{ij} - x_j^{min}}{\sum_{i=1}^{m}\left(x_{ij} - x_j^{min}\right)} \quad \text{(Non-beneficial Criteria)} \tag{8}$$

Step 2. Entropy calculation for the criterion

Entropy of the j^{th} criterion is given by:

$$H_j = -\frac{\sum_{i=1}^{m} f_{ij}\ \ln f_{ij}}{\ln m}, i = 1,2,\dots m; j = 1,2,..n \tag{9}$$

Where,

$$f_{ij} = \frac{r_{ij}}{\sum_{i}^{m} r_{ij}}, i = 1, 2, \dots m; j = 1,2, \dots \tag{10}$$

Step 3. Calculation of the entropy weight for the criterion

Entropy weight of the j^{th} criterion is determined by:

$$w_j = \frac{1 - H_j}{n - \sum_{j=1}^{n} H_j}, \text{where } \sum_{j=1}^{n} w_j = 1 \tag{11}$$

3.5. Multi-Attribute Border Approximation Area Comparisons (MABAC)

Since its proposal (Pamučar & Ćirović, 2015), this method has drawn significant attention from the researchers for its inherent computational ease and stability. Unlike TOPSIS, this method classifies the performances of the criteria into two areas such as Upper Approximation Area (UAA) for ideal solutions and Lower Approximation Area (LAA) for non-ideal solutions instead of calculating the distance of any solution from the ideal and non-ideal solutions. In a sense, this method examines the relative strength and weakness of each alternative with respect to the others pertaining to each criterion (Roy et al., 2016). This method has been widely applied by the researchers for solving multi-criteria decision making problems such as railway management (Sharma et al., 2018; Vesković et al., 2018) medical tourism site selection (Roy et al., 2018) and selection of hotels (Yu et al., 2017).

Let, D is the initial decision matrix represented by

a_i: i^{th} alternative where i = 1,2,3,.....m;

c_j: j^{th} criterion where j = 1,2,3,.....n;

x_{ij}: j^{th} criterion value for the i^{th} alternative;

The broad steps under this method are given below.

Step 1. Normalization of the criteria values

$$r_{ij} = \frac{(x_{ij} - x_i^-)}{(x_i^+ - x_i^-)} \text{; For beneficial criteria} \quad (12)$$

$$r_{ij} = \frac{(x_{ij} - x_i^+)}{(x_i^- - x_i^+)} \text{; For non-beneficial criteria} \quad (13)$$

Where, x_i^+ and x_i^- are the maximum and minimum criteria values respectively.

Step 2. Construction of weighted normalization matrix (Y)

Elements of Y are given by:

$$y_{ij} = w_j(r_{ij} + 1) \text{ ; Where, } w_j \text{ are the criteria weight.} \quad (14)$$

Step 3. Determination of the Border Approximation Area (BAA)

The elements of the Border Approximation Area (BAA) T is given by:

$$t_j = \left(\prod_{i=1}^{m} y_{ij}\right)^{1/m} \quad (15)$$

Where, m is the total number of alternatives &t_j corresponds to each criterion.

Step 4. Calculation of the matrix Q related to the separation of the alternatives from BAA

$$Q = Y\text{-}T \quad (16)$$

A particular alternative a_i is said to be belonging to the Upper Approximation Area (UAA) i.e. T^+ if $q_{ij} > 0$ or Lower Approximation Area (LAA) i.e. T^- if $q_{ij} < 0$or BAA i.e. T if $q_{ij} = 0$.

The alternative a_i is considered to be the best among the others if more numbers of criteria pertaining to it possibly belong to T^+.

Step 5. Ranking of the alternatives

It is done according to the final values of the criterion functions as given by

$$S_i = \sum_{j=1}^{n} q_{ij} \text{ for } j = 1,2, \dots n \text{ and } i = 1,2, \dots m \quad (17)$$

Higher the value, the better is the rank.

In this study for carrying out DEA, we have used Lingo (version 11) software while for MCDM related calculations, Microsoft Office excel (version 2010) is utilized.

