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A Multi-period Assessment of Firm Efficiency in the Stock Market using the DEA Approach

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ABSTRACT

Structural issues and cyclical fluctuations owing to various macroeconomic events affect stock market performance. This paper aims to evaluate the efficiency of leading firms listed on the National Stock Exchange (NSE) in India over a five-year period. We apply an input-oriented super-efficiency Data Envelopment Analysis (DEA) approach with Variable Returns to Scale (VRS) and also account for Constant Returns to Scale (CRS), with input variables namely Beta, the price-earnings (PE) ratio, and price-to-book, and output variables namely return on equity (ROE), earnings per share (EPS), and market capitalization, to reveal a strong foundation of best-in-class companies. Power Grid Corporation, ONGC, Hindustan Unilever, Cipla, and Dr. Reddy's Laboratories are the companies that reach efficiency in all five years of our analysis, i.e., Tier 1 efficiency. This establishes that underlying valuation multiples, alongside strong underlying fundamental outputs, reveal underlying structural efficiency.

1. Introduction

Corporate efficiency measurement is now a vital theme in today's financial and managerial literature, particularly for larger publicly traded firms that compete in fast-paced, highly competitive capital markets. In rising economies such as India, not only does the overall health of the local stock exchange serve as a proxy for economic conditions, but also for the overall operation and efficiency of firms in terms of capital usage and market valuation [1, 2]. Among such measures, the Nifty 50 plays a essential role in this environment in terms of understanding how some of the larger and more actively traded firms on the National Stock Exchange of India are operating [3]. These firms show a range of industries, from banking to pharmaceuticals to energy to infrastructure. Typically, conventional approaches to measuring the financial condition of a firm rely on various financial ratios, including earnings per share, return on equity, market capitalization, and others. While these

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metrics are useful, they do not capture the overall essence of the problem, which involves a multi-dimensional process with various inputs generating several outputs simultaneously.

To deal with such a complex issue, non-parametric approaches to efficiency analysis, such as Data Envelopment Analysis (DEA), have gained popularity in operations research, finance, and productivity studies. The basic principle of DEA is to evaluate and compare decision units to form an efficiency frontier. The units on the frontier are considered to be efficient, while the units below the frontier are considered to be relatively inefficient in comparison to other units. In addition, the study of the volatility of the Nifty 50 index highlights the changes in the efficiency of the market and the performance of companies over time [4, 5].

Data Envelopment Analysis (DEA) was first introduced in 1978 by Abraham Charnes, William W. Cooper, and Edwardo Rhodes. Since its creation, DEA has found its applications in the fields of banking, education, healthcare, and manufacturing, etc., in determining the efficiency of organizations with varying conditions [6, 7]. One of the greatest advantages of DEA is that it can handle several inputs and outputs variable at one time without the need to establish a priori relationship between them [6]. While carrying out financial market analysis, this aspect can prove to be highly useful because companies are evaluated in a complex environment of market valuation signals. When it comes to judging efficiency in a stock market environment, things become more complicated due to the presence of firm fundamentals and investor perceptions, which are reflected in stock prices [8, 9]. Important parameters such as beta, price-earnings ratio and price-book ratio help in understanding investor sentiment and risk perception. On the other hand, parameters such as return on equity, earnings per share, and market capitalization support in assessing a firm's financial performance [10, 11]. Recent studies have further enhanced DEA applications in stock selection by integrating advanced techniques such as Shannon entropy and inverse DEA to improve ranking and decision-making accuracy [12].

The research aims to assess the efficiency with which thirty-nine Nifty 50 companies are operating for five financial years—from the year 2020-21 to the year 2024-25—using the input-oriented super-efficient DEA framework. It also evaluates the performance of the firms under VRS and CRS conditions. This helps in identifying the changing efficiency levels of the companies overtime [13-15].

The data for the input and output variables are found from the valuation ratios namely beta values, P/E ratio, and the P/B ratio. On the other hand, the output variables are got from the financial ratios namely return on equity, earnings per share, and market capitalization. These data are then used for the construction of the efficiency frontier [16, 17].

The super-efficient DEA model not only identifies the efficient companies but also ranks the companies. This is more useful for companies with larger market capitalization. In the case of the traditional DEA framework, there are chances for the firms to appear equally efficient. However, the actual performance strength of the companies may vary [18-20].

During this time, there were significant changes in the financial markets and macro economy. After the COVID-19 pandemic, the government's actions resulted in an increase in liquidity and sectoral demand shocks. This had an impact on the performance of companies [21, 22]. The commodity segment saw robust trends, the infrastructure sector saw an uptick in spending, and the pharmaceutical sector saw an uptick as healthcare spending increased [23, 24]. Overall, this has been a unique period with Nifty 50 companies showing divergent trends in terms of valuation, earnings growth, and operational performance [25, 26].

The efficiency in the index is not static; it is constantly changing under the impact of a multitude of factors in motion. Macroeconomic trends, sectoral shifts, market sentiment, and company-level strategies are some such influences that impact the efficiency with which things operate in the market [27-29]. There are some companies that continue to operate near the efficiency frontier due to superior financial performance and prudent use of capital, while others oscillate in line with the changing market conditions. The DEA framework assists in identifying efficient companies and studying the movement in the efficiency frontier over time. This paper contributes to the body of financial efficiency by studying large-cap Indian companies across years and linking it to valuation drivers and profitability and company sizes to advance our understanding of efficiency and explain how macroeconomic trends and sectoral shifts and company-level factors combine to impact the efficiency of Nifty 50 companies [30].

1.1 Research Gap

There is a rising literature using Data Envelopment Analysis (DEA) to discover financial efficiency, though this literature is limited to particular domains, such as banking, health, or manufacturing, rather than taking a wide view of broad market indices such as the Nifty 50. Much of finance literature, especially related to stock markets, relies on conventional financial ratios or one-dimensional measures, which do not account for the interaction of multiple inputs and outputs to determine firm performance. In the case of India, literature related to the Nifty 50 is focused on aspects such as volatility, patterns of return, or short-term comparisons, while neglecting aspects such as a long-term multi-year efficiency analysis using DEA.

Few studies have attempted to incorporate valuation parameters such as the price-earnings ratio, beta, and the price-book ratio with output parameters such as earnings per share, return on equity, and market capitalization. There is a research gap in the area of how investor perception and financial performance together affect efficiency. Also, the application of more sophisticated data envelopment analysis techniques such as the super efficiency model for firms that are already efficient is an unexplored area for Indian large-cap stocks.

It is also seen that there is a significant research gap when it comes to understanding the impact of major macroeconomic events, especially the post-COVID-19 economic growth phase, on the firm's efficiency over the years. This is because there is a clear impact of the changes in the level of liquidity and policy interventions, as well as sectoral realignments, on the performance of firms, which is yet to be understood through existing research. To bridge the existing research gap, the study employs a rigorous research methodology by conducting an input-oriented super-efficiency DEA model for Nifty 50 firms with constant returns to scale (CRS) and variable returns to scale (VRS) results.

1.2 Research Objectives

The purpose of this research is to determine how efficiently a set of large-cap companies from the Nifty 50 can translate their financial inputs for valuation into concrete, tangible performance over a period of years, guided by Data Envelopment Analysis. Essentially, we are examining how well these companies can translate inputs into outputs that correspond to fundamental performance.

The research objectives are:

i. To determine the relative efficiency of the chosen set of Nifty 50 companies using an input-oriented DEA method.
ii. To determine the efficiency of the companies under both Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) assumptions to determine the impact of scale on company performance.
iii. To determine the ranking of efficient companies using a super-efficiency DEA method, allowing for comparisons between efficient companies.

iv. To monitor changes in efficiency over a five-year period to determine structural and cyclical changes.
v. To determine benchmark companies that can serve as a model of excellence for other companies in the index.
vi. To examine the impact of macroeconomic factors, particularly the post-COVID-19 scenario, on efficiency trends in the index.

