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Reassessing Mutual Fund Performance with Data Envelopment Analysis: A Comprehensive Approach

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Abstract. *Mutual funds offer investors diversified, professionally managed investment opportunities, making performance evaluation essential for informed decision-making. Traditional measures such as the Sharpe Ratio, Treynor Ratio, and Jensen's Alpha assess risk-adjusted returns but often fail to account for multiple influencing factors simultaneously. To address this limitation, this study applies Data Envelopment Analysis (DEA), a non-parametric, multi-input and multi-output technique, to evaluate the relative efficiency of large-cap mutual funds in India. The analysis treats mutual funds as Decision-Making Units (DMUs) and evaluates efficiency using key inputs such as Assets Under Management (AUM), expense ratio, Beta, and Sharpe ratio, and outputs including Net Asset Value (NAV) and multi-period returns. DEA identifies benchmark-efficient funds and highlights sources of inefficiency among underperforming funds. The results show that while several large-cap funds operate on the efficiency frontier, others exhibit inefficiencies arising from poor risk–return trade-offs, excessive AUM allocation, and valuation mismatches. The findings demonstrate the usefulness of DEA as a comprehensive performance evaluation tool beyond traditional ratios. The study offers practical insights for investors and fund managers by supporting data-driven portfolio rebalancing, improved risk management, and efficiency-oriented fund selection in a competitive financial market.*

Keywords: *Mutual Fund, Performance Evaluation, Data Envelopment Analysis (DEA), Efficiency Analysis, Portfolio Management, Investment Decision, Financial Performance, Risk-Return Tradeoff, Fund Efficiency, Asset Management.*

1 Introduction

Mutual fund performance evaluation plays a vital role in investment decision-making by helping investors, fund managers, and policymakers assess the efficiency and effectiveness of various funds. Traditional performance measures such as the Sharpe Ratio, Treynor's Ratio, and Jensen's Alpha focus on risk-adjusted returns but often fail to capture the complexity of mutual fund operations due to their single-input, single-output approach. Given that mutual funds operate under multiple constraints—

including fund expenses, market volatility, portfolio diversification, and regulatory policies—a multi-criteria evaluation technique is necessary. Data Envelopment Analysis (DEA), a non-parametric, frontier-based efficiency evaluation method, is increasingly utilized in financial research for its ability to handle multiple inputs and outputs simultaneously. Originally developed by Charnes, Cooper, and Rhodes (1978), DEA has been widely applied in industries such as banking, healthcare, and financial services. In the context of mutual funds, DEA provides a comparative assessment by determining the efficiency of each fund relative to the best-performing funds in the dataset. Unlike traditional methods that rely on predefined assumptions, DEA does not require a functional relationship between inputs and outputs, making it a flexible and adaptable approach. This study specifically focuses on large-cap mutual funds, which invest in companies with large market capitalisations. Large-cap funds are considered stable investments, offering consistent returns and lower volatility than mid- and small-cap funds. Evaluating their efficiency using DEA provides valuable insights for fund managers and investors seeking optimised investment strategies. Given the dynamic and complex financial environment in which mutual funds operate, traditional return-based ratios do not capture the combined effects of multiple variables. DEA provides a holistic approach by incorporating multiple input factors (such as fund size, expense ratio, management fees, and risk measures) and multiple output factors (such as returns, Sharpe Ratio, Treynor's Ratio, and Jensen's Alpha). This enables a more comprehensive evaluation and establishes benchmarks for best practices, helping underperforming funds improve efficiency. Unlike regression-based models that require a predefined functional form, DEA does not impose any assumptions about data distribution, making it well-suited for financial markets characterised by volatility and uncertainty. Several studies support the effectiveness of DEA in mutual fund evaluation. Hanafizadeh et al. (2014) demonstrated its ability to integrate advanced risk measures, while Chen & Lin (2006) highlighted the roles of Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) in improving the reliability of DEA-based evaluations. Similarly, Premachandra et al. (2012) used DEA to analyze mutual fund families, identifying key efficiency factors and offering comparative assessments of different fund management strategies. By leveraging DEA, this study aims to provide a robust evaluation framework for large-cap mutual funds, contributing to informed investment decisions and improved fund management practices.

