Journal of Business Thought, *DOI: 10.18311/jbt/2024/44696, Vol. 15, 2024*

Measuring Operational Efficiency of Restructured Companies: A DEA-MI Approach

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Received: 27 June 2024 **Accepted:** 31 October 2024 **Published:** 18 December 2024

Abstract

The current study attempts to assess the operational efficiency of the firms restructured to resolve their situation of financial distress. Efficiency evaluation of the firms helps to understand the firm's performance after it goes through the restructuring process as opposed to liquidation. Thus, it is a measure to validate the decision of the Tribunal to allow the firm to continue as a going concern against liquidation. Malmquist Index, a data envelopment analysis technique, has been utilised to measure the efficiency of firms for three years after restructuring. A study of 40 manufacturing firms reveals that the firms' efficiency has declined over three years (2017 to 2020) primarily due to the inability of the firms to achieve optimal scale of production. While there has been an improvement in technological advancement, the overall technical efficiency has been reduced. The study thus provides valuable insights to management and practitioners regarding the areas that require attention post-restructuring and separates performance changes due to other factors like technological advancement or scale efficiencies.

Keywords: Data Envelopment Analysis, Efficiency, Malmquist Index, NCLT, Restructuring
JEL Classification: C23, G34, L25, O33

1. Introduction

Efficiency analysis is a vital tool for assessing a company's performance. It indicates how the company optimally uses the limited available inputs to obtain the maximum output. Minimising the input utilised can also achieve the same output level.

An efficient company demonstrates good financial health, which is vital for the various stakeholders. The shareholders, creditors and management analyse it for their decision-making and the government to assess its financial and economic policies (Stanková & Hampel, 2023). One primary reason for a company's failure is its poor management, and its efficiency is a significant indicator of the quality of management. A company's inefficiency can strongly indicate corporate indebtedness, financial distress, and, thus, bankruptcy. Companies going through financial distress attempt to get out of the situation to avoid the risk of bankruptcy. One such attempt by the firms is financial restructuring, in which the companies redefine their capital structure to reduce their debt obligations. To undergo financial restructuring, a company approaches the Company Law Tribunal, which approves the resolution plan that the committee of creditors has approved.

Data Envelopment Analysis (DEA), a linear programming model, assesses the relative efficiency of a company (decision-making unit) with multiple inputs and outputs, employing a non-parametric approach. It is a valuable tool for evaluating and benchmarking the efficiency of firms in various sectors, thereby contributing to better decision-making and resource allocation. Researchers can identify firms that operate at the production frontier (fully efficient) and those that are less efficient.

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Assessing a firm's efficiency over a particular period or for one year is a static concept; one assesses the firm's efficiency in a specific period concerning the peer firms. It is imperative to assess how efficiency changes over time as the changes in the business environment are dynamic, and so is the firm's performance.

When DEA efficiency is a factor in dynamic models, assessing it across multiple periods is crucial. Traditional DEA models, being static, are designed to evaluate efficiency within a single period. However, significant interest is in extending these models to track efficiency changes over time. If a Decision-Making Unit (DMU) can be studied and analysed at various times, the efficiency changes can provide valuable insights for predicting future financial distress.

The present research employs the efficient frontier method, utilising the Malmquist productivity index based on DEA. It assesses the company's efficiency over some time. This index alters two distinct and comprehensive elements: variations in the firm's technical efficiency as time progresses and technological shifts over time.

This study's main contribution is providing an overview of Data Envelopment Analysis and using the Malmquist index as a technique for assessing the efficiency of restructured firms. It delves into the comprehensive literature review of techniques applied by researchers worldwide to assess firms' efficiency. Moreover, the reasons for the change (increase or decrease in the efficiency of the firms due to various factors like scale change and technological change or change in technical efficiency) are also identified.

The rest of the paper is organised as follows: Section 2 looks into the literature review, identifying the research conducted on efficiency analysis and the gaps in the literature. Section 3 explains the techniques of DEA and the Malmquist Productivity Index (MPI) and provides an overview of the data and the methodology adopted. In Section 4, we report the results and conclude by summarising the findings in Section 5.

2. Literature Review

The seminal work on DEA was done by Farrell in 1957. Farrell (1957) classified efficiency into technical efficiency and allocatable efficiency. Since then, several studies have been conducted using the DEA technique to calculate the efficiency of firms. It is an optimisation method that determines the productivity and efficiency change in the firms due to various inputs and outputs using linear programming. The basic idea behind the DEA technique is that a firm should be able to obtain maximum output using minimum inputs. It can also be interpreted as the firm receiving the same amount of production by minimising the use of its resources, *i.e.* the inputs. DEA is a non-parametric approach that ranks a firm, *i.e.*, the DMU, about its peers (other DMUs in the sample). It was employed by Banker and Morey (1986) to analyse the efficiency based on fixed input and output variables. DEA has seen wide application in the past few years. DEA has been applied across various industries, including education, banking, agriculture, manufacturing and health. Due to the complex nature of multiple inputs and outputs used by different firms, DEA has proved to be a saviour by providing benchmarking practices. It allows for consideration of numerous inputs and multiple outputs simultaneously.