2. Literature Review

Authors in [17] applied Data Envelopment Analysis to estimate the technical efficiency of banks, particularly in developing countries. They frequently use financial analysis tools such as the CAMEL Rating System and DuPont Analysis to estimate financial performance and efficiency. However, there are relatively few comparative studies that examine how these measures compare with each other using statistical analysis such as the Mann-Whitney U Test, particularly in the context of Indian public sector banks.

In paper [31] authors point out that pandemics have adversely impacted financial stability, economic performance, and investor sentiment in the world's leading economies. Nevertheless, recent literature also indicates that despite the short-term setback, global stock markets showed signs of resilience and recovery after the shock impact of the pandemic. In the paper [32], the researchers used Data Envelopment Analysis to evaluate the financial efficiency of companies listed on the Indian stock market. The paper revealed that only a few companies have achieved financial efficiency using models such as the BCC model. The paper also indicated that financial efficiency can be used in conjunction with financial ratios to improve investment decisions. Authors in [33] used a multi-stage data envelopment analysis to evaluate financial ratios for profitable share selection in the stock market. The paper concluded that data envelopment analysis can be used to uncover complex relationships between financial ratios and identify financial ratios that have the greatest impact on investment performance. The empirical analysis revealed that the Calmar ratio is the most effective in building profitable portfolios for varying periods. A hybrid method combining data envelopment analysis and data mining to evaluate the impact of the COVID-19 pandemic on industry efficiency in the Tehran stock market is used in [34]. The paper revealed that the number of efficient industries decreased during the pandemic period due to the significant impact of the pandemic on financial performance. Some industries also became inefficient due to the pandemic's economic impact. Authors in [35] have extended the use of data envelopment analysis to evaluate left and right returns to scale in crisp and fuzzy data sets. The researchers recommended using non-parametric data envelopment analysis to evaluate returns to scale due to infeasibility in parametric methods. The paper also revealed that fuzzy data envelopment analysis is effective in evaluating company performance using fuzzy data sets for the Iranian stock market. The efficiency of companies in various industries of the Lima Stock Exchange from 2015 to 2020 is compared in [36]. Data Envelopment Analysis is used to calculate the efficiency of companies in Agrarian, Industrial, Public Services, and Mining industries. Mining industries ranked first in efficiency and stability, while the Agrarian industry performed worst. Notably, technological advancements contributed little to productivity growth, but efficiency gains contributed. The study implies that it is important to be aware of the sector-specific factors to make informed investment choices in the Peruvian market. The research in [37] uses the combination of DEA and portfolio optimization as a tool for balancing the risks and returns of investments. In this research, they also include other risk measures such as Conditional Value at Risk (CVaR) for more accurate estimation of the risks. For accurate optimization and finding efficient portfolios, they use evolutionary optimization approaches such as the Particle Swarm Optimization

(PSO) and the Imperial Competitive Algorithm (ICA). Their research result show that DEA-based portfolio optimization with the help of evolutionary optimization approaches increases the returns of the portfolio without increasing the risks beyond a certain limit. Authors in [38] use the combination of DEA and the Malmquist productivity index for the performance analysis of the firms operating in the fishery industry and listed on the stock exchange. The result of the research shows that the inclusion of industry context with financial analysis increases the operating efficiency and total factor productivity of the firms operating in the fishery industry.

In the paper [39], the increasing trend of using Machine Learning algorithms for predicting stock market price movements is emphasized. Studies using the Transformer model show the ability to analyze financial time series data using sophisticated encoding techniques like time2vec. These studies have been used to predict stock prices in stock exchanges such as the Dhaka Stock Exchange using past stock market data. Paper [40] examines the co-movements of carbon markets, stock markets, and renewable energy markets in a low-carbon economy. The researchers use the Time Varying Parameter Vector Auto Regression method to assess the impact of major events such as Brexit, the European Green Deal, and the COVID-19 pandemic on the co-movements of these markets. The researchers' results suggest that the pandemic strengthened the short-term co-movements among these markets, whereas the long-run co-movements among these markets are relatively low. Authors in [41] examine the efficiency of Saudi Arabian agricultural and food companies using DEA, finding large variations in efficiency. The variations are attributed to factors such as administrative expenses, equity, and capital expenditure. The study helps investors to reduce costs in specific sectors for long-term growth. The effects of oil price fluctuations on Tehran Stock Exchange companies using DEA to measure efficiency and ranking is examined in [42], together with identifying efficient companies such as Mahram Production. DEA is used to compare similar companies based on input and output data to measure efficiency. The study helps policymakers to understand the effects of oil price fluctuations on stock market performance for informed decision-making. Authors in [43] examine stock market performance using evidential reasoning and hierarchical belief rule base. The study aims to help investors make informed decisions by looking at numbers and expert views. The study applied this method to the Shanghai Stock Index from 2010 to 2019, demonstrating its ability to assist in making buy, sell, or hold decisions. Paper [44] employs Data Envelopment Analysis (DEA) to analyze the effect of the COVID-19 pandemic on the efficiency of stock markets in Africa. The results show that the pandemic has adversely affected the efficiency of stock markets in 2021, and efficiency has persisted only in the short term. The authors emphasize the need for diversification of investment portfolios and better information dissemination to improve market stability during times of crisis. Authors in [45] use Data Envelopment Analysis (DEA) to analyze stock efficiency and decision-making of retail investors under risk in the Croatian capital market. By using an input-oriented DEA model, studies analyzing the efficiency of selected stocks and indices during the period of 2016-2021 conclude that only a few stocks have high levels of efficiency. The results indicate that investing in the general CROBEX stock index could be an effective approach for retail investors who lack financial knowledge and have limited time. Authors in [46] conducted a study to determine how effectively Vietnamese seaports operate, using a combination of Delphi method and Data Envelopment Analysis (DEA). Management ability and scale efficiency were found to be significant factors affecting port performance. Sophisticated computational techniques, such as belief rule base (BRB) models, are utilized in [47] to predict changes in stock prices using technical analysis signals. Technical indicators, such as moving average (MA), moving average convergence divergence (MACD), stochastic oscillator (KD), were incorporated to enhance the precision of their predictions. Studies conducted using data from the Chinese stock market show that BRB models, if optimized using maximum likelihood estimation, can be useful tools in financial modelling.

Authors in [48] have proposed using Data Envelopment Analysis in conjunction with Recurrent Neural Networks for improved stock selection as well as stock price predictions. The researchers have used Data Envelopment Analysis to select stocks based on financial ratios. Recurrent neural networks, such as Long Short-Term Memory networks, have been used for stock price predictions based on historical stock prices. The empirical results have shown that Long Short-Term Memory networks have better predictive power compared to simple RNNs for stock market predictions. Data Envelopment Analysis (DEA) is employed in [49] to determine investment portfolios that have demonstrated high financial performance as well as Environmental, Social, and Governance (ESG) efficiency in energy markets. The two-stage DEA model is commonly employed to first derive financial efficient portfolios and then rank them according to ESG performance. The empirical results suggest that companies in the renewable energy sector have demonstrated better financial and ESG performance than companies in the non-renewable energy sector, especially during the COVID-19 era. Data Envelopment Analysis (DEA) based on the CCR approach to measure the financial efficiency of firms listed on Bursa Malaysia is employed in [50]. Efficiency analysis is conducted based on financial ratios including return on equity, asset turnover, market capitalization, and debt-to-equity ratio. The results indicate that only a few firms are completely efficient, and the Super Efficiency approach is used to identify the best-performing firms among efficient firms.