4. Results and discussions

We have considered total 48 funds initially. However, before analyzing them using DEA, we have checked whether the condition of the required number of DMUs is satisfied or not. In this regard, though there are several studies, we have followed one of the widely accepted study conducted by Banker et al. (1989). According to the study, the rule of the thumb is $n >= \max \{p \times q, 3(p + q)\}$ where, p be the number of inputs and q is the number of outputs used in the analysis, and n is the number of DMUs to be considered. Our model has two inputs and two outputs. Hence, it satisfies the condition. The top 20 funds (i.e. DMUs) based on the result of DEA considering VRS model is given in the Table 1 while the details is included in the Appendix 2.

The performance criteria values of the above funds (Table 1) are given in the Appendix 1. We then have used MCDM model for ranking the above mentioned funds. For calculating criteria weights, we have used a modified Entropy method. The results are listed in Tables 2-3. After calculating the criteria weights, we then proceed to the stage 2 i.e. ranking of the funds (primary selection through DEA) using the MABAC technique. The results are given in Tables 4-6.

From the result, it is evident that the top five funds (i.e. A27, A19, A38, A22 and A25; the names are given in Appendix 1) are rated 4-star and 5-star by Value research and except one of them, and their risk grades are above average or more. On the other hand, bottom five funds (i.e. A40, A42, A21, A3 and A5; the names are given in Appendix 1) are rated 2-star or below and having an overall average risk grade. Hence, this study also conforms to the market based rating of the funds by Value research.

In order to check the dependability of the result obtained from MABAC, we have also ranked the funds selected from DEA result using TOPSIS technique. In line with the method suggested by Hwang and Yoon (1981), we have obtained the rankings as given in the Table 7. For checking consistency with MABAC based ranking, we have performed Spearman's Rank Correlation test using IBM SPSS 22, which is 0.952 (significant at 0.01 level). Hence, the result obtained from MABAC is acceptable.

Table 1. DEA result (Top 20 Funds)

Funds under study	Kurtosis	Kurtosis (Normalized)(Input)	Expense Ratio(Input)	PSV/NSV (Output)	Q3 (Output)	VRS Result	Rank VRS
DMU3	-0.994218297	0.228357785	0.51	0.692524206	6.325	0.277	20
DMU5	0.430052796	1	1.05	1.190759453	7.5125	0.4196	17
DMU10	0.068745875	0.804250978	2.09	1.712988573	6.065	1	7
DMU13	-1.392072451	0.012808188	0.15	1.024946667	7.3475	1.5272	2
DMU14	-1.069736073	0.187443732	0.15	0.697821479	6.6575	0.8342	11
DMU15	-0.986286229	0.232655225	1.26	1.65839919	8.5375	1	7
DMU19	-0.867681981	0.296912686	0.44	1.167185892	9.8025	1.46	3
DMU21	-1.047245089	0.199628907	0.43	0.708575851	6.5225	0.3276	18
DMU22	-0.914640359	0.271471555	0.56	1.177342789	9.7425	1.02	6
DMU24	-1.020204286	0.214279085	0.17	0.702101309	6.5925	0.7349	13
DMU25	-0.756941711	0.356909598	0.75	0.703951659	8.09	0.3169	19
DMU27	-1.340703715	0.040638764	2.94	0.703018825	12.0225	1	7
DMU32	-1.415713371	0	1.15	1.038445735	7.18	1	7
DMU36	-0.9687944	0.242131955	0.29	0.706595066	6.61	0.4586	16
DMU37	-1.414566835	0.000621171	0.29	1.02757939	7.045	3.0343	1
DMU38	-0.950082133	0.252269895	1.32	1.528358013	7.07	0.7819	12
DMU40	-1.046793817	0.199873397	0.29	0.703356945	6.6075	0.4689	15
DMU42	-1.063892456	0.190609689	0.21	0.702148768	6.685	0.6264	14
DMU43	-1.403733132	0.006490659	0.22	1.033529532	7.24	1.4103	4
DMU48	-1.072451509	0.185972562	0.12	0.691073629	6.5875	1.25	5