The DEA approach has been used across various industries in India as well as across the globe. Most studies have been in the financial sector, dealing with banks and other financial institutions. The literature dealing with the non-financial sector has been limited.

DEA methods, which integrate non-financial and financial factors as input/output variables, provide a standardised approach for measuring performance across industries and firms. Numerous studies have specifically employed DEA methods to assess industry performance (Destefanis & Sena (2007) ; Majumdar & Chang, (1996); Sun, 2011). Siriopoulos and Tziogkidis (2010) point out that the reliance on financial ratio analysis—particularly return on equity (ROE), return on assets (ROA), and the cost/income ratio—by researchers and practitioners often does not yield a comprehensive efficiency score when multiple inputs or outputs are considered. In contrast, the Global DEA Model (GDM), which incorporates all selected variables, provides a consolidated performance metric (Gonzalez-Bravo, 2007). Berger and Humphrey (1997) employed DEA to evaluate the efficiency of banks in the United States and Canada. They discovered that Canadian banks outperformed their American counterparts in terms of efficiency, a difference they attributed to the distinct regulatory environments in the two countries. Mester, (1996) also used DEA to examine the performance of Australian banks and found a wide range of efficiency levels, which he attributed to differences in business strategies and operating environments among

the banks. These studies emphasise the importance of DEA in assessing bank performance and pinpointing areas for enhancement.

Apart from the banking sector, DEA has been utilised to assess the efficiency of firms in other industries. For instance, Ozcan *et al.,* (1992) applied DEA to evaluate hospitals' performance in Turkey, concluding that size, location, and ownership influenced their efficiency. Zhu (2003) used DEA to evaluate the performance of Chinese manufacturing firms and found a broad spectrum of efficiency levels, which he attributed to variations in management practices and the adoption of technology among the firms. Hollingsworth (2008) applied DEA to assess hospitals' performance in the United States, noting a wide range of efficiency levels due to differences in management practices and patient demographics. Tone and Tsutsui (2010) applied DEA to evaluate Japanese manufacturing firms' performance, finding varying efficiency levels. Zhu (2000) studied Fortune 500 companies to examine profitability and marketability. These studies collectively highlight DEA's utility and ability to evaluate performance and identify areas for improvement across various industries.

An inter-country comparison of Chinese and Turkish manufacturing firms by Bayyurt and Duzu, (2008), using DEA, revealed that the Chinese manufacturing firms were more efficient than the Turkish firms. Memon *et al.* (2012) studied 14 manufacturing firms in Pakistan. They concluded that the technical efficiency of the firms was on an average 0.82, with only one firm reaching an efficiency score of 1. Excess capital usage and mismanagement led to inefficiency in the Greek meat products industry, as Keramidou *et al.* (2011) pointed out. The technical efficiency of companies is influenced by certain factors like automation, technological innovation, and workers' training, as pointed out by Batra and Tan (2003). During the early 2000s, the DEA analysis shifted to large public sector undertakings characterised by low operating efficiency and poor performance. Subrahmanya (2004) compared the efficiency scores obtained from DEA and Stochastic Frontier Analysis (SFA) for a sample of Indian manufacturing firms. The author found that the two methods yielded similar results, but DEA was more accessible to implement and interpret. Din *et al.* (2007) pointed out the same in their study of manufacturing units in Pakistan. Singh (2007) studied Haryana's private and public sector sugar mills and found the former are far more efficient.

Majumdar (1994) found a high rate of inefficiencies in the pharmaceutical industry. A study by Meenakumari and Kamaraj (2008) revealed a 24 per cent efficiency level of state-owned electricity companies in India.

Pandey *et al.* (2013) used DEA to assess the efficiency of Indian textile manufacturing firms. The authors found that the firms varied widely in terms of efficiency and suggested several strategies for improving efficiency.

Mehta *et al.* (2019) assigned efficiency scores and ranked the Indian Companies known for their best practices in controlling environmental carbon emissions. The authors used a hybrid model of DEA and technique for order performance by similarity to ideal solution (TOPSIS) to measure the efficiency and ranking of various decision-making units based on specified variables.