An increasing trend in the application of inverse models in DEA for performance measurement and management decisions is reported in [51]. Initially, the focus of research was limited to measuring technical efficiency; however, with time, the focus has been broadened to include cost and revenue efficiency for improved allocation. Due to the lack of data in terms of prices in the real world, inverse DEA models were developed for the measurement of cost and revenue efficiency and have been extensively applied. Authors in [52] investigate the link between a company's ESG performance and the efficiency of green innovation in Chinese manufacturing industries. The authors apply a two-stage network data envelopment analysis (DEA) and conclude that a better ESG performance increases knowledge creation and the efficiency of innovation output. The authors also reveal that increased investor attention may strengthen the link between ESG and green innovation. Paper [53] integrates Data Envelopment Analysis (DEA) with Goal Programming (GP) to take the analysis of the portfolio beyond the traditional risk-return perspective. The super efficient DEA model determines the efficient units, while the GP determines the optimal portfolio weights in line with the goals and objectives of the investor. Market results, including the Tehran Stock Exchange, indicate the efficiency of the hybrid DEA-GP in the selection of the portfolio even in a volatile market.

Authors in [54] examine the efficiency of airports through Data Envelopment Analysis, which considers multiple inputs and outputs together. The method extends the model proposed by Charnes, Cooper, and Rhodes and its subsequent modifications, such as the slacks-based measure developed by Kaoru Tone, incorporating undesirable outputs such as emissions. The authors' research work focuses on infrastructure variables such as terminal size, runway capacity, and flights, but point out that few studies have employed network DEA to measure both infrastructure and environmental efficiency of Vietnamese airports. It is pointed out in [55] that there has been increasing interest in the integration of Data Envelopment Analysis and Machine Learning to improve the accuracy of efficiency measurement and prediction analysis. The early literature focused on the combination of DEA with other approaches such as Artificial Neural Networks and Support Vector Machines, but later studies proposed more sophisticated hybrid approaches such as deep learning and ensemble methods. Recent advances have focused on interpretable frontier models such as Efficiency Analysis Trees and DEA machines, and the global DEA-ML literature has grown rapidly since 2015.

3. Methodology

3.1 Data Collections

The data for the study was collected from secondary sources over a period of five financial years, namely 2020-21 to 2024-25. Out of the Nifty 50, 39 companies were selected as the Decision-Making Units (DMUs) for the study. These companies are the best, large-cap players in various sectors of the Indian economy and are also actively listed on the National Stock Exchange of India (Table 1). The financial data was collected from reliable secondary sources, which include the official website of the NSE, the annual reports of the respective companies, and popular financial websites such as the Prowess Data Base. The data was collected and compiled on a yearly basis to create a balanced dataset for the five-year period. This dataset was then used to apply the Data Envelopment Analysis (DEA) model to measure the efficiency of the selected companies (Table 2).

Table 1
List of companies

Company Name	DMU	Company Name	DMU
Adani Enterprises Ltd.	DMU 1	Kotak Mahindra Bank Ltd.	DMU 21
Asian Paints Ltd.	DMU 2	Larsen & Toubro Ltd.	DMU 22
Axis Bank Ltd.	DMU 3	Mahindra & Mahindra Ltd.	DMU 23
Bajaj Auto Ltd.	DMU 4	Maruti Suzuki India Ltd.	DMU 24
Bajaj Finance Ltd.	DMU 5	N T P C Ltd.	DMU 25
Bajaj Finserv Ltd.	DMU 6	Nestle India Ltd.	DMU 26
Bharat Electronics Ltd.	DMU 7	Oil & Natural Gas Corpn. Ltd.	DMU 27
Cipla Ltd.	DMU 8	Power Grid Corpn. Of India Ltd.	DMU 28
Coal India Ltd.	DMU 9	Reliance Industries Ltd.	DMU 29
Dr. Reddy'S Laboratories Ltd.	DMU 10	Shriram Finance Ltd.	DMU 30
Eicher Motors Ltd.	DMU 11	State Bank Of India	DMU 31
Grasim Industries Ltd.	DMU 12	Sun Pharmaceutical Inds. Ltd.	DMU 32
H C L Technologies Ltd.	DMU 13	Tata Consultancy Services Ltd.	DMU 33
H D F C Bank Ltd.	DMU 14	Tata Consumer Products Ltd.	DMU 34
Hindalco Industries Ltd.	DMU 15	Tata Steel Ltd.	DMU 35
Hindustan Unilever Ltd.	DMU 16	Tech Mahindra Ltd.	DMU 36
I C I C I Bank Ltd.	DMU 17	Titan Company Ltd.	DMU 37
I T C Ltd.	DMU 18	Ultratech Cement Ltd.	DMU 38
Infosys Ltd.	DMU 19	Wipro Ltd.	DMU 39
J S W Steel Ltd.	DMU 20		

3.2 Selection of Input and Output Variable

Table 2
List of variables

S/L	Variable	UOM	Types in DEA	Remarks
1	ROE	%	Output	Return on Equity is a financial performance metric that reflects the company’s capacity to generate profit based on the shareholders’ equity invested in the company. It reflects the efficiency with which the company’s management is employing the company’s equity base in generating earnings.

Table 2 *Continued*

2	Beta	No.	Input	The term beta in finance refers to the amount that the stock moves with the market. It measures the sensitivity of the stock's performance with respect to the movement of the market index. In other words, beta is the reflection of the movement of the market and the movement of the stocks.
3	Market Cap.	Rs. In Crore	Output	Market capitalisation is the total value of all the company's shares currently in circulation. This is a measure of how much the market believes a company is worth, and it is a common method of measuring companies. To do this, you simply multiply the price per share by the number of shares.
4	EPS	Rs.	Output	Earnings Per Share (EPS) is an essential financial metric that indicates the proportion of net profit earned by a company that corresponds to each share of common stock issued by the company. In simpler words, EPS indicates the amount of profit earned for each unit of equity held by the shareholder. EPS is an important financial metric that investors use to evaluate the financial performance of a company.
5	P/E ratio	Times	Input	Price to Earnings Ratio is a financial indicator that is used to compare the price paid per share of a company's common stock with its earnings per share. This indicator is used to determine how much investors are willing to pay per unit of earnings.
6	P/B ratio	Times	Input	The price-to-book ratio is a financial indicator that compares the company's current market price per share with its book value per share. It represents the amount for which the company's net assets are being traded and assists in determining whether the company's stocks are overpriced or underpriced.

3.3 Methodology

Data Envelopment Analysis (DEA) is proposed in 1978 [56], extending the groundwork laid by Farrell in the last era. The basic idea behind DEA is the use of linear programming in finding the best practice frontier units, i.e., the units for which there exists no decision-making unit (DMU) or a combination of units that can beat all the outputs for the current input levels, or beat all the inputs for the current output levels [57]. There are primarily two forms of DEA: the input-oriented DEA, which tries to minimize the inputs while keeping the outputs the same, and the output-oriented DEA, which tries to maximize the outputs while keeping the inputs the same [58].

DEA is the main technique used for evaluating the efficiency, performance, or productivity of DMUs, with the efficiency measures taken as the units' outputs [59]. The DEA literature identifies several DEA models, with the CCR model proposed by Charnes, Cooper, and Rhodes in 1978, and the BCC model proposed by Banker, Charnes, and Cooper in 1984, being the dominant models in DEA practice. The main difference between the models is the assumption of returns to scale, with the BCC model allowing variable returns to scale, while the CCR model assumes constant returns to scale [60]. In the CCR DEA, the efficiency of the DMUs is determined using the linear programming technique, in which the ratio of weighted outputs to weighted inputs is maximized for a DMU [60].

$$\max_u z_0 = \sum_{r=1}^{s} u_r y_{r0} \quad (1)$$

subject to:

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, j = 1,2....,n \quad (2)$$

$\sum_{i=1}^{m} v_i$ x_{i0} = 1 (3)

$u_r \geq 0$, r = 1,2…..,s (4)

$v_i \geq 0$, i = 1,2…..,m (5)

Here, x_{ij} is used to represent the perceived amount of inputs of type "*i*" for the "*j*-th" DMU, while y_{rj} is used to represent the perceived output amount of type "*r*" for the "*j*-th" DMU. The dual form of the above-stated linear programming problem is defined as follows:

$\min_{\lambda} z_0 = \theta_0$ (6)

subject to:

$\sum_{r=1}^{s} \lambda_r$ $y_{rj} \geq y_{r0}$, r = 1,2…..,s (7)

$\theta_0 x_{i0}$ - $\sum_{j=1}^{n} \lambda_r$ $x_{ij} \geq 0$, i = 1,2…..,m (8)

$\lambda_j \geq 0$,j = 1,2…n (9)

The efficiency score defined by θ0∗, regardless of whether it is derived from the primal or dual formulation, represents the optimal solution and is referred to as CCR efficiency or technical efficiency for the DMU under evaluation. If a DMU has θ0∗ = 1, it is said to be relatively efficient; otherwise, it is said to be relatively inefficient.