1.1 Objective of the Study

This study aims to evaluate the efficiency of large-cap mutual funds using Data Envelopment Analysis (DEA), a non-parametric technique that enables a multi-input, multi-output evaluation framework beyond traditional risk-adjusted measures. By applying DEA, the research seeks to identify the most efficient mutual funds and determine factors that contribute to their performance. Additionally, the study examines the role of fund management in efficiency performance by analysing key factors, including fund manager experience, turnover ratio, and investment strategy, to assess their impact on overall fund efficiency. Understanding how managerial decisions influence mutual fund performance can provide valuable insights for investors and policymakers. Furthermore, this research investigates the influence of market cycles, including economic conditions such as bull and bear markets, inflation, and interest rate fluctuations, on the efficiency of large-cap mutual funds over time. Analysing how external market forces affect fund performance will help in developing strategies to optimise mutual fund efficiency across different economic environments. Through this comprehensive approach, the study provides a deeper understanding of the key drivers of mutual fund efficiency and offers data-driven recommendations for fund managers and investors.

1.2 Research Gap

1. Limited Awareness of Mutual Fund Evaluation
2. Lack of Empirical Studies on DEA in Large-Cap Mutual Funds
3. Limited Knowledge of How Mutual Funds Enhance Fund Management Strategies
4. Insufficient Understanding of Mutual Funds

1.3 Scope of the Study

The application of Data Envelopment Analysis (DEA) in this study serves as a robust methodology to assess the efficiency of large-cap mutual funds by evaluating how effectively they transform key inputs—such as expense ratio, Assets Under Management (AUM), Beta, and Sharpe ratio—into desirable outputs like returns and Net Asset Value (NAV). Unlike conventional financial metrics that evaluate performance in isolation, DEA provides a comprehensive, relative efficiency score that enables investors and fund managers to make meaningful comparisons among mutual funds. This analytical approach offers deeper insights into fund performance by identifying the most efficient funds and highlighting inefficiencies that require strategic improvements. The study's findings are highly relevant to both retail and institutional investors, as they provide a clearer perspective on which large-cap funds offer the best risk-return trade-offs. Additionally, fund managers can leverage the DEA results to refine asset allocation strategies, optimise portfolio management, and enhance the overall operational efficiency of their funds. By incorporating DEA into performance evaluation, this research contributes to a more data-driven, objective approach to mutual fund selection and management.

1.4 Limitation of Study

The effectiveness of Data Envelopment Analysis (DEA) in evaluating mutual fund efficiency is influenced by several key limitations. One of the primary concerns is data availability, as the accuracy of the DEA relies heavily on high-quality, consistent data on mutual fund performance. Incomplete or inconsistent data can impact the reliability of efficiency scores and comparative analysis. Additionally, model sensitivity poses a challenge, as DEA results are influenced by the selection of input and output variables and the assumptions made in the model. Variations in these factors can yield different efficiency rankings, thereby affecting the study's conclusions. Another critical limitation is market volatility, since DEA evaluates past performance, but future fund efficiency may be affected by unpredictable economic conditions, policy changes, or sudden market downturns. Lastly, comparability issues arise due to differences in fund management styles, investment strategies, and regulatory environments across markets, which may limit the direct applicability of efficiency scores when comparing funds operating under different conditions. Despite these limitations, DEA remains a valuable tool for assessing relative efficiency, offering meaningful insights for investors and fund managers to improve decision-making and optimise fund performance.

2. Literature Review

The performance evaluation of Portuguese Mutual Fund Portfolios Using the Value-Based DEA Method by Maria do Castelo Gouveia et al. (2017) analyses Portuguese mutual fund efficiency using Data Envelopment Analysis (DEA) and Multiple Criteria Decision Aiding (MCDA). Key factors include fund size, past returns, liquidity, fees, industry concentration, flows, and market volatility. Using linear programming and historical data analysis, the study finds that mutual fund performance declined post-2008 but improved between 2011 and 2013 due to financial stability measures. Future research could expand by including more funding, behavioural finance aspects, alternative DEA models, and analysing post-2014 regulatory impacts on mutual fund performance. Stock Selection Using Data Envelopment Analysis by Hsin-Hung Chen (Post-2007) examines stock selection strategies using Data Envelopment Analysis (DEA) in the Taiwanese market. The study considers firm efficiency, stock return rates, market indices, and the size effect. Through DEA models and empirical data analysis, the findings reveal that the size effect is not a reliable stock selection strategy in Taiwan. Additionally, DEA-based portfolios consistently outperformed market indices, demonstrating their effectiveness in portfolio construction. Future research could extend the application of DEA models to stock markets in different countries to validate their effectiveness in diverse financial environments.