Table 2. Normalization Table

Alt.	C1	C2	C3	C4	C5	C6	C7	C8
A3	0.9450	0.9338	0.9315	0.9315	0.8427	0.9350	1.0000	0.9600
A5	0.9477	0.9561	0.8910	0.8883	0.9688	0.9165	0.8951	0.9850
A10	0.9450	0.9446	0.9688	0.9694	0.9866	0.9611	0.9161	1.0000
A13	0.9453	0.9381	0.9564	0.9514	0.9839	0.9499	0.9930	0.9600
A14	0.9460	0.9406	0.9470	0.9477	0.9304	0.9453	1.0000	0.9600
A15	1.0000	0.9627	0.9315	0.9333	0.9831	0.9350	0.9510	0.8650
A19	0.9454	0.9834	0.9844	1.0000	0.9914	0.9815	0.7832	0.9800
A21	0.9453	0.9359	0.9377	0.9369	0.8585	0.9389	1.0000	0.9550
A22	0.9446	0.9809	0.9782	0.9928	0.9902	0.9784	0.7762	0.9850
A24	0.9449	0.9400	0.9470	0.9459	0.9346	0.9446	1.0000	0.9550
A25	0.9459	0.9509	0.9751	0.9712	0.9917	0.9655	0.9231	0.9550
A27	0.9446	1.0000	1.0000	0.9946	1.0000	1.0000	0.8531	0.7850
A32	0.9445	0.9314	0.9315	0.9279	0.9634	0.9363	0.9930	0.9600
A36	0.9449	0.9383	0.9377	0.9405	0.9144	0.9399	1.0000	0.9550
A37	0.9445	0.9333	0.9470	0.9441	0.9756	0.9452	0.9930	0.9700
A38	0.9841	0.9808	0.9502	0.9423	0.9848	0.9491	0.9301	0.9400
A40	0.9456	0.9371	0.9439	0.9459	0.8882	0.9435	1.0000	0.9550
A42	0.9445	0.9375	0.9439	0.9441	0.8936	0.9426	1.0000	0.9550
A43	0.9445	0.9345	0.9470	0.9441	0.9774	0.9457	0.9930	0.9600
A48	0.9478	0.9401	0.9502	0.9477	0.9405	0.9459	1.0000	0.9600

Table 3. H_j values and criteria weights

Hj	0.748	0.748	0.748	0.748	0.747	0.748	0.747	0.747
w_j	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125

Table 4. Normalization Result

Alt.	C1	C2	C3	C4	C5	C6	C7	C8
A3	0.009	0.035	0.371	0.387	0.000	0.221	1.000	0.814
A5	0.058	0.359	0.000	0.000	0.802	0.000	0.531	0.930
A10	0.009	0.193	0.714	0.726	0.915	0.534	0.625	1.000
A13	0.016	0.098	0.600	0.565	0.898	0.399	0.969	0.814
A14	0.028	0.134	0.514	0.532	0.558	0.345	1.000	0.814
A15	1.000	0.456	0.371	0.403	0.892	0.221	0.781	0.372
A19	0.017	0.759	0.857	1.000	0.945	0.779	0.031	0.907
A21	0.014	0.065	0.429	0.435	0.100	0.268	1.000	0.791
A22	0.003	0.722	0.800	0.935	0.938	0.741	0.000	0.930
A24	0.007	0.125	0.514	0.516	0.584	0.336	1.000	0.791
A25	0.026	0.284	0.771	0.742	0.947	0.587	0.656	0.791
A27	0.002	1.000	1.000	0.952	1.000	1.000	0.344	0.000
A32	0.001	0.000	0.371	0.355	0.767	0.237	0.969	0.814
A36	0.008	0.100	0.429	0.468	0.456	0.280	1.000	0.791
A37	0.000	0.028	0.514	0.500	0.845	0.344	0.969	0.860
A38	0.714	0.720	0.543	0.484	0.904	0.390	0.688	0.721

Alt.	C1	C2	C3	C4	C5	C6	C7	C8
A40	0.021	0.083	0.486	0.516	0.289	0.324	1.000	0.791
A42	0.000	0.088	0.486	0.500	0.323	0.313	1.000	0.791
A43	0.000	0.045	0.514	0.500	0.856	0.350	0.969	0.814
A48	0.061	0.126	0.543	0.532	0.622	0.351	1.000	0.814