Variable returns to scale require us to impose a convexity constraint on X, which adds one more constraint to our previous formulation [60]:

$\sum_{j=1}^{n} \lambda_j$ = 1 (10)

This ensuing DEA model is known as the BCC model. The input-oriented BCC model for the DMUs is formally expressed as follows [60]:

$\min_{\lambda} z_0 = \theta_0$ (11)

subject to:

$\sum_{j=1}^{n} \lambda_j$ $y_{rj} \geq y_{r0}$, r = 1,2…..,s (12)

$\theta_0 x_{i0}$ - $\sum_{j=1}^{n} \lambda_j$ $x_{ij} \geq 0$, i = 1,2…..,m (13)

$\sum_{j=1}^{n} \lambda_j$ = 1 (14)

$\lambda_j \geq 0$,j = 1,2…n (15)

These scores are called 'pure technical efficiency' scores, as this model allows variable returns to scale, eliminating the scale effect [60]. Typically, for any DMU, the CCR score is not greater than the BCC score.

DMUs in DEA are ranked according to their scores, i.e., θ. Issues arise if there are multiple DMUs with θ = 1, indicating all DMUs have achieved full efficiency. To determine which is best, super-efficiency is used. Authors in [61] introduced super-efficiency analysis for efficient DMUs, where θ = 1, as follows:

Min θ

Subject to

$\sum_{j=1}^{n} w_j\, x_i^j \leq \theta x_i^t; i = 1,2,3 \ldots.m$ (16)

$\sum_{j=1}^{n} w_j y_r^j \geq y_r^t; r = 1,2,3 \ldots s$ (17)

$\sum_{j=1}^{n} w_j = 1;$ (18)

$w_j \geq 0$(j = 1, 2, 3,…..n); where, j ≠ t. (19)

4. Result and Discussion

The study applies Data Envelopment Analysis (DEA) to measure the efficiency with which 39 companies of the Nifty 50 index functioned during Financial Year 2020-21. The study is conducted using the input-oriented approach under Variable Returns to Scale (VRS) and Constant Returns to Scale (CRS) with super-efficiency scoring using the Peel-the-Onion method. The inputs considered are the Price-to-Earnings (PE) ratio, Beta, and Price-to-Book (PB) ratio, while the output considered is Earnings Per Share (EPS), Return on Equity (ROE), and Market Capitalisation (Table 3).

Table 3
Company Performance in the Financial Year – 2020-21

DMU	Company Name	VRS Score	CRS Score	Returns	Tier / Status	Remarks
DMU38	Ultratech Cement Ltd.	7.8679	1.0645	IRS	Tier 1 (Super-eff.)	Highest VRS in entire 5-yr panel; extreme outlier
DMU9	Coal India Ltd.	3.8376	1.8967	IRS	Tier 1	Super-efficient; strong ROE vs low inputs
DMU35	Tata Steel Ltd.	3.2085	3.1860	IRS	Tier 1	VRS-CRS near parity; scale-optimal
DMU27	ONGC	1.4573	0.8235	IRS	Tier 1	Consistent long-run benchmark
DMU28	Power Grid Corp.	1.3093	1.1552	IRS	Tier 1	Efficient under both VRS & CRS
DMU4	Bajaj Auto Ltd.	1.2686	1.2530	IRS	Tier 1	Near VRS-CRS parity; scale-optimal
DMU10	Dr. Reddy's Labs (2)	1.2408	0.9549	IRS	Tier 1	Strong pharma performer; near CRS frontier
DMU25	NTPC Ltd.	1.1992	0.8739	IRS	Tier 1	Efficient; consistent near-frontier across years
DMU16	Hindustan Unilever Ltd.	1.0431	0.7667	CRS	Tier 1	Only CRS-classified efficient firm
DMU19	Infosys Ltd.	1.0384	0.8855	IRS	Tier 1	IT sector benchmark; consistent performer
DMU8	Cipla Ltd.	1.0188	0.4728	IRS	Tier 1	VRS efficient; large CRS gap
DMU14	HDFC Bank Ltd.	0.9725	0.9508	IRS	Near-frontier	Near CRS frontier; consistent across years
DMU18	ITC Ltd.	0.9760	0.7451	IRS	Near-frontier	Persistent near-frontier; never breaches
DMU1	Adani Enterprises Ltd.	0.2949	0.1041	IRS	Infeasible/Unb.	Lowest VRS across all years in panel
DMU6	Bajaj Finserv Ltd.	0.3709	0.0513	CRS	Infeasible/Unb.	Lowest CRS in panel; extreme valuation drag

Source: Author's Calculation

Note: VRS/CRS ≥ 1.0 = efficiency or super-efficiency. IRS = Increasing Returns to Scale; CRS = Constant Returns to Scale. Tier 1 benchmarks, near-frontier performers, and persistent underperformers. Green = VRS efficient (≥ 1.0); Red = infeasible/lowest performers.

Out of these, 36 firms were successful in generating a feasible VRS, while Nestle India (DMU26), Reliance Industries (DMU29), and TCS (DMU33) failed or strayed into unbounded space. Among these successful firms, 11 firms were successful in achieving or surpassing the efficiency frontier of 1.0. Ultratech Cement (DMU38) had a super-efficiency score, the highest in the five-year period, at 7.868. This is because these firms had high growth rates in EPS and market capitalization, accompanied by low PE multiples during the infrastructure rally of FY 2020-21. Coal India (DMU9, VRS: 3.838) and Tata Steel (DMU35, VRS: 3.209) were next best, with Tata Steel's VRS and CRS values almost similar, indicating that Tata Steel had optimally scaled up production levels during a time of increasing commodity prices across global markets. Power Grid Corp. (DMU28) had the maximum number of peer benchmark uses, 21 out of 36 successful DMUs.

Out of these, 34 firms fall under Increasing Returns to Scale, while Hindustan Unilever (DMU16) and Bajaj Finserv (DMU6) fall under Constant Returns to Scale. This is the maximum variation observed in any of the years, with all firms under IRS except these two. This is also the only time when there were two firms under CRS, while all other years had one firm under CRS or all firms under IRS.

Company performance in the financial year – 2021-22 is given in Table 4.

Table 4
Company Performance in the Financial Year – 2021-22

DMU	Company Name	VRS Score	CRS Score	Returns	Tier / Status	Peer / Remarks
DMU9	Coal India Ltd.	4.8208	2.5038	IRS	Tier 1 (Super-eff.)	Highest VRS; extreme outlier
DMU27	ONGC	1.4773	1.1767	IRS	Tier 1	Strong benchmark; peer for many
DMU28	Power Grid Corp.	1.2956	0.8412	IRS	Tier 1	Most referenced peer (Tier 1)
DMU25	NTPC	1.1866	0.6449	IRS	Tier 1	Peer for multiple DMUs
DMU10	Dr. Reddy's Labs (2)	1.1212	0.7259	IRS	Tier 1	Peer for 8 DMUs
DMU38	Ultratech Cement	1.0918	1.0829	IRS	Tier 1	Near CRS-efficient
DMU16	Hindustan Unilever	1.0899	0.5578	CRS	Tier 1	Only CRS-efficient at frontier
DMU4	Bajaj Auto	1.0603	0.9343	IRS	Tier 1	Near fully efficient (both)
DMU8	Cipla	1.0427	0.5007	IRS	Tier 1	Efficient under VRS
DMU14	HDFC Bank	0.9761	0.9006	IRS	Near-frontier	Requires marginal improvement
DMU18	ITC Ltd.	0.9451	0.6788	IRS	Near-frontier	Close to VRS frontier
DMU19	Infosys	0.9431	0.7614	IRS	Near-frontier	Strong IT sector performer
DMU30	Shriram Finance	0.8236	0.3845	IRS	Inefficient	Mid-range VRS score
DMU1	Adani Enterprises	0.2705	0.0901	CRS	Infeasible/Unb.	Lowest efficiency in sample
DMU6	Bajaj Finserv	0.3739	0.0965	CRS	Infeasible/Unb.	Second lowest; CRS

Source: Author's Calculation

Note: VRS/CRS scores ≥ 1.0 denote efficiency or super-efficiency. IRS = Increasing Returns to Scale; CRS = Constant Returns to Scale. Infeasible DMUs (Nestle, Reliance, TCS, Tata Steel) excluded from tier ranking. Showing efficient benchmarks, near-frontier performers, and underperformers. Green = efficient (VRS ≥ 1); Red = infeasible/lowest performers.