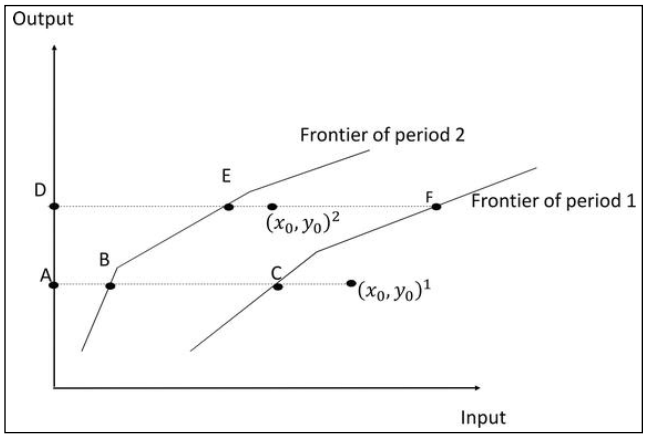
Sinha (2022) worked on the efficiency of fifteen Indian insurance companies from 2011-12 to 2016-17 and calculated the profit efficiency scores. The scores were decomposed into revenue and cost efficiency components. The study concluded that the solvency ratio is a significant explanatory variable of profit efficiency.

DEA has also been used as a technique for bankruptcy prediction. The initial concept of using the DEA method for bankruptcy prediction was introduced by Simak (1997), who was the pioneer in comparing its outcomes with Altman's Z-score results. Other researchers who worked on bankruptcy prediction using DEA as a technique include Cielen *et al.* (2004). They applied the DEA radial model for bankruptcy prediction and compared the results with those from Discriminant Analysis (DA). Paradi *et al.* (2004) implemented additive and radial models alongside the peeling technique in the same year, achieving 100 per cent accuracy in predicting business bankruptcy. Premachandra *et al.* (2011) also utilised an additive super-efficiency DEA model and compared its results with logistic regression, demonstrating a satisfactory level of accuracy in predicting business bankruptcy, though the prediction rate was less reliable for financially stable firms. Sueyoshi and Goto (2009) employed the additive (ADD) model to determine a threshold below which companies face bankruptcy, comparing the results with the DEA-DA approach. Premachandra *et al.,* (2011) combined radial and ADD models to develop a DEA ranking index. Shetty *et al.* (2012) used the DEA model to evaluate their firms' bankruptcy likelihood. They examined a business sample. The outcome of their research led to the creation of measures that bankruptcy forecasters could use.

As suggested by Bryan, Fernando, and Tripathy (2013), one approach involves solving DEA problems for each period individually and constructing a panel dataset of the resulting efficiency scores. Alternatively, the *window* DEA method, introduced by Charnes, Clark, Cooper, and Golany (1984), is designed to analyse efficiency changes in a time series context. This method employs a fixed observation window that shifts across the entire period, enabling the evaluation of result trends and stability within different panel subsets. However, as Cooper, Seiford, and Tone (2006) noted, a limitation of *window* DEA arises in the initial and final periods, where observations may not be as comprehensively assessed.

The Malmquist DEA model is especially effective for handling panel data. The Malmquist Index (MI), originally designed to compare two economies in terms of their production technology, was incorporated into DEA by Färe, Grosskopf, Lindgren, and Roos (1992). Later on, Färe, Grosskopf, Norris, and Zhang (1994), developed a DEA-based Malmquist productivity index. The disintegrated elements of the MI can identify how much of an efficiency change (increase or decrease) from period t to $t+1$ is due to individual effort versus industry innovation. Efficiency change refers to the extent to which a DMU's performance improves or deteriorates over time, whereas technological change captures the shift in the efficiency frontier between two periods.

Figure 1 illustrates two observations in the input x and output y domains at period 1 and period 2. The objective is to measure productivity growth between period 1 and period 2, in terms of the transition from one period to another, achieved by imposing a potential production frontier, as depicted in Figure 1. These frontiers represent the efficient levels of output y that can be produced from a given level of input x. A shift in the frontier signifies the shift due to technological or technical efficiency changes.



Source: Sanchez (2018)

Figure 1. Malmquist frontier for subsequent periods.

Since the introduction of the MI, numerous studies have investigated productivity changes across various sectors, including Italian manufacturing firms (Costa, 2012), Spanish government tax offices (Fuentes & Lillo-Banuls, 2015), Taiwanese banks (Shyu & Chiang, 2012), and Korean universities (Sohn & Kim, 2012). These studies primarily examined efficiency changes over time to derive managerial insights and strategic recommendations, without addressing the issue of distress prediction.

2.1 Gaps in the Literature

The DEA analysis has been applied to various sectors in India and globally. However, the studies relating to the study of firms over time have been few and sparse. The current research is an essential contribution to the existing literature as it studies the efficiency of firms over several years. Thus, it tries to assess the efficiency frontier shift over time. Secondly, the sample consists of the firms that the National Company Law Tribunal (NCLT) has restructured. The study undertaken is novel in its attempt to work on a sample of firms restructured by NCLT. There are presently no studies on calculating the efficiency scores of firms revived by NCLT through a resolution plan. The present study assesses the firm's performance over several years after restructuring and thus tries to evaluate its efficacy and efficiency. It, therefore, assesses the financial health of the revived companies, thereby pointing out the efficacy of the Tribunal.