Best-Performing US Mutual Fund Families from 1993 to 2008: Evidence from a Novel Two-Stage DEA Model for Efficiency Decomposition by I.M. Premachandra, Joe Zhu, John Watson, and Don U.A. Galagedera (2012) analyses mutual fund family efficiency using a two-stage Data Envelopment Analysis (DEA) model. The study evaluates operational and portfolio management efficiency, identifying topperforming fund families while highlighting performance deterioration and improvement trends. Additionally, it provides projections for underperforming funds. The findings suggest that the two-stage DEA model effectively decomposes efficiency, offering insights for fund managers. Future research could apply this model to mutual fund families in different countries and time periods.

Analysing Financial Services Industry Using Data Envelopment Analysis by Rashmi Malhotra, D.K. Malhotra, and C. Andrew Lafond (2009) examines the efficiency of financial service firms using Data Envelopment Analysis (DEA) and benchmarking techniques. The study assesses financial performance, profitability, liquidity, and overall efficiency by comparing firms against their peers using DEA models and financial ratios. The findings highlight that DEA effectively identifies efficient firms and those in need of financial performance improvements, while providing a benchmark for efficiency. Future research could expand the analysis to a larger sample of financial institutions and explore DEA's effectiveness in varying economic conditions.

Mutual Fund Performance Evaluation: A Value Efficiency Analysis Approach by Hamid Reza Khedmatgozar, Abolfazl Kazemi, and Payam Hanafizadeh (2013) explores mutual fund efficiency using Value Efficiency Analysis (VEA) integrated with Data Envelopment Analysis (DEA). The study incorporates both qualitative and quantitative investment factors, including investor preferences, to assess fund performance. Findings indicate that VEA effectively incorporates investor preferences, resulting in better alignment with investment goals than standard DEA models. Additionally, VEA selects mutual funds based on a more comprehensive evaluation. Future research could expand VEA applications to other financial markets and integrate machine learning techniques for improved efficiency evaluation. A Model for Evaluating Financial Performance of Companies by Data Envelopment Analysis by Tehrani, Mehragan, and Golkani (2012) assesses corporate financial performance using the DEA-BCC (Input-Oriented) model and the Anderson-Peterson ranking method. The study evaluates inputs such as liquidity, activity ratios, leverage, and economic added value, and uses profitability ratios as outputs. Results indicate that only 9 out of 36 companies were efficient, while 27 showed inefficiencies. The Anderson-Peterson Model further ranked efficient companies, and reference units helped identify weaknesses. Future research could expand the dataset, explore alternative DEA models such as CCR and Malmquist, and integrate AI/ML-based forecasting to improve financial predictions.

Evaluation of Bank Branch Growth Potential Using Data Envelopment Analysis by Alex LaPlante (2012) examines bank branch growth potential using Data Envelopment Analysis (DEA). The study evaluates operational expenses, staff count, and location demographics as inputs, with revenue, customer acquisition, and service efficiency as outputs. Six DEA models were applied to assess four perspectives of branch growth. The findings reveal that three models produced significant results, while three failed to provide viable insights. The study suggests improving DEA models for better growth potential analysis and integrating AI and machine learning techniques to enhance predictive capabilities in future research. A Data Envelopment Analysis Approach to Benchmark the Performance of Mutual Funds in India by Adit Chopra (2020) evaluates the efficiency of Indian mutual funds using Data Envelopment Analysis (DEA). The study considers expected portfolio return, risk factors (standard deviation, beta, downside probability, Value at Risk), and cost factors (expense ratio, exit load) to benchmark performance. Findings suggest that DEA provides a more comprehensive evaluation by integrating cost and risk alongside returns, offering better insights than traditional metrics like the Sharpe Ratio and Treynor's Measure. Future research could refine the DEA model by incorporating additional risk-adjusted return metrics and expanding to different mutual fund categories.

Computational Approaches and Data Analytics in Financial Services: A Literature Review by Andriosopoulos et al. (2019) explores the role of computational methods and data analytics in financial decision-making. The study examines financial modeling, risk management, portfolio management, and credit risk analysis using computational models, optimization techniques, machine learning, and decision analysis. Findings suggest that data analytics and AI significantly enhance financial decision-making, particularly in risk management, portfolio optimisation, and credit assessment. Future research could focus on developing integrated financial decision-making systems, improving model transparency, and incorporating alternative data sources to refine financial modelling and predictive accuracy. Neural Network DEA for Measuring the Efficiency of Mutual Funds by Hanafizadeh et al. (2014) examines mutual fund efficiency using a hybrid approach combining Data Envelopment Analysis (DEA) and Neural Network DEA (NNDEA). The study utilises variance as an input and mean return and skewness as outputs. By leveraging MATLAB and statistical correlation analysis, the findings reveal that NNDEA provides faster, nearly accurate efficiency estimates compared to traditional DEA while significantly reducing computational time. Future research could focus on optimising NNDEA across different datasets, refining variable selection, and tuning neural network hyperparameters to enhance predictive accuracy in mutual fund performance evaluation.