The table designated as 4 indicates that out of 39 companies, 35 companies have feasible solutions, while Nestle India (DMU26), Reliance Industries (DMU29), TCS (DMU33), and Tata Steel (DMU35) have infeasible or unbounded solutions under VRS, which indicates that these companies have high input and output ratios. Out of 39 companies, under VRS super-efficiency, 9 companies have reached or surpassed the efficiency frontier score of 1.0. Coal India (DMU9) has obtained the highest VRS score of 4.82 and is a super-efficient company due to high ROE and market capitalization compared to input values. ONGC (DMU27) and Power Grid Corp. (DMU28) have VRS efficiency scores of 1.48 and 1.30, respectively, and are the most efficient companies and main peers for other DMUs. On average, VRS efficiency for 35 feasible companies is 0.888, which indicates that each company in the Nifty 50 group has the potential to reduce input values by 11% without changing output values and hence is moderately inefficient.

The returns to scale analysis indicates that 33 out of 35 companies have Increasing Returns to Scale (IRS), which indicates that these companies are operating below optimal scale and have potential for increased efficiency by expanding operations. Only Adani Enterprises (DMU1) and Bajaj Finserv (DMU6) have Constant Returns to Scale (CRS), which indicates that these companies are already operating at optimal scale. However, both companies have extremely low absolute VRS efficiency values of 0.27 and 0.37, respectively, which indicates that these companies are inefficient in some other area. The near-frontier group comprises HDFC Bank (0.976), ITC Ltd. (0.945), and Infosys (0.943), which need to improve by a small margin to become efficient companies and join the efficient frontier group. However, Adani Enterprises (VRS: 0.27), Bajaj Finserv (VRS: 0.37), and Bharat Electronics (VRS: 0.54) have large gaps to be filled due to high PE and PB values in relation to output generation values. Tier 1 Benchmark Companies such as Power Grid Corp., ONGC, Bajaj Auto, Cipla, NTPC, Ultratech Cement, and Hindustan Unilever form the efficient frontier and provide input and output targets for inefficient companies. Company performance in the financial year – 2022-23 is given in Table 5.

Table 5
Company Performance in the Financial Year – 2022-23

DMU	Company Name	VRS Score	CRS Score	Returns	Tier / Status	Peer / Remarks
DMU9	Coal India Ltd.	6.5724	3.8798	IRS	Tier 1 (Super-eff.)	Highest VRS; extreme super-efficient outlier
DMU30	Shriram Finance Ltd.	2.2301	2.2260	IRS	Tier 1	VRS & CRS near equal; optimal scale
DMU27	ONGC	2.1186	2.0916	IRS	Tier 1	Consistently strong; peer for 8 DMUs
DMU28	Power Grid Corp.	1.4446	0.8669	IRS	Tier 1	Key benchmark; most cited peer
DMU10	Dr. Reddy's Labs (2)	1.3451	1.1907	IRS	Tier 1	Efficient under both VRS & CRS
DMU4	Bajaj Auto Ltd.	1.2667	1.1959	IRS	Tier 1	Near CRS-efficient; top performer
DMU16	Hindustan Unilever Ltd.	1.1485	0.6849	IRS	Tier 1	VRS efficient; scale gap to CRS
DMU8	Cipla Ltd.	1.1249	0.3961	IRS	Tier 1	VRS efficient; large CRS gap
DMU31	State Bank of India	1.0341	0.9859	IRS	Tier 1	Near CRS frontier; strong bank
DMU14	HDFC Bank Ltd.	1.0322	1.0225	IRS	Tier 1	Efficient under both VRS & CRS
DMU25	NTPC Ltd.	1.0253	0.5426	IRS	Tier 1	VRS efficient; below CRS frontier
DMU18	ITC Ltd.	0.9690	0.7339	IRS	Near-frontier	Close to VRS frontier

Table 5 *Continued*

DMU19	Infosys Ltd.	0.9062	0.7894	IRS	Near-frontier	Strong IT sector; needs marginal improvement
DMU1	Adani Enterprises Ltd.	0.2717	0.1388	IRS	Infeasible/Unb.	Lowest VRS in sample; high PE drag
DMU6	Bajaj Finserv Ltd.	0.3441	0.1151	IRS	Infeasible/Unb.	Second lowest; high valuation inputs

Source: Author's Calculation

Note: VRS/CRS scores ≥ 1.0 denote efficiency or super-efficiency. IRS = Increasing Returns to Scale. Infeasible DMUs: Maruti Suzuki (DMU24), Nestle India (DMU26), Reliance Industries (DMU29), TCS (DMU33). Showing Tier 1 benchmarks, near-frontier performers, and underperformers. Green = efficient (VRS ≥ 1.0); Red = infeasible/lowest performers.

From Table 5, it is observed that 35 firms reported feasible results, while for Maruti Suzuki (DMU24), Nestle India (DMU26), Reliance Industries (DMU29), and TCS (DMU33), the results were either infeasible or unbounded under VRS, reflecting extremely high input-output ratios for FY 2022-23. When evaluated under VRS for super-efficiency, results for 11 firms were already on or beyond the efficiency frontier of 1.0. The results of the returns-to-scale analysis show that all 35 firms with feasible results for FY 2022-23 reported Increasing Returns to Scale (IRS), indicating that the firms are operating at sub-optimal scale. This is a clear reflection of potential gains for the firms. Among the firms that entered the list of efficient firms for FY 2022-23, Bajaj Auto (DMU4) with VRS of 1.27, HDFC Bank (DMU14) with VRS of 1.03, State Bank of India (DMU31) with VRS of 1.03, and Dr. Reddy's Laboratories (DMU10) with VRS of 1.35 reflect positive growth in the post-pandemic period. Bajaj Auto and Dr. Reddy's Laboratories also report efficiency under constant returns-to-scale (CRS) of 1.20 and 1.19, respectively, reflecting scale-optimal performance. ITC Ltd. (0.969) and Infosys (0.906) are near the efficiency frontier; hence, with a slight boost, both firms can achieve full efficiency. Adani Enterprises (VRS: 0.272) and Bajaj Finserv (VRS: 0.344) are the least efficient firms, with high PE and PB ratios compared to their output. Company performance in the financial year – 2023-24 is given in Table 6.