2.2 Research Objective

This paper assesses the efficiency of firms restructured through the NCLT over a specified period. The enhancement in the financial health of these firms post-restructuring highlights the tribunal's effectiveness in determining whether a firm should undergo liquidation or restructuring. Consequently, this study addresses the following research questions:

- Do firms restructured by the NCLT exhibit improvements in their operational performance following the restructuring process?

- What factors, beyond financial performance, contribute to the enhancement of firms' operational efficiency?

3. Data and Methodology

3.1 Data Envelopment Analysis and Malmquist Index

3.1.1 Data Envelopment Analysis

The business environment conditions are never static. It leads to a dynamic environment where DMUs or firms operate. There is a change in the efficiency of the DMUs over time. This change can be relevant for predicting the firm's financial health in the future. DEA utilises mathematical programming to retrospectively assess the relative efficiency of managerial performance, regardless of how it was originally planned or executed. This extends the application of mathematical programming, allowing it to serve not only as a tool for future planning but also for the evaluation and control of past outcomes. The CCR (Charnes, Cooper, and Rhodes) ratio model within DEA accounts for both technical and scale inefficiencies in these assessments (Banker *et al.,* 1984).

Klopp (1985) introduced *window analysis* to deal with the dynamic nature of the business environment in which the firms function. A fixed observation window was used to analyse the observations as they moved through the period. After that, the movement and stability were analysed across the panel set. The shortcoming of *window analysis* was that the DMUs were evaluated less in the last period. Frontier production estimation and efficiency measurement originated with Farrell (1957), who employed an econometric approach. He assessed technical efficiency by examining absolute deviations from an idealised frontier isoquant. Subsequent studies delved into production function estimation using various specifications, recognising that the chosen functional form impacts the concept of implied isoquants and the dimensions of efficiency frontiers. The mathematical programming approach, employing DEA, superseded the econometric approach. DEA, an optimisation method utilising linear programming, evaluates the overall productivity and efficiency of DMUs by considering proportional changes in inputs or outputs. Technical efficiency is attained through maximising outputs given a specific set of inputs.

This approach is typically deterministic, positioning all DMUs in a sample on a graph to depict their performances as points. This leads to the formation of an efficiency frontier, connecting points that constitute the upper boundary of a cluster of points. Units falling on this efficiency frontier are considered efficient, while those below it are deemed *inefficient* or *under-efficient*. The relative distance of each point from the frontier indicates its level of technical efficiency, which depends on the most efficient units in the sample.

DEA is a nonparametric method incorporating two main models: Constant Return to Scale (CRS) and Variable Return to Scale (VRS). The output-oriented DEA model concentrates on identifying and assessing changes in output, achieving enhanced efficiency by proportionally increasing outputs while maintaining constant input quantities. The CRS assumption is only valid for DMUs operating at an optimal scale. When DMUs operate at a different optimal level, the measurement of technical efficiency becomes intertwined with scale efficiency.

DEA is used to locate the DMUs responsible for these technical inefficiencies, and to identify the sources and amounts of inefficiency in each of its inputs and outputs (Banker *et al*., 1984).

Coelli *et al.* (2005) suggested that the difference between the technical efficiency ratios derived from DEA-CRS and DEA-VRS for the same firm serves as a reliable indicator of the firm's scale efficiency. To assess this, both DEA-CRS and DEA-VRS models should be applied to the same dataset. If a firm shows a difference in efficiency ratios between these two DEA models, it signals that the firm is operating at a suboptimal scale.

The gap between CRS technical inefficiency and VRS technical inefficiency can determine scale inefficiency. This method facilitates an investigation into the factors that influence the levels of efficiency or inefficiency.

Consider a set of DMUs indexed by $i = 1, 2, 3 \ldots, m$. Let x_{ij} denote the amount of input j used by DMU i and y_{ik} denote the amount of output k produced by DMU i.

For DEA-VRS, the efficiency score E_i for each DMU i can be derived by using the following linear programming problem.