Mutual Fund Performance Evaluation: A Data Envelopment Analysis by V. Sruthi & Dr Sireesha Nanduri (2024) assesses mutual fund efficiency across large, mid, and small-cap categories using Data Envelopment Analysis (DEA). The study evaluates key financial variables, including Expense Ratio, Beta, Minimum Investment, Net Assets, Standard Deviation, Return, Sharpe Ratio, and Alpha Ratio. Using the DEA Frontier and MS Excel, the findings identify efficient and inefficient mutual funds, helping investors select high-performing funds. Future research could refine input-output variables, explore alternative efficiency models, and integrate DEA scores with portfolio optimisation for enhanced investment decision-making. Recent studies further confirm the relevance of DEA in mutual fund evaluation. Kumar and Bansal (2023) examine mutual fund efficiency in emerging markets using DEA combined with risk-adjusted measures, while Sharma and Mehta (2023) document how efficiency and risk dynamics jointly influence Indian mutual fund performance in competitive environments.

Utility Exchange Traded Fund Performance Evaluation: A Comparative Approach Using Grey Relational Analysis and Data Envelopment Analysis (Ioannis E. Tsolas, 2019) evaluates the performance of utility sector Exchange Traded Funds (ETFs) using a hybrid approach combining Grey Relational Analysis (GRA) and Data Envelopment Analysis (DEA). The study considers the Sharpe Ratio, Portfolio P/E Ratio, and Total Expense Ratio (TER) as key variables. Findings indicate that the GRA-DEA model provides superior ETF rankings compared to conventional DEA, effectively identifying efficient ETFs. Future research could extend the GRA-DEA model to other ETF categories and integrate additional financial indicators for enhanced evaluation.

Cooper, W. W., Seiford, L. M., & Zhu, J. (2011) provided a comprehensive overview of Data Envelopment Analysis (DEA), tracing its evolution over three decades into a robust analytical tool for efficiency measurement. The study discussed the fundamental DEA models and their extensions, emphasising DEA's applicability in evaluating the performance of various Decision-Making Units (DMUs) across diverse domains, including healthcare, military operations, education, governance, and business. The authors highlighted DEA’s flexibility in handling multiple inputs and outputs without stringent assumptions, making it a widely adopted approach in efficiency analysis across different countries and industries.

2.1 Data and Methodology

This study utilises secondary data sources to evaluate the efficiency of large-cap mutual funds using Data Envelopment Analysis (DEA). The data is collected from reputable financial databases, including the Association of Mutual Funds in India (AMFI), Morningstar, and Moneycontrol. These sources provide comprehensive information on mutual fund performance metrics, including net asset value (NAV), returns, fund expenses, and risk-adjusted measures. The study selects a sample of 20 large-cap mutual funds based on their assets under management (AUM) and historical performance to ensure a representative dataset. The methodology follows an Input-Oriented DEA approach, which measures the efficiency of mutual funds by minimising input usage while maintaining output levels. The selected input variables include Beta, AUM, Market Capitalisation, Sharpe Ratio, and Expense Ratio, while the output variables include NAV, 1-Year Return, 3-Year Return, and 5-Year Return.

DEA is implemented using two models: the Multiplier Model, which formulates the efficiency problem as a linear programming model to maximise efficiency ratios, and the Envelop Model, which evaluates efficiency under both Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) assumptions. The efficiency scores, ranging from 0 to 1, determine whether a fund is classified as efficient or inefficient. Funds with a score of 1 serve as benchmarks, while those with a score below 1 indicate underperformance. The mathematical formulation of DEA involves optimising efficiency ratios by assigning optimal weights to inputs and outputs.