Table 5. Border Approximation Area Matrix

BAA	0.1347	0.1552	0.1907	0.1919	0.2066	0.1730	0.2181	0.2189

Table 6. Ranking of the Funds

Fund	A3	A5	A10	A13	A14	A15	A19	A21	A22	A24
Sum (S_i)	-0.134	-0.154	0.101	0.056	0.002	0.073	0.173	-0.101	0.144	-0.005
Rank	19	20	6	8	12	7	2	18	4	13
Fund	A25	A27	A32	A36	A37	A38	A40	A42	A43	A48
Sum (S_i)	0.111	0.173	-0.050	-0.048	0.019	0.156	-0.050	-0.051	0.017	0.017
Rank	5	1	15	14	9	3	16	17	11	10

Table 7. TOPSIS Ranking

Fund	A3	A5	A10	A13	A14	A15	A19	A21	A22	A24
TOPSIS Rank	20	15	7	8	12	3	4	19	5	13
Fund	A25	A27	A32	A36	A37	A38	A40	A42	A43	A48
TOPSIS Rank	6	1	14	16	10	2	17	18	9	11

5. Conclusion

We have made an attempt to assess the funds from two perspectives such as efficiency and performance. Accordingly, we have filtrated the funds through a two stage process using DEA at stage 1 and MABAC at stage 2. The rationale behind this study lies in the selection of the funds to form an investment portfolio based on their return distribution and performance parameters encompassing risk-return tradeoff. In effect, this study not only has adjudged the funds on efficiency dimension, but also sets out to establish a ranking based on risk-return criteria. Our results conform to the market based rating of the funds. A combination of DEA-Entropy-MABAC turns this study considerably different from the existing contributions in the Indian context as far as the approach is concerned. The results of this study provide the investors a broader perspective for selection of the portfolio. However, future research shall be required to focus more clinical approach by considering fundamental parameters and stock level analysis. It is important to analyze the stocks on which the fund managers invest the amount invested by the investors both on fundamental dimension and organizational dimensions to ascertain the decision and establish a causal relationship among the stock performance and MF performance. Further, the efficiencies of the fund houses need to be examined. There are requirements to investigate the relationship between investors' sentiments and market performance of the MF. Also, a consistency between the performances of the funds belonging to different categories can be thought of. Finally, the framework used in this study can be further explored for different other applications.

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Appendix 1. Descriptive Statistics

S/L	Fund	Rating	Risk Grade	Net Assets (Cr) (C1)	5-Year annualized Ret (C2)	Sharpe Ratio (C3)	Sortino Ratio (C4)	Information Ratio (C5)	Alpha (C6)	R-Squared (C7)	Beta (C8)	SD	Expense Ratio
A1	Aditya Birla Sun Life Focused Equity Fund - Direct Plan	****	Below Average	4239.39	21.98	0.36	0.55	-0.16	-0.12	0.93	0.92	13.22	1.26
A2	Aditya Birla Sun Life Frontline Equity Fund - Direct Plan	****	Below Average	21380.42	21.39	0.38	0.60	-0.38	0.13	0.94	0.93	13.32	1.31
A3	Aditya Birla Sun Life Index Fund - Direct Plan	*	Above Average	142.91	16.19	0.31	0.50	-4.75	-1.09	1.00	0.99	13.84	0.51
A4	Axis Bluechip Fund - Direct Plan	*****	Low	2568.10	20.77	0.59	0.78	0.24	3.06	0.87	0.87	13.00	0.94
A5	BNP Paribas Large Cap Fund - Direct Plan	**	Average	892.52	19.71	0.18	0.26	-0.51	-2.52	0.85	0.94	14.22	1.05
A6	Canara Robeco Bluechip Equity Fund - Direct Plan	***	Below Average	131.66	18.72	0.40	0.61	0.09	0.49	0.92	0.97	14.07	1.48
A7	DHFL Pramerica Large Cap Fund - Direct Plan	***	Below Average	414.49	19.85	0.35	0.60	-0.34	-0.44	0.97	0.93	13.18	1.51
A8	DSP Top 100 Equity Fund - Direct Plan	*	High	3007.80	17.40	0.25	0.41	-0.33	-1.69	0.90	1.02	14.99	1.47
A9	Edelweiss Large Cap Fund - Direct Plan	***	Average	140.81	20.33	0.38	0.59	0.00	0.02	0.94	1.00	14.28	0.58
A10	Essel Large Cap Equity Fund - Direct Plan	***	Below Average	150.66	17.90	0.43	0.71	0.09	0.93	0.88	0.91	13.47	2.09
A11	Franklin India Bluechip Fund - Direct Plan	**	Average	8107.94	18.84	0.23	0.43	-0.79	-1.87	0.95	0.90	12.84	1.16
A12	Franklin India Index Fund - NSE Nifty Plan - Direct Plan	**	Average	253.21	16.64	0.32	0.52	-3.68	-0.86	1.00	0.99	13.77	0.64