Maximise: E_i

Subject to:

$$\sum_{j=1}^{n} \lambda_i x_{ij} < E_i x_{ik} \text{ (for all k inputs)} \quad (1)$$

$$\sum_{k=1}^{s}\mu_k y_{ik} \geq y_{ij} \text{ (for all j outputs)} \quad (2)$$

$$\sum \lambda_j = 1$$

E_i, λ_j, $\mu_k \geq 0$ (non – negativity constraints)

For DEA-CRS, the efficiency score E_i for each DMU i can be derived using the following linear programming problem:

Maximise: E_i

Subject to :

$$\sum_{j=1}^{n}\lambda_j x_{ij} \leq E_i x_{ik} \text{ (for all k inputs)} \quad (3)$$

$$\sum_{k=1}^{s}\mu_k y_{ik} \geq y_{ij} \text{ (for all j outputs)} \quad (4)$$

E_i, λ_j, $\mu_k \geq 0$ (non – negativity constraints)

Our study uses sales as output, raw material expense, salaries and wages, and investment in property, plant, and equipment as inputs.

To identify the inefficiency arising out of scale and the one occurring due to technical inefficiency, we calculate scale efficiency as

Scale Efficiency = CRS Efficiency/VRS Efficiency

3.1.2 Malmquist Productivity Index

While traditional DEA models are designed for a single period, scholars and professionals are significantly interested in tracking efficiency changes over time. In particular, observing a DMU at various time points can provide valuable insights into its efficiency evolution, which can be instrumental in forecasting potential financial difficulties.

Productivity change is driven by efficiency and technical changes in firms. We have employed the adjacent-period version of the Malmquist Productivity Index, as proposed by Färe *et al.* (1989), to measure firms' productivity. The Malmquist Productivity Index is defined by Färe *et al.* (1989) using the Shephard's distance function for period t and $t+1$ in terms of the following equation-

$$\text{MI}=\sqrt{\frac{D^t\left(x^{t+1},y^{t+1}\right)}{D^t\left(x^t,y^t\right)}*\frac{D^{t+1}\left(x^{t+1},y^{t+1}\right)}{D^{t+1}\left(x^t,y^t\right)}} \quad (5)$$

where, $D^t\left(x^t,y^t\right)=\min\left(\theta_j^k;\left(x_j^k,\theta^{-1}y_j^k\right)\in S^{kt}\right)$

The distance function represents the maximum proportion by which a firm's output in period t can be expanded while keeping the input constant. Similarly, $D_{t+1}\left(x_t,y_t\right)$ reflects the proportional expansion of the same firm's output relative to the technology set in period t+1.

The ratio of the distance function $\left[\frac{D^t\left(x^{t+1},y^{t+1}\right)}{D^t\left(x^t,y^t\right)}\right]$ (6) measures the change in the productivity of a DMU taking the base period as the benchmark for comparison.

The MI is calculated as the geometric mean of two distance function ratios. An MI greater than 1 indicates productivity growth, while an MI less than 1 signifies a decline in productivity. The MI is chosen for its ability to be decomposed into two distinct and exhaustive components: Technical Change (TC) and Efficiency Change (EC) (Färe *et al.* (1989)).

$$i.e.,\ MI = EC * TC \quad (7)$$

Malmquist Index= Technical Efficiency Change (catching up effect) * Technological Change (innovation effect)

where, $\text{TC}=\left[\frac{D^t\left(x^{t+1},y^{t+1}\right)}{D^{t+1}\left(x^{t+1},y^{t+1}\right)}*\frac{D^t\left(x^t,y^t\right)}{D^{t+1}\left(x^t,y^t\right)}\right]$ and

$$\text{EC}=\left[\frac{D^{t+1}\left(x^{t+1},y^{t+1}\right)}{D^t\left(x^t,y^t\right)}\right] \text{ and} \quad (8)$$

TC represents Technical Change, and a value greater than one indicates progress in technology practice, whereas a value less than one signals a technical regress. It signifies adopting best practices and measures the DMU's innovation effect. EC represents a firm's efficiency change and is known as the catching-up effect. It is characterised by the relative shift of a firm towards or away from the production possibility frontier and is hence also known as the frontier shift.

A firm's output level increases due to an increase in its efficiency level or technological advancement. The improvement in the efficiency level is either due to pure technical efficiency or due to the efficiency of scale.

Using the Färe *et al.* (1989) approach, we can thus have four efficiency indices for each DMU and a measure of technological progress over time. These indices are-

- Pure technical efficiency change (concurrent to VRS technology) {PT}

- Scale efficiency change {S}
- Technical efficiency change (relative to CRS technology) {E}
- Technological progress change {T}
- Total factor productivity (Malmquist index) {MI}

Färe *et al.* (1989) defined technical efficiency change as follows-

Technical efficiency Change = Pure Technical Efficiency Change* Scale Efficiency, $E = PT * S$ (9)

After incorporating the impact of technological advancement into the above equation, we get the Total Factor Productivity (known as the Malmquist Index) as:

Total Factor Productivity = Technical Efficiency Change * Technological Progress change,

$$MI = E * T \quad (10)$$

Or $$MI = PT * S * T \quad (11)$$

The calculation of various efficiency scores and the decomposition of the Malmquist Index into technical efficiency and technological change can be summarised as shown in Figure 2.