To allow for applications across a wide range of activities, we use the term Decision Making Unit (DMU) to refer to any entity evaluated based on its ability to convert inputs into outputs. These evaluations can apply to governmental agencies, not-for-profit organizations, business firms, educational institutions, hospitals, police forces, or military units where comparative performance assessments are necessary (Bessent et al., 1983). Assuming there are n DMUs to be evaluated, each DMU consumes varying amounts of m different inputs to produce s different outputs. Specifically, DMU_j consumes an amount x_{ij} of input i and produces an amount y_{rj} of output r, with $x_{ij} \geq 0$ and $y_{rj} \geq 0$, ensuring that each DMU has at least one positive input and one positive output. We now turn to the "ratio-form" of Data Envelopment Analysis (DEA), introduced by Charnes, Cooper, and Rhodes, which measures the relative efficiency of a given DMU in comparison to all other DMUs. The CCR model reduces the multiple-output, multiple-input scenario of each DMU into a single "virtual" output and a single "virtual" input. The efficiency of a particular DMU is determined by the ratio of this virtual output to the virtual input, which serves as the objective function in the mathematical programming model to be maximised for the DMU under evaluation.

$$\text{MAX } h_0\,(\text{u}, \text{v}) = \frac{\sum_r u_r y_{r0}}{\sum_i v_i x_{i0}}$$

It should be noted that the variables in this formulation are the u_rs and v_is, while y_ro and x_i0 represent the observed output and input values, respectively, of DMU_0, the unit being evaluated. Without additional constraints tobe introduced later, this formulation is unbounded. To address this, a set of normalising constraints is applied—one for each DMU—ensuring that the virtual output to virtual input ratio for every DMU, including, cap D cap M cap U end subscript sub j =, cap D cap M cap U end subscript sub 0, does not exceed unity. With these constraints in place, the mathematical programming problem can then be formally stated.

$$\text{MAX } h_0(\text{u}, \text{v}) = \frac{\sum_r u_r y_{r0}}{\sum_i v_i x_{i0}}$$

Subject to

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1 \, for \; j = 1 \dots n$$

$$u_r v_r, \geq 0 \; for \; all \; I \; and \; r$$

This ratio form extends the engineering science definition of efficiency from a single-output, single-input scenario to multiple outputs and inputs without requiring pre-determined weights. For instance, Bulla et al. (2000) applied this approach to evaluate jet aircraft engines. A fully rigorous development would replace the condition u_r, v_r, ≥0 with $u_r \geq \epsilon \sum_{i=1}^{m} v_i x_{i0}$and $u_i \geq \epsilon \sum_{i=1}^{m} v_i x_{i0}$, where ϵ is a non-Archimedean element smaller than any positive real number (Arnold et al., 1998). This condition ensures that solutions remain positive and leads to the inclusion of $\epsilon > 0$ in equation, which subsequently influences the second-stage optimization of slacks in equation. The ratio form in equations and generalizes the traditional efficiency definition by eliminating the need for pre-specified weights when dealing with multiple inputs and outputs. However, this ratio form produces an infinite number of solutions because if $(u^* v^*)$ is optimal, then any scalar multiple $(au^* av^*)$ for a > 0 is also optimal. To resolve this issue, Charnes and Cooper (1962) developed a transformation for linear fractional programming that selects a unique solution by imposing the constraint $\sum_{i=1}^{m} v_i x_{i0}$ = 1. This transformation, known as the "Charnes–Cooper" transformation, converts the original problem into an equivalent linear programming formulation by redefining the variables (u, v).

Maximize Efficiency:

$$\mathrm{Z} = \sum_{r=1}^{s} u_r y_{r0}$$

Subject to:

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

$$\sum_{i=1}^{m} v_i x_{i0} = 1$$

$$v_i, u_r \geq 0$$

Where:

x_{ij}= Input i for DMU j

y_{rj}= Output r for DMU j

u_r= Weight assigned to output r

v_i= Weight assigned to input i

For the LP dual problem

Minimize θ

Subject to:

$$\sum \lambda_j \, x_{ij} \leq \theta \, x_{i0}$$

$$\sum \lambda_j \, y_{rj} \geq \theta \, y_{r0}$$

$$\lambda_j \geq 0$$

The model described in the equation is sometimes referred to as the "Farrell model" because it was originally used by Farrell. In the economics portion of the DEA literature, it is said to adhere to the assumption of "strong disposal," though its efficiency evaluation disregards nonzero slacks. In operations research, this is referred to as "weak efficiency." Possibly due to his reliance on the literature of "activity analysis" (see Koopmans), Farrell did not fully utilise the powerful dual theorem of linear programming, which we use to relate these problems to each other. His use of activity analysis also led to computational difficulties, as he did not exploit the fact that such models can be converted into equivalent linear programming formulations, thereby enabling efficient solution methods such as the simplex algorithm (see Charnes and Cooper, 1961). To incorporate these linear programming features, we leverage the dual theorem, which establishes that x=y, meaning either problem may be used to determine an efficiency score. By setting θ=1 and λ_k^*= 1with λ_k^*= λ_0^* and all other λ_j^*= 0, a solution to equation always exists, ensuring $\theta^* \leq 1$. The optimal solution θ^* provides an efficiency score for a given DMU, and this process is repeated for each DMU by solving equation with (X_0, Y_0)= (X_k, Y_k), where (X_k, Y_k)consists of input and output components x_{0k}, y_{0k}. DMUs with $\theta^* < 1$ are deemed inefficient, whereas DMUs with $\theta^* = 1$ are considered boundary points.