A13	HDFC Index Fund - Sensex Plan - Direct Plan	* * *	Below Average	244.04	16.87	0.39	0.61	0.00	0.06	0.99	0.99	13.84	0.15
A14	HDFC Index Fund Nifty 50 Plan - Direct Plan	* * *	Average	435.89	17.26	0.36	0.59	-1.80	-0.29	1.00	0.99	13.84	0.15
A15	HDFC Top 100 Fund - Direct Plan	* * *	High	15260.79	20.76	0.31	0.51	-0.03	-1.09	0.93	1.18	16.99	1.26
A16	HSBC Large Cap Equity Fund - Direct Plan	* * *	Average	729.82	18.90	0.41	0.66	0.21	0.49	0.95	1.04	14.85	1.51
A17	ICICI Prudential Bluechip Fund - Direct Plan	* * * *	Low	18747.28	20.62	0.47	0.73	0.25	1.21	0.94	0.93	13.27	1.17
A18	ICICI Prudential Nifty Index Fund - Direct Plan	* *	Average	357.34	17.20	0.34	0.56	-3.55	-0.62	1.00	0.99	13.84	0.57
A19	ICICI Prudential Nifty Next 50 Index Fund - Direct Plan	* * * * *	Above Average	265.36	24.04	0.48	0.88	0.25	2.51	0.69	0.95	15.85	0.44
A20	IDBI India Top 100 Equity Fund - Direct Plan	* *	Average	417.49	18.94	0.16	0.28	-0.71	-2.67	0.89	0.89	13.13	1.06
A21	IDBI Nifty Index Fund - Direct Plan	* *	Above Average	224.64	16.52	0.33	0.53	-4.22	-0.79	1.00	1.00	13.87	0.43
A22	IDBI Nifty Junior Index Fund - Direct Plan	* * * * *	Above Average	55.99	23.64	0.46	0.84	0.21	2.27	0.68	0.94	15.79	0.56
A23	IDFC Large Cap Fund - Direct Plan	* * *	Below Average	373.25	17.30	0.44	0.65	0.17	0.92	0.95	0.93	13.26	1.83
A24	IDFC Nifty Fund - Direct Plan	* * *	Average	117.70	17.17	0.36	0.58	-1.66	-0.35	1.00	1.00	13.85	0.17
A25	Indiabulls Bluechip Fund - Direct Plan	* * * *	Average	401.75	18.89	0.45	0.72	0.26	1.27	0.89	1.00	14.70	0.75
A26	Invesco India Largecap Fund - Direct Plan	* * * *	Low	152.26	21.05	0.47	0.72	0.28	1.25	0.96	0.92	12.99	0.96
A27	JM Core 11 Fund - Direct Plan	* * * * *	High	36.22	26.66	0.53	0.85	0.54	3.94	0.79	1.34	20.89	2.94
A28	JM Large Cap Fund - Direct Plan	*	Below Average	2818.01	17.25	0.06	0.09	-1.31	-3.57	0.96	0.80	11.36	1.61
A29	Kotak Bluechip Fund - Direct Plan	* * *	Below Average	1423.60	20.42	0.35	0.56	-0.23	-0.41	0.96	0.95	13.52	1.15