The blue box signifies the input required to obtain the output that has been shown in the white boxes. The software or mechanism used has been indicated below each step. The flowchart reflects the mechanism adopted to calculate the MI score and categorise the change in the efficiency scores of the companies into pure technological change and changes due to operational efficiency and scale efficiency. Using the input and output values of each firm the CRS and VRS are calculated with the help of Excel Solver. Also, the MI score of each company is calculated, through R software, using the same input and output values. The results obtained are then used to disintegrate the MI score into technological change, pure technical efficiency change and scale efficiency changes using the equations mentioned above.

Productivity experiences an increase when MI>1 and decreases when MI<1. The increase or decrease of technical efficiency is determined by whether E is more or less than one, respectively. Similarly, T is more or less than one, indicates technological advancements or setbacks. One can identify the main contributors to productivity changes by comparing E and T. If E exceeds T, efficiency improvements are the primary driver of productivity gains. On the other hand, if E is less than T, technological advancements are the primary source of productivity gains. Furthermore, if PT is more significant than S, the primary factor in efficiency change is an enhancement in pure technical efficiency. However, if PT is less than S, the main factor in efficiency change is scale improvement.

3.1.3 Data and Methodology

The data used in the present study is taken from the Insolvency and Bankruptcy Board of India (IBBI) website. The Law Tribunal that investigates the matters of the companies is the NCLT. The NCLT (under IBBI) approved the resolution plan for the financial restructuring of 677 companies up to March 31, 2023. Out of these, the listed manufacturing companies were 230. The dataset is complete for only 104 companies. Out of these, companies restructured till March 2020 have been considered to avoid distortion of efficiency parameters. This leaves us with 40 companies in the sample. The companies selected for the study are listed in Table 1.

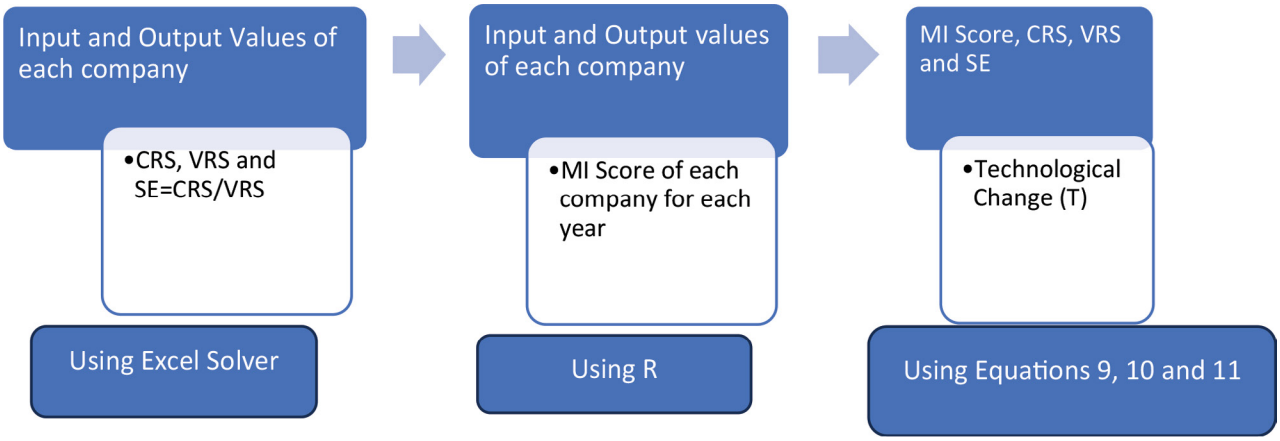


Figure 2. Flowchart for calculation.

The overall efficiency of the 40 firms in the sample was evaluated using firm-level data for three years following their resolution. The analysis employs an event-year window, rather than a calendar-year approach, to ensure consistent measurement of performance and the impact of the Insolvency and Bankruptcy Code. For example, a firm that initiated resolution in 2018 and resolved in 2019 would be matched with another firm that filed for resolution in 2020 and resolved in 2021, allowing for a comparative analysis of resolution outcomes. Consequently, performance is tracked on an event basis, such as one- and two years post-resolution.

The MI scores were calculated for the 40 DMUs in the sample three years after resolution; they were then decomposed into technical efficiency and technological change. The technical efficiency has been further decomposed into pure technical efficiency and scale efficiency.

The mathematical equations used for the above analysis have been discussed above (in section 3.1.2). The efficiency scores relating to pure technical efficiency (VRS), technical efficiency (CRS) and scale efficiency have been calculated in Excel. R software was used to calculate the Malmquist index using the Technical efficiency and scale efficiency.