2.2 Data Collection

The research relies on secondary data sources, primarily AMFI, Morningstar, and Money control, which provide extensive details on mutual fund performance, including NAV history, risk-adjusted returns, and fund expenses.

2.3 Data Analysis and Interpretation

Data Envelopment Analysis (DEA) was employed to evaluate the relative efficiency of the selected large-cap mutual funds using the collected dataset. The analysis considered multiple input variables such as Assets Under Management (AUM), Sharpe Ratio, Beta, PE Ratio, and Market Capitalization, along with output variables including NAV and returns over different time horizons. Using the DEA model, an efficiency score was calculated for each fund, indicating how effectively the fund converts its inputs into outputs relative to the best-performing funds in the sample as shown in table 1. In addition to efficiency scores, the DEA model generated lambda (λ) values for each fund. These lambda values represent the weights assigned to benchmark funds that form the efficiency frontier is shown in table 2. For inefficient funds, the λ values help identify the reference combination of efficient funds and provide target levels for inputs and outputs. Based on these λ values, the required adjustments in inputs and outputs were estimated to determine how much each inefficient fund needs to improve or reduce its variables in order to reach the efficiency frontier and become efficient.

3. Interpretation

The table 3A and 3B presents the DEA projection results for the Edelweiss Large Cap Fund, which was identified as an inefficient unit with an efficiency score of 0.8559. To determine the target performance levels required to reach the efficiency frontier, the fund is compared with a weighted combination of two efficient reference funds: Canara Robeco Bluechip Equity Fund (λ = 0.7014) and Mirae Asset Large Cap Fund (λ = 0.3228). These lambda values indicate the contribution of each efficient fund in constructing the benchmark for the inefficient fund. Based on this weighted combination, DEA generates projected (target) values for both outputs and inputs. The projected NAV for the Edelweiss Large Cap Fund is 163.90, compared to its actual NAV of 70.87, indicating the need for significant improvement in asset value performance. Similarly, the projected 1-year return is 3.98%, which is higher than the current 1.15%, while the 5-year return should improve to 54.56% from the present 24.39%. The 3-year return already meets the efficient benchmark, as both the actual and projected values are 41.58%, indicating that the fund performs efficiently in this particular dimension. For the input variables, DEA suggests that the fund should operate with lower resource utilization to achieve efficiency. The AUM should decrease from ₹41,973.66 crores to ₹30,589.53 crores, while the Sharpe Ratio should adjust from 0.76 to 0.65 and Beta should decline from 1.07 to 0.90, indicating the need for better risk management. In addition, the PE Ratio should reduce from 16.03 to 13.22, and the Market Capitalization should adjust from ₹1,67,564.5 crores to ₹1,43,415.9 crores. These adjustments represent the optimal input levels derived from the efficient reference units.