A30	L&T India Large Cap Fund - Direct Plan	**	Average	423.85	18.74	0.21	0.38	-0.62	-2.16	0.92	0.95	13.77	2.04
A31	LIC MF Index-Nifty Plan - Direct Plan	*	Above Average	23.77	16.39	0.30	0.49	-3.49	-1.17	1.00	1.00	13.96	0.69
A32	LIC MF Index-Sensex Plan - Direct Plan	*	Average	20.69	15.81	0.31	0.48	-0.69	-0.99	0.99	0.99	13.86	1.15
A33	LIC MF Large Cap Fund - Direct Plan	**	Below Average	245.09	18.09	0.19	0.32	-0.77	-2.35	0.93	0.90	13.02	1.52
A34	Motilal Oswal Focused 25 Fund - Direct Plan	****	Low	1170.53	21.94	0.38	0.55	-0.06	0.72	0.72	0.78	12.83	1.15
A35	Principal Nifty 100 Equal Weight Fund - Direct Plan	*	Above Average	18.17	15.84	0.23	0.39	-1.26	-2.16	0.98	0.99	13.92	0.50
A36	Reliance Index Fund - Nifty Plan - Direct Plan	**	Above Average	132.99	16.90	0.33	0.55	-2.34	-0.71	1.00	1.00	13.97	0.29
A37	Reliance Index Fund - Sensex Plan - Direct Plan	**	Average	7.63	16.11	0.36	0.57	-0.28	-0.30	0.99	0.97	13.55	0.29
A38	Reliance Large Cap Fund - Direct Plan	****	Above Average	10897.82	23.62	0.37	0.56	0.03	0.00	0.90	1.03	15.06	1.32
A39	SBI Bluechip Fund - Direct Plan	*****	Low	20283.92	22.61	0.41	0.62	-0.03	0.53	0.90	0.87	12.83	1.18
A40	SBI Nifty Index Fund - Direct Plan	**	Average	320.99	16.71	0.35	0.58	-3.22	-0.43	1.00	1.00	13.93	0.29
A41	Sundaram Select Focus Fund - Direct Plan	****	Below Average	835.70	18.62	0.43	0.66	0.05	0.69	0.95	0.90	12.82	0.55
A42	Tata Index Nifty Fund - Direct Plan	**	Average	12.06	16.77	0.35	0.57	-3.04	-0.50	1.00	1.00	13.87	0.21
A43	Tata Index Sensex Fund - Direct Plan	***	Average	5.87	16.30	0.36	0.57	-0.22	-0.26	0.99	0.99	13.81	0.22
A44	Tata Large Cap Fund - Direct Plan	***	Below Average	803.29	18.50	0.29	0.47	-0.45	-1.15	0.95	0.95	13.53	0.74
A45	Taurus Largecap Equity Fund - Direct Plan	*	High	39.38	17.04	0.00	0.00	-1.27	-5.35	0.91	0.99	14.41	2.15
A46	Taurus Nifty Index Fund - Direct Plan	***	Average	19.06	17.11	0.37	0.60	-0.26	-0.20	0.99	0.98	13.63	1.22
A47	UTI Mastershare Fund - Direct Plan	***	Below Average	5530.66	19.57	0.30	0.53	-0.49	-0.97	0.96	0.91	12.96	1.43
A48	UTI Nifty Index Fund - Direct Plan	***	Average	935.94	17.18	0.37	0.59	-1.46	-0.25	1.00	0.99	13.79	0.12