4. Analysis of Results

Based on the calculation of efficiency scores obtained for the various firms over three years post-restructuring through NCLT, the average MI score has been 0.69 for all the decision-making units in the sample. Based upon this, there have been 20 DMUs with above-average performance compared to 20 DMUs whose performance has been below average, as given in Table 2.

Table 1. Companies restructured by NCLT from 2017 to 2020.

2017-18 [3 companies]	2018-19 [14 companies]	2019-20 [23 companies]
Sree Metaliks Ltd.	Raj Oil Mills Ltd.	Star Agro Marine Exports Pvt. Ltd.
Shirdi Industries Ltd.	Ved Cellulose Ltd.	Danalakshmi Paper Mills Pvt. Ltd.
Trinity Auto Components Ltd.	Tata Steel B S L Ltd. [Merged]	S P S Steels Rolling Mills Ltd.
	Ellora Paper Mills Ltd.	Calyx Chemicals and Pharmaceuticals Ltd.
	Paragon Steels Pvt. Ltd.	Maiyas Beverages and Foods Pvt. Ltd.
	Cosmic Ferro Alloys Ltd.	Tehri Iron and Steel Casting Ltd.
	Sun Paper Mill Ltd.	Allied Strips Ltd.
	Ultratech Nathdwara Cement Ltd.	Deccan Chronicle Holdings Ltd.
	G B Global Ltd.	Uttam Strips Ltd.
	Bansal Steel and Power Ltd.	Orchid Pharma Ltd.
	Amalgam Steel and Power Ltd.	Olive Lifesciences Pvt. Ltd.
	Bafna Pharmaceuticals Ltd.	Patanjali Foods Ltd.
	Swadisht Oils Pvt. Ltd.	M I C Electronics Ltd.
	Alok Industries Ltd.	Bhushan Power and Steel Ltd.
		Sunstar Overseas Ltd.
		Icomm Tele Ltd.
		New Phaltan Sugar Works Ltd.
		Shaifali Rolls Ltd.
		A R G L Ltd.
		Logic Eastern India Pvt. Ltd.
		Era T and D Ltd.
		Tantia Constructions Ltd.
		F M Hammerle Textiles Ltd.

Subsequently, the MI and efficiency scores (Appendix) were calculated for various firms, and a quadrant analysis was done to find out the relative impact of technical efficiency and technological change on the efficiency of the firms. A firm's total factor productivity or the MI is influenced by either the change in its technical efficiency or technological change, which brings along progress or regress in efficiency. Figure 3 shows the technological change and change in efficiency of the firms.

The x-axis shows the DMU's average technical efficiency change (E) three years after reorganisation. The y-axis represents the average pure technological change (T) three years after reorganisation. The dots represent the 40 DMUs. The first quadrant represents a significant technological change while a low technical efficiency change is present. We can see only two firms, *i.e.*, Star Agro Marine (Firm 18) and MIC Electronics Ltd. (Firm 30), in the quadrant, signifying that in these two firms, the level of technological progress was high as compared to the technical efficiency change in determining the total factor productivity of the firm; reflecting a higher impact of technological change as compared to the change in the efficiency of the firm.

Most DMUs lie in the second quadrant, reflecting low technical efficiency and technological change. This implies that post-reorganisation, these firms didn't make much technological progress and experienced low technical efficiency.

Few firms, in quadrant 3, experienced low technological progress and high technical efficiency. Their productivity growth is mainly due to efficiency changes rather than technological progress.

Out of all the 40 DMUs included in the study, only two firms, Ellora Paper Mills Ltd. (Firm 7) and Bhushan Power and Steel Ltd. (Firm 31), had high technological progress and technical efficiency post-reorganisation. The average MI of the two firms is also high (1 and 0.9981, respectively), signifying a positive effect on factor productivity.

Table 2. Malmquist index of companies.