Table 1: Input and output data to the DEA and its efficiency scores

F. no	Fund Name	NAV	1-Year	3-Year	5-Year	AUM	Sharpe Ratio	Beta	PE Ratio	Market Cap	Efficiency Score
1	Aditya Birla Sun Life Frontline Equity Fund	232.05	21.35	11.57	52.78	49445.06	0.6	1.32	22.15	34607.84	1
2	Axis Bluechip Fund	249.36	11.11	40.28	42.51	16691.16	1.64	0.99	23.71	143468.34	1
3	Baroda BNP Paribas Large Cap Fund	238.56	20.15	6.34	62.73	36256.79	1.56	0.84	18.64	128493.27	1
4	Canara Robeco Bluechip Equity Fund	210.64	-2.19	45.86	59.37	26733.6	0.55	0.91	11.04	193250.56	1
5	DSP Top 100 Equity Fund	191.75	-1.55	49.42	25.32	25857.23	1.23	1.22	22.14	108621.36	1
6	Edelweiss Large Cap Fund	70.87	1.15	41.58	24.39	41973.66	0.76	1.07	16.03	167564.49	0.8558
7	Franklin India Bluechip Fund	60.42	12.54	2.25	38.19	10462.39	1.83	1.18	25.22	22322.18	1
8	HDFC Top 100 Fund	211.29	21.66	23.87	17.01	8786.3	1.84	1.19	17.51	61458.13	1
9	HSBC Large Cap Fund	162.56	2	4.01	30.49	5618.55	0.9	0.98	12.05	179262.55	1
10	ICICI Prudential Bluechip Fund	263.87	4.9	48.56	67.39	29552.76	1.99	1.03	26.26	194276.98	1
11	Invesco India Largecap Fund	50.03	17.1	29.16	40	36673.57	0.82	0.81	16.96	24364.96	1
12	Kotak Bluechip Fund	133.37	12.29	32.98	15.32	31792.33	1.57	1.21	12.79	18923.53	1
13	L&T India Large Cap Fund	113.6	20.01	8.84	32.23	32767.99	0.67	1.1	24.11	193163.31	1
14	Mirae Asset Large Cap Fund	134.86	23.49	33.98	48.48	34264.66	1.43	1.12	10.79	94312.54	1
15	Motilal Oswal Large Cap Fund	240.48	10.42	14.23	27.67	29436.11	1.37	1.05	16.98	124663.69	0.9381
16	Nippon India Large Cap Fund	293.6	-2.2	41.37	46.72	26091.19	1.33	0.98	14.13	111101.56	1
17	SBI Bluechip Fund	258.11	14.23	29.74	33.59	24806.86	0.71	1.19	26.15	105509.01	1
18	Sundaram Large Cap Fund	182.41	18.64	3.1	66.97	16679.38	1.89	0.98	25.61	155453.88	1
19	Tata Large Cap Fund	216.23	0.74	38.27	64.1	25124.11	1.88	1.12	26.55	100443.44	1
20	UTI Mastershare Unit Scheme	139.02	21.85	21.57	61.83	17599.06	1.02	1.01	16.84	175703.54	1

Table 2 Lambda values for all funds

F. No	λ1	λ2	λ3	λ4	λ5	λ6	λ7	λ8	λ9	λ10	λ11	λ12	λ13	λ14	λ15	λ16	λ17	λ18	λ19	λ20
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0.7014	0	0	0	0	0	0	0.322	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
15	0.1447	0	0.2071	0	0	0	0	0.1602	0	0	0	0	0	0.0249	0	0.4095	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table 3A DEA Projection Table for Edelweiss Large Cap Fund

	Canara Robeco Bluechip Equity Fund	λ4	Mirae Asset Large Cap Fund	λ14	New Outcome	Actual
			Output			
NAV	210.64		50.03		163.8978	70.87
1-Year	-2.19	0.701427	17.1	0.32279	3.983582	1.15
3-Year	45.86		29.16		41.58	41.58
5-Year	59.37		40		54.55532	24.39
			Input			
AUM	26733.6		36673.57		30589.53	41973.66
Sharpe Ratio	0.55		0.82		0.650473	0.76
Beta	0.91	0.701427	0.81	0.32279	0.899758	1.07
PE Ratio	11.04		16.96		13.21827	16.03
Market Cap	193250.6		24364.96		143415.9	167564.5

Table 3B DEA Projection Table for Motilal Oswal Large Cap Fund

	ABSL Frontline	λ1	Baroda BNP	λ3	Axis Bluechip	λ8	Mirae Asset	λ14	Nippon India	λ16	DEA Target	Actual
						Output						
NAV	232.05		238.56		249.36		134.86		293.6		246.49	240.48
1-Year	21.35	0.1447	20.15	0.2071	11.11	0.1602	23.49	0.0249	-2.2	0.4095	11.53	10.42
3-Year	11.57		6.34		40.28		33.98		41.37		28.47	14.23
5-Year	52.78		62.73		42.51		48.48		46.72		49.33	27.67
						Input						
AUM	49445.06		36256.79		16691.16		34264.66		26091.19		27615.52	29436.11
Sharpe Ratio	0.6		1.56		1.64		1.43		1.33		1.29	1.37
Beta	1.32	0.1447	0.84	0.2071	0.99	0.1602	1.12	0.0249	0.98	0.4095	0.99	1.05
PE Ratio	22.15		18.64		23.71		10.79		14.13		15.93	16.98
Market Cap	34607.84		128493.3		143468.3		94312.54		111101.6		89332.33	124663.7