Appendix 2. Calculation of efficiency using DEA

Funds under study	Kurtosis	Input		Output		VRS result	Rank VRS
		Kurtosis (normalized)	Expense Ratio	PSV/ NSV	Q3		
DMU1	-0.4904	0.5013	1.2600	1.0549	6.6575	16.07%	31
DMU2	-0.7490	0.3612	1.3100	1.0393	7.1600	13.37%	36
DMU3	-0.9942	0.2284	0.5100	0.6925	6.3250	27.70%	20
DMU4	-0.5445	0.4720	0.9400	0.5358	7.4000	16.62%	30
DMU5	0.4301	1.0000	1.0500	1.1908	7.5125	41.96%	17
DMU6	0.2381	0.8960	1.4800	0.7074	5.9725	9.31%	43
DMU7	-0.0014	0.7662	1.5100	0.7634	5.5975	9.27%	44
DMU8	-0.9583	0.2478	1.4700	0.6868	6.0125	10.06%	41
DMU9	-0.5300	0.4798	0.5800	0.6661	6.8850	22.95%	25
DMU10	0.0687	0.8043	2.0900	1.7130	6.0650	100%	7
DMU11	-0.5220	0.4842	1.1600	0.7371	4.7950	12.24%	38
DMU12	-1.0308	0.2085	0.6400	0.7048	6.3925	22.51%	26
DMU13	-1.3921	0.0128	0.1500	1.0249	7.3475	152.72%	2
DMU14	-1.0697	0.1874	0.1500	0.6978	6.6575	83.42%	11
DMU15	-0.9863	0.2327	1.2600	1.6584	8.5375	100%	7
DMU16	-0.5595	0.4639	1.5100	0.7604	6.7950	9.57%	42
DMU17	-1.2878	0.0693	1.1700	0.9866	6.7800	15.06%	32
DMU18	-1.0226	0.2130	0.5700	0.7052	6.5200	25.08%	22
DMU19	-0.8677	0.2969	0.4400	1.1672	9.8025	146.00%	3
DMU20	-0.0496	0.7401	1.0600	1.0686	6.1950	21.37%	27
DMU21	-1.0472	0.1996	0.4300	0.7086	6.5225	32.76%	18
DMU22	-0.9146	0.2715	0.5600	1.1773	9.7425	102.00%	6
DMU23	-1.0924	0.1751	1.8300	0.5602	6.7950	8.18%	46
DMU24	-1.0202	0.2143	0.1700	0.7021	6.5925	73.49%	13
DMU25	-0.7569	0.3569	0.7500	0.7040	8.0900	31.69%	19
DMU26	-0.7229	0.3754	0.9600	0.6534	6.3100	14.85%	33
DMU27	-1.3407	0.0406	2.9400	0.7030	12.0225	100%	7
DMU28	-0.6121	0.4354	1.6100	0.7645	3.8550	9.03%	45
DMU29	-0.5916	0.4465	1.1500	1.0974	5.9675	24.09%	24
DMU30	-0.3986	0.5510	2.0400	0.7255	6.5800	7.13%	47
DMU31	-1.0855	0.1789	0.6900	0.6874	6.5025	21.11%	28
DMU32	-1.4157	0.0000	1.1500	1.0384	7.1800	100%	7
DMU33	-1.3228	0.0504	1.5200	0.5927	5.8700	14.05%	35
DMU34	-0.8733	0.2939	1.1500	0.6444	7.5100	14.71%	34
DMU35	-0.7201	0.3768	0.5000	0.7821	4.9900	26.93%	21
DMU36	-0.9688	0.2421	0.2900	0.7066	6.6100	45.86%	16
DMU37	-1.4146	0.0006	0.2900	1.0276	7.0450	303.43%	1
DMU38	-0.9501	0.2523	1.3200	1.5284	7.0700	78.19%	12
DMU39	-0.6039	0.4398	1.1800	0.8370	7.2125	12.26%	37
DMU40	-1.0468	0.1999	0.2900	0.7034	6.6075	46.89%	15
DMU41	-0.1160	0.7042	0.5500	0.8305	5.9050	24.10%	23
DMU42	-1.0639	0.1906	0.2100	0.7021	6.6850	62.64%	14

Funds under study	Kurtosis	Input		Output		VRS result	Rank VRS
		Kurtosis (normalized)	Expense Ratio	PSV/ NSV	Q3		
DMU43	-1.4037	0.0065	0.2200	1.0335	7.2400	141.03%	4
DMU44	-0.8221	0.3216	0.7400	0.6315	6.6900	19.13%	29
DMU45	-1.0498	0.1983	2.1500	0.4023	6.5025	6.97%	48
DMU46	-0.6233	0.4293	1.2200	0.7896	6.4950	11.76%	39
DMU47	-0.8883	0.2857	1.4300	0.7594	5.8050	10.29%	40
DMU48	-1.0725	0.1860	0.1200	0.6911	6.5875	125.00%	5

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