Table 6
Company Performance in the Financial Year – 2023-24

DMU	Company Name	VRS Score	CRS Score	Returns	Tier / Status	Remarks
DMU9	Coal India Ltd.	3.8803	2.9501	IRS	Tier 1 (Super-eff.)	Highest VRS; strong ROE vs low PE
DMU27	ONGC	1.5931	1.5914	IRS	Tier 1	VRS ≈ CRS; scale-optimal operation
DMU10	Dr. Reddy's Labs (2)	1.5814	1.3961	IRS	Tier 1	Efficient under both VRS & CRS
DMU30	Shriram Finance Ltd.	1.4033	1.3469	IRS	Tier 1	Near parity VRS-CRS; top performer
DMU28	Power Grid Corp.	1.2852	0.8869	IRS	Tier 1	Most cited peer; 18 DMUs reference
DMU31	State Bank of India	1.1946	1.1668	IRS	Tier 1	Efficient under both VRS & CRS
DMU14	HDFC Bank Ltd.	1.1846	1.1452	IRS	Tier 1	Efficient under both VRS & CRS

Table 6 *Continued*

DMU16	Hindustan Unilever Ltd.	1.0910	0.5932	IRS	Tier 1	VRS efficient; large CRS gap
DMU8	Cipla Ltd.	1.1135	0.5517	IRS	Tier 1	VRS efficient; scale gap to CRS
DMU25	NTPC Ltd.	0.9832	0.5892	IRS	Near-frontier	Near-efficient; close to VRS frontier
DMU18	ITC Ltd.	0.9509	0.7190	IRS	Near-frontier	Consistent near-frontier across years
DMU19	Infosys Ltd.	0.9490	0.8164	IRS	Near-frontier	Strong IT performer; near-frontier
DMU4	Bajaj Auto Ltd.	0.9323	0.8143	IRS	Near-frontier	Dropped from frontier vs FY23
DMU1	Adani Enterprises Ltd.	0.2706	0.1559	IRS	Infeasible/Unb.	Lowest score; persistently inefficient
DMU6	Bajaj Finserv Ltd.	0.3447	0.1395	IRS	Infeasible/Unb.	Chronically low; high valuation drag

Source: Author's Calculation

***Note*:** VRS/CRS ≥ 1.0 = efficiency or super-efficiency. IRS = Increasing Returns to Scale. All 35 feasible DMUs operate under IRS. Infeasible: Maruti Suzuki (DMU24), Nestle India (DMU26), Reliance Industries (DMU29), TCS (DMU33). Tier 1 benchmarks, near-frontier performers, and persistent underperformers. Green = VRS efficient (≥ 1.0); Red = infeasible/lowest performers.

In FY2023-24, out of the total of 39 companies, 35 companies reported feasible VRS results. Maruti Suzuki (DMU24), Nestle India (DMU26), Reliance Industries (DMU29), and TCS (DMU33) continued with infeasible and unbounded results. Of the companies with feasible results, 9 companies reported super efficiency with VRS efficiency above 1.0. This indicates a slight tightening of the efficiency frontier compared to the previous year. Coal India (DMU9) retained its top super-efficient position with VRS efficiency of 3.88. However, this is slightly lower than its previous peak and suggests a slight erosion of its relative competitive advantage. ONGC (DMU27) reported near-perfect VRS (1.593) and CRS (1.591) efficiency scores. This suggests that the company is operating at an almost optimal scale. Dr. Reddy's Laboratories (DMU10), VRS: 1.58, and Shriram Finance (DMU30), VRS: 1.40, also reported top efficiency. Both companies reported excellent scale efficiency. The average VRS efficiency of the companies with feasible results increased to 0.918. This suggests a continued tightening of the efficiency frontier for the sample as a whole. From the returns-to-scale perspective, all the companies with feasible VRS results reported Increasing Returns to Scale (IRS), indicating that they are operating below the optimal scale and thus have scope for increasing efficiency by increasing the scale of operations. With regard to the composition of the efficiency frontier, Bajaj Auto (DMU4), VRS: 0.932, slipped out of the efficiency frontier. On the other hand, HDFC Bank (DMU14), VRS: 1.185; State Bank of India (DMU31), VRS: 1.195; ONGC; and Power Grid Corporation (DMU28) reported improved efficiency. Power Grid Corporation reported the highest number of references and ONGC reported the second highest number of references. Both companies are considered the best industry comparators. NTPC (0.983), ITC Ltd. (0.951), Infosys (0.949), and Bajaj Auto (0.932) reported high efficiency but could not reach the efficiency frontier. At the other extreme, Adani Enterprises reported the lowest VRS efficiency of 0.271 and Bajaj Finserv reported the second lowest VRS efficiency of 0.345. Both companies reported low efficiency due to high valuation multiples compared to output. Company performance in the financial year – 2024-25 is given in Table 7.

Table 7
Company Performance in the Financial Year – 2024-25

DMU	Company Name	VRS Score	CRS Score	Returns	Tier / Status	Remarks
DMU26	Nestle India Ltd.	1.7732	1.7668	IRS	Tier 1 (Super-eff.)	Highest VRS in FY25; strong VRS-CRS parity
DMU27	ONGC	1.6591	1.3973	IRS	Tier 1	Consistently efficient across all 4 years
DMU14	HDFC Bank Ltd.	1.5898	1.4185	IRS	Tier 1	Efficient under both VRS & CRS
DMU31	State Bank of India	1.3923	1.3581	IRS	Tier 1	Near VRS-CRS parity; scale-optimal
DMU10	Dr. Reddy's Labs (2)	1.1921	1.0086	IRS	Tier 1	Efficient under both VRS & CRS
DMU16	Hindustan Unilever Ltd.	1.1555	0.5886	IRS	Tier 1	VRS efficient; significant CRS gap
DMU4	Bajaj Auto Ltd.	1.0967	1.0667	IRS	Tier 1	Re-entered frontier after FY24 dip
DMU8	Cipla Ltd.	1.0828	0.7179	IRS	Tier 1	VRS efficient; moderate CRS gap
DMU18	ITC Ltd.	1.0211	0.8407	IRS	Tier 1	Newly efficient; crossed frontier in FY25
DMU28	Power Grid Corp.	1.0411	0.8868	IRS	Tier 1	Consistent benchmark; 4th consecutive year
DMU25	NTPC Ltd.	0.9087	0.6885	IRS	Near-frontier	Closest to frontier for 4 straight years
DMU19	Infosys Ltd.	0.9212	0.8418	IRS	Near-frontier	Persistent near-frontier IT performer
DMU17	ICICI Bank Ltd.	0.8213	0.8154	IRS	Near-frontier	Near VRS-CRS parity; close to efficient
DMU1	Adani Enterprises Ltd.	0.3791	0.3680	IRS	Infeasible/Unb.	Lowest VRS all 4 years; structural laggard
DMU6	Bajaj Finserv Ltd.	0.3381	0.1562	IRS	Infeasible/Unb.	Lowest CRS; chronic high-valuation drag

Source: *Author's Calculation*

Note: VRS/CRS ≥ 1.0 = efficiency or super-efficiency. IRS = Increasing Returns to Scale. All 35 feasible DMUs operate under IRS. Infeasible in FY25: Coal India (DMU9), Maruti Suzuki (DMU24), Reliance Industries (DMU29), TCS (DMU33). Tier 1 benchmarks, near-frontier performers, and persistent underperformers. Green = VRS efficient (≥ 1.0); Red = infeasible/lowest performers.

In the 2024-25 financial year, all 35 out of 39 firms had VRS results that were deemed feasible, while Maruti Suzuki (DMU24), Coal India (DMU9), Reliance Industries (DMU29), and TCS (DMU33) were deemed to have failed to achieve feasibility or had unbounded results. Nestle India (DMU26) led the pack with a VRS score of 1.773, almost comparable to its CRS score of 1.767, indicating that the firm is operating optimally. ONGC (DMU27) with a VRS score of 1.659 remained one of the elite, while HDFC Bank (DMU14) with a VRS score of 1.590, and State Bank of India (DMU31) with a VRS score of 1.392, remained high on scale efficiency. On average, the VRS scores of all firms were found to have declined to 0.826.

All firms were found to have Increasing Returns to Scale (IRS) results, indicating that all firms were undersized, thus indicating scope for growth-driven efficiency improvements. ITC Ltd. (DMU18) with a VRS score of 1.021 entered the efficient frontier, while Bajaj Auto (DMU4) with a VRS score of 1.097 re-entered the efficient frontier. Dr. Reddy's Laboratories (DMU10) remained high on scale efficiency with VRS scores of 1.192 and CRS scores of 1.009, indicating that scale efficiency is still high. Shriram Finance (DMU30) plummeted to a VRS score of 0.635. While firms such as NTPC (0.909), Infosys (0.921), ICICI Bank (0.821) remained near the efficient frontier, they failed to attain it. Bajaj Finserv (0.338) and Adani Enterprises (0.379) remained near the lowest point, constrained by high valuation multiples vis-à-vis their output, while ONGC remained the top peer benchmark, with Power Grid Corporation (DMU28) serving as a reference point for all. Company performance in the financial year from 2020-21 to 2024-25 is given in Table 8.