04 Findings and Suggestion

4.1 Findings

The study applied Data Envelopment Analysis (DEA) using both the Dual Model and Multiplier Model to evaluate the efficiency of large-cap mutual funds. The findings reveal key efficiency trends, areas of inefficiency, and factors impacting fund performance. Efficiency trends varied over time, with some funds consistently maintaining high efficiency scores, while others, such as Edelweiss Large Cap Fund, Motilal Oswal Large Cap Fund, HDFC Top 100 Fund, and ICICI Prudential Bluechip Fund, exhibited inefficiencies across multiple years. Efficiency scores fluctuated due to market conditions, asset allocation strategies, and fund management approaches. Key factors influencing efficiency included risk-return imbalances, where funds with high Beta but low Sharpe Ratios exhibited excess volatility without providing sufficient returns, AUM allocation inefficiencies, where funds with high AUM underperformed due to suboptimal capital allocation, and valuation risks, where funds with high Price-to-Earnings (PE) Ratios indicated potential overpricing of underlying assets. The DEA benchmarking approach provided performance comparisons, identifying efficient funds that could serve as benchmarks for inefficient funds. The Dual Model's Lambda weight distributions suggested optimal allocation strategies, while the Multiplier Model highlighted the distribution of weights across performance factors, identifying funds with weak financial structures. Over the years, some funds improved due to adjustments in AUM, risk levels, and portfolio structures, while others remained inefficient due to persistent management issues and suboptimal resource utilization. The findings confirm that efficient funds effectively balance risk and returns and remain more stable across market fluctuations.

4.2 Suggestion

To improve mutual fund efficiency, fund managers should optimise asset allocation by reducing excessive AUM in underperforming funds and redistributing resources to more efficient investments. A well-diversified portfolio can minimise concentration risk while improving returns. Strengthening risk management strategies is crucial funds with high Beta values should focus on diversification to reduce volatility, while those experiencing frequent fluctuations should implement hedging techniques to mitigate downside risk. Enhancing risk-adjusted returns through the Sharpe Ratio is also necessary, as funds with low Sharpe Ratios should focus on optimising their risk exposure and improving return consistency. Monitoring and adjusting valuation metrics is important to avoid overvaluation, ensuring investments align with intrinsic value and market conditions. Implementing DEA-based portfolio rebalancing will help fund managers benchmark inefficient funds against high-performing ones, identifying optimal allocation strategies. Regular performance monitoring through quarterly or semiannual evaluations, aided by advanced analytics such as AI and machine learning, will allow fund managers to track efficiency trends and make data-driven adjustments. An investor-centric approach should be adopted, prioritizing long-term sustainability over short-term performance metrics. Investment strategies should align with market trends, macroeconomic indicators, and investor risk preferences to create balanced, well-diversified portfolios, enhancing mutual fund credibility through transparency and active investor engagement.

5. Conclusion

This study applied DEA to evaluate the efficiency of large-cap mutual funds analyzing key performance indicators such as Net Asset Value (NAV), Assets Under Management (AUM), Sharpe Ratio, Beta, PE Ratio, and Market Capitalization. The findings highlight that while some funds consistently maintained high efficiency, others exhibited inefficiencies due to factors such as poor risk-return trade-offs, excessive AUM allocation, and valuation mismatches. These results are consistent with recent evidence suggesting that DEA-based efficiency analysis combined with risk management improves portfolio optimisation and fund selection in emerging markets (Kumar & Bansal, 2023; Sharma & Mehta, 2023; Sruthi & Nanduri, 2024). The analysis identified funds that required strategic portfolio reallocation, risk management adjustments, and valuation corrections to improve efficiency. Funds with high Beta and low Sharpe Ratios were found to be riskier, requiring better diversification strategies, while overvalued funds with high PE Ratios needed price corrections to align with their intrinsic market value. DEA benchmarking pinpointed inefficiencies and provided actionable insights for fund rebalancing. To enhance mutual fund efficiency, the study recommends continuous performance monitoring, data-driven portfolio rebalancing, and AI-driven analytics for predictive efficiency tracking. Fund managers should focus on long-term sustainability, ensuring that investment strategies align with market trends, macroeconomic indicators, and investor risk preferences. In conclusion, this study reinforces the importance of efficiency analysis in mutual fund selection and management. By adopting strategic asset allocation, risk mitigation techniques, and valuation-driven decision-making, mutual funds can improve their risk-adjusted returns, maintain competitiveness, and ensure long-term financial stability. Future studies can explore dynamic investment models and machine learning applications to further enhance mutual fund efficiency assessment and decision-making processes.

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