Table 8
Company Performance in the Financial Year from 2020-21 to 2024-25

DMU	Company Name	FY20-21	FY21-22	FY22-23	FY23-24	FY24-25	Trend / Cross-Year Observation
DMU9	Coal India Ltd.	3.838	4.821	6.572	3.880	Infeasible	Peak performer FY21-24; infeasible FY25 — structural reversal
DMU38	Ultratech Cement Ltd.	7.868	1.092	—*	—*	—*	Highest single score in panel (FY21); moderate thereafter
DMU27	ONGC	1.457	1.477	2.119	1.593	1.659	Only firm Tier 1 across all 5 years; most resilient benchmark
DMU28	Power Grid Corp.	1.309	1.296	1.445	1.285	1.041	Most cited peer all 5 years; stable frontier anchor
DMU16	Hindustan Unilever Ltd.	1.043	1.090	1.149	1.091	1.156	Tier 1 all 5 years; CRS-classified in FY21 only
DMU8	Cipla Ltd.	1.019	1.043	1.125	1.114	1.083	Consistently Tier 1 across all 5 years
DMU10	Dr. Reddy's Labs (2)	1.241	1.121	1.345	1.581	1.192	Tier 1 all 5 years; VRS-CRS parity in FY24-25
DMU4	Bajaj Auto Ltd.	1.269	1.060	1.267	0.932	1.097	Tier 1 in 4 of 5 years; dipped FY24, re-entered FY25

Table 8 *Continued*

DMU25	NTPC Ltd.	1.199	1.187	1.025	0.983	0.909	Tier 1 FY21-23; persistent near-frontier FY24-25
DMU14	HDFC Bank Ltd.	0.973	0.976	1.032	1.185	1.590	Steadily rising; strongest uptrend in panel
DMU31	State Bank of India	0.727	—	1.034	1.195	1.392	Joined frontier FY23; rising trajectory
DMU26	Nestle India Ltd.	Infeasible	Infeasible	Infeasible	Infeasible	1.773	Infeasible FY21-24; highest VRS in FY25 (turnaround)
DMU18	ITC Ltd.	0.976	0.945	0.969	0.951	1.021	Near-frontier 4 years; finally crossed in FY25
DMU19	Infosys Ltd.	1.038	0.943	0.906	0.949	0.921	Tier 1 only in FY21; persistent near-frontier
DMU30	Shriram Finance Ltd.	0.634	0.824	2.230	1.403	0.635	Volatile — peak in FY23; dropped sharply FY25
DMU1	Adani Enterprises Ltd.	0.295	0.271	0.272	0.271	0.379	Lowest VRS in all 5 years; chronic underperformer
DMU6	Bajaj Finserv Ltd.	0.371	0.374	0.344	0.345	0.338	Lowest CRS in panel; declining trend across 5 years

Source: Author's Calculation

Note: * DMU38 (Ultratech Cement) not among top-tier firms in FY 22-25 extracted data. Infeasible DMUs excluded from peer rankings. All scores are VRS super-efficiency from input-oriented DEA. VRS super-efficiency scores by fiscal year. Green = Tier 1 (≥ 1.0); Yellow = near-frontier (0.9–0.99); Red = infeasible or lowest. Panel summary row shows mean VRS across all feasible firms.

This is a five-year DEA panel study of FY 2020-21 to FY 2024-25, comparing 39 Nifty 50 giants on how efficiently they operate, using inputs such as price to earnings, beta, and price to book, and outputs such as earnings per share, return on equity, and market capitalization. The Peel-the-Onion method is used, which "peels back" frontier membership step by step to show the various levels of efficiency. During these years, there were four companies whose VRS scores were always infeasible: Reliance Industries (DMU29) and TCS (DMU33) every year, Nestle India (DMU26) every year from FY21 to FY24, showing a remarkable turnaround in FY25, and Maruti Suzuki (DMU24) every year from FY22 onwards. Coal India (DMU9) was always super-efficient, peaking in FY23 with a VRS score of 6.572, but was infeasible in FY25, indicating a major shift in its input-output behavior. This shows how the efficiency frontiers of India's large-cap stocks ebb and flow through macroeconomic turbulence.

For the firms that were classified as feasible, the average VRS efficiency trace resembled a jagged heartbeat. It rose to 1.125 in FY21 due to COVID recovery outliers, dipped to 0.888 in FY22 as valuations reset, rose gradually through FY23 (0.904), FY24 (0.918), before dipping again to 0.826 in FY25 as Coal India exited and broad adjustments kicked in. Five companies held their Tier 1 frontier status across all five years: ONGC (DMU27), Power Grid Corp. (DMU28), Hindustan Unilever (DMU16), Cipla (DMU8), and Dr. Reddy's Laboratories (DMU10), solidifying their status as industry benchmarks. ONGC held Tier 1 status in every year and was the most frequently cited peer in FY25. Power Grid Corp. held the top spot in peer citations in FY21-FY24, with a high of 21 DMUs in a single year. HDFC

Bank exhibited the greatest growth in efficiency, rising from 0.973 in FY21 to 1.590 in FY25, reflecting a steadily improving fundamental story. ITC Limited (DMU18) held steady near the frontier in four years at 0.945-0.976 before breaking through in FY25 at 1.021. Infosys achieved this in FY21 but failed to sustain it.

Adani Enterprises (DMU1) and Bajaj Finserv (DMU6) ended up at the bottom with the lowest VRS and CRS values in all years. Their low EPS, high ROE, and slow market-cap growth were due to high PE and high price-to-book values. Shriram Finance's (DMU30) journey has been a rollercoaster—it lagged in years FY21-22, then shot up to 2.230 in FY23 and 1.403 in FY24, only to crash to 0.635 in FY25 by the largest decline in the entire panel. In FY25, there was a more balanced spread in efficiency values without Coal India dominating. Nestle India topped with VRS 1.773, just shy of CRS 1.767—it's a dramatic turnaround from four years of infeasibility to a single year in this study's biggest turnaround. In conclusion, it's evident that there are clear winners in public utilities and pharma/FMCG sectors and losers in this entire universe that comprises the Nifty 50.

Radar chart plotting (Figure 1) each company's VRS super-efficiency score across five fiscal year axes (FY20-21 to FY24-25). The dashed red circle depicts the efficiency frontier at 1.0. For clarity, scores are capped at 4.0, though in this case, Coal India's actual score in the FY23 was 6.572. Infeasible years are placed on the score axis at zero. The style of the lines distinguishes the groups of companies: solid lines for Persistent Tier 1, dashes for Rising, Volatile/cyclical in dash-dot, and Chronic laggards in dotted lines.

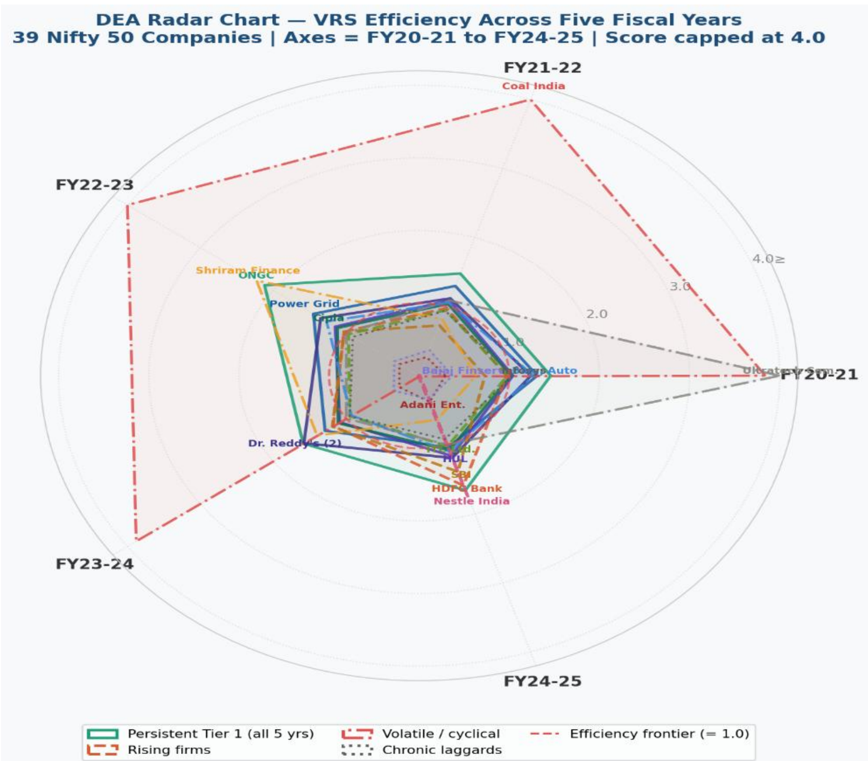

Fig. 1. Efficiency Radial Chart for Five Year Panel (FY 2020-21 to 2024-25)

The structural arc for this five-year period is given in the radar chart. The high performers in this period, namely ONGC, Power Grid Corporation, HUL, Cipla, and Dr. Reddy's, have broad and sweeping shapes that touch every axis in the chart. Among the rising stocks in this period, HDFC Bank shows a steady rise from FY 2020-21 to FY 2024-25. Nestle also shows a rising trend and reaches a high of 1.773 in FY 2024-25. Coal India shows a broad sweeping rise from FY 2020-21 to FY 2023-24 and then falls back to zero. This gives a clear rise and fall pattern. The low performers in this period, namely Adani Enterprises and Bajaj Finserv, are clustered in the center in a low zone.

5. Research Implication

This study acts as a guideline for investors, managers, policymakers, and researchers interested in understanding the efficient use of resources by large-scale organizations in India. It helps investors design a more efficient stock selection strategy using multiple criteria, as opposed to relying on traditional financial parameter-based investment strategies. Large-scale organizations like ONGC, Power Grid, HUL, Cipla, and Dr. Reddy's are the ones that are highly efficient in the market, thus representing the right investment opportunities, especially during a period of economic uncertainty.

For managers, the study reveals the need for organizations like Adani Enterprises and Bajaj Finserv to focus on the financial aspects of the business. It is observed that while the price-earnings ratio, price-book ratio, and market capitalization are strong, the earnings, return on equity, and market capitalization are low, thus indicating the need for these organizations to focus on the financial aspects of the business, as opposed to market sentiment alone. The DEA model helps these organizations learn from the best performers in the industry.

From a sectoral perspective, the study indicates that public sector utilities and pharmaceutical companies become steadier and more efficient with the passage of time. This is good news for fund managers because sectors like energy and pharmaceuticals will continue to do well even in the face of a changing economy. However, companies in cyclical industries like coal will have a greater fluctuation in their efficiency, depending on global price fluctuations and not necessarily in the long term.

Another interesting aspect of the research is how the post-COVID-19 world impacted the results. Efficiency is at a high in FY 2020-21, driven by government support and increasing demand. However, it may not be a good indicator of long-term health and policymakers should be cautious in interpreting the results.

The research provides a different perspective for researchers by integrating super efficiency DEA with VRS and CRS approaches. It links market-based inputs with financial performance outputs. It also proves that DEA infeasibility does not always imply low performance; sometimes it simply reflects a short-term disconnect between the market and fundamentals. In conclusion, the research helps advance our knowledge of firm efficiency and sets the stage for research in the Indian and other emerging markets.

6. Conclusion

Over a five-year period, a study of 39 constituents of the Nifty 50 uses Data Envelopment Analysis to analyze a space characterized by structural gaps, cyclical volatilities, and limited but real efficiency improvements. Taking inputs such as price-earnings ratio, beta, price-book ratio, and output measures such as earnings per share, return on equity, and market capitalization, we apply a super-efficient data envelopment analysis, using Variable and Constant Returns to Scale, to identify a group of best practice companies that have remained on the frontier despite changes in macroeconomic environments.

ONGC, Power Grid Corporation, Hindustan Unilever, Cipla, and Dr. Reddy's Laboratories have Tier 1 efficiency for each and every one of the five years under consideration, which demonstrates that companies that have shown prudent valuation multiples and have a consistent track record of generating actual business fundamentals at a high rate are indeed at the apex of the flagship index in India. It is also interesting to note that Power Grid Corporation is a company whose ideas and practices have been followed by up to 21 peers in a particular financial year from FY21 to FY24.

The panel also points out how macro-level events impact efficiency in a cascading effect. In the COVID-19 recovery rally in FY 2020-21, the highest average VRS efficiency (1.125) and highest number of frontier firms (11) were observed in this study due to extreme super-efficiency in the commodity sector, infrastructure sector, and pharma sector, which benefited from policy stimulus and a rise in global commodity prices in the pandemic years. The most striking case is that of Coal India's efficiency journey from a VRS score of 3.838 in FY21 to a high of 6.572 in FY23, after which it dipped to 3.880 in FY24 and then became infeasible in FY25. This represents a microcosm of how commodity sector firms may achieve exceptional relative efficiency in a super cycle high but then reverse as input/output dynamics change. Nestle India's efficiency journey represents a mirror image in that it becomes infeasible in four consecutive years and then achieves the highest VRS efficiency in FY25 at a score of 1.773. This proves that infeasibility in DEA does not necessarily reflect a company's low efficiency; it may be a result of a temporary discrepancy between high optimistic valuations and actual output values that will normalize as market prices adapt. The low efficiency of Adani Enterprises and Bajaj Finserv across all five years, due to high price-to-earnings and price-to-book ratios that surpass actual output values, demonstrates what high levels of market speculation can do to a company's efficiency in a DEA model based on fundamental values. In this model, efficiency in the Nifty 50 across a five-year period demonstrates a fluid quality based on market influences and sector dominance rather than a static attribute.

7. Future Scope

The present study also indicates several possible avenues for future research. First, whereas this paper employs a static cross-sectional DEA for individual years in isolation, future studies may employ Malmquist Productivity Index Decomposition over the five-year panel. This will help us differentiate between efficiency change and technological progress.

Second, this paper employs an input-output specification with market-based inputs such as Price Earnings, Beta, and Price Book in relation to fundamental output measures such as EPS, ROE, and Market Cap, future studies may include additional variables such as leverage ratios or dividend yield as additional inputs or output measures. This will test the robustness of our efficiency rankings with alternative input-output specifications.

Third, whereas this paper examines the top 39 constituents of the Nifty Index, future studies must address the infeasibility problems faced in Reliance Industries, TCS, Maruti Suzuki, and Nestle India in most years. This may be achieved by employing alternative DEA formulations such as bounded super efficiency or context-dependent DEA.

Fourth, future studies can also expand the sample period beyond FY 2024-25 to see if the FY25 market, which has Coal India exiting, Nestle India entering, and the average VRS score converging to 0.826, represents a structural shift or merely a cycle.

Finally, the research could also use the sectoral lens for the above analysis by employing the Data Envelopment Analysis (DEA) methodology for individual sectors such as banking, pharmaceuticals, energy, FMCG, IT, and industrials. This will enable the development of sectoral best practice frontiers based on the input-output characteristics of the sectors.

Another alternative is the use of network DEA or two-stage DEA for the decomposition of overall efficiency into its sub-process efficiencies such as operating efficiency and capital allocation efficiency. This facilitates the portfolio managers and practitioners in identifying the exact causes of underperformance for individual Nifty 50 stocks.

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Conflicts of Interest
The authors declare no conflicts of interest.

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