Companies Above Average	Malmquist Index	Companies Below Average	Malmquist Index
Tata Steel B S L Ltd. [Merged]	1	Amalgam Steel and Power Ltd.	0.6544
Ellora Paper Mills Ltd.	1	M I C Electronics Ltd.	0.6296
Ultratech Nathdwara Cement Ltd.	1	Uttam Strips Ltd.	0.5883
S P S Steels Rolling Mills Ltd.	1	Raj Oil Mills Ltd.	0.5682
Tehri Iron and Steel Casting Ltd.	1	Other electronics	0.5632
Olive Lifesciences Pvt. Ltd.	1	Danalakshmi Paper Mills Pvt. Ltd.	0.5536
Patanjali Foods Ltd.	1	Icomm Tele Ltd.	0.5518
Logic Eastern India Pvt. Ltd.	1	Calyx Chemicals and Pharmaceuticals Ltd.	0.5351
Tantia Constructions Ltd.	1	G B Global Ltd.	0.5349
Bhushan Power and Steel Ltd.	0.9981	Orchid Pharma Ltd.	0.4847
Paragon Steels Pvt. Ltd.	0.9	Sun Paper Mill Ltd.	0.4766
Swadisht Oils Pvt. Ltd.	0.8591	Trinity Auto Components Ltd.	0.4730
Bansal Steel and Power Ltd.	0.8048	Allied Strips Ltd.	0.4723
Ved Cellulose Ltd.	0.7939	Shirdi Industries Ltd.	0.4672
Deccan Chronicle Holdings Ltd.	0.7722	Bafna Pharmaceuticals Ltd.	0.4315
Shaifali Rolls Ltd.	0.7581	Star Agro Marine Exports Pvt. Ltd.	0.4173
Alok Industries Ltd.	0.7518	Cosmic Ferro Alloys Ltd.	0.4097
Sree Metaliks Ltd.	0.7515	F M Hammerle Textiles Ltd.	0.2978
Era T and D Ltd.	0.7304	New Phaltan Sugar Works Ltd.	0.2867
Sunstar Overseas Ltd.	0.7007	Maiyas Beverages and Foods Pvt. Ltd.	0.2695

The firms' technical efficiency results from either pure technical efficiency or a change in scale. Figure 4 reflects the firm's technical efficiency change vis-a-vis pure technical efficiency and changes in the scale of operations.

On the x-axis is the average change in pure technical efficiency over three years post-reorganisation; on the y-axis is the change in the scale of operations during the same period.

Figure 4 reveals that the change in technical efficiency and the scale of operations could have been higher for most firms. Only two firms, *i.e.* Dhanalakshmi Paper Mills Pvt. Ltd. (Firm 19) and Era T and D Ltd. (Firm 38), have improved their scale of operations. However, on the other hand, the technical efficiency has been low, reflecting a below-average MI Score of 0.55. This implies that even a substantial positive change in the firm's scale of operations was insufficient to improve its productivity score. This means that the firm needs to be higher in terms of pure technical efficiency.

Out of the 40 firms, only 14 lie in quadrant 3, reflecting low efficiency in scale operations but a positive technical efficiency improvement. At the same time, no firm could

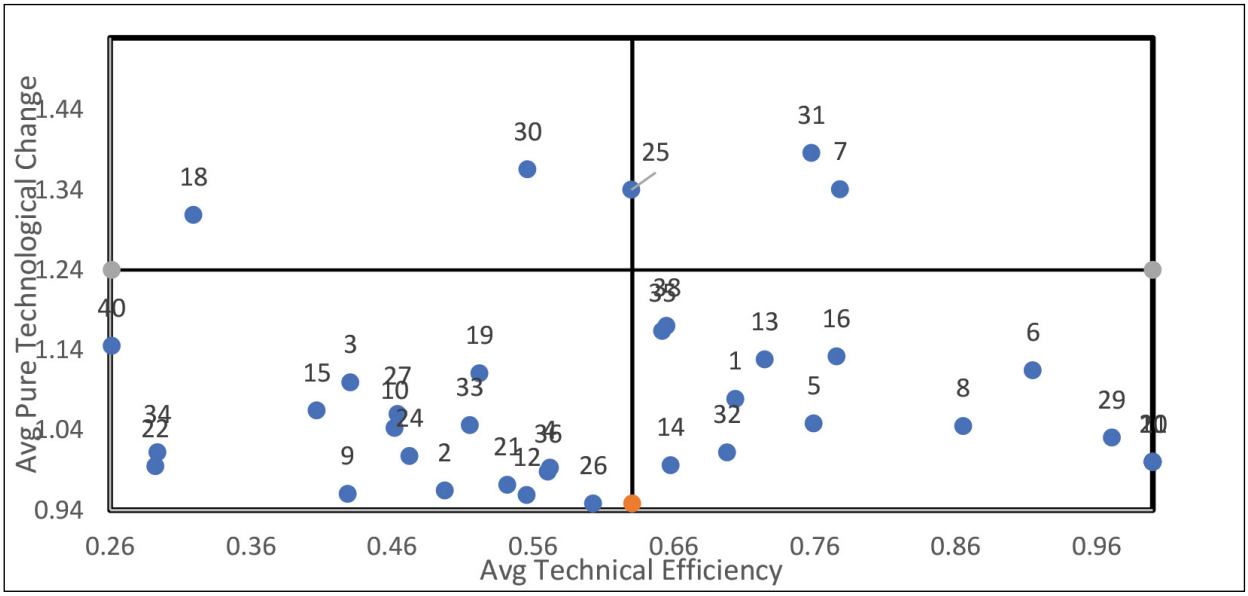


Figure 3. Pure technological change v/s technical efficiency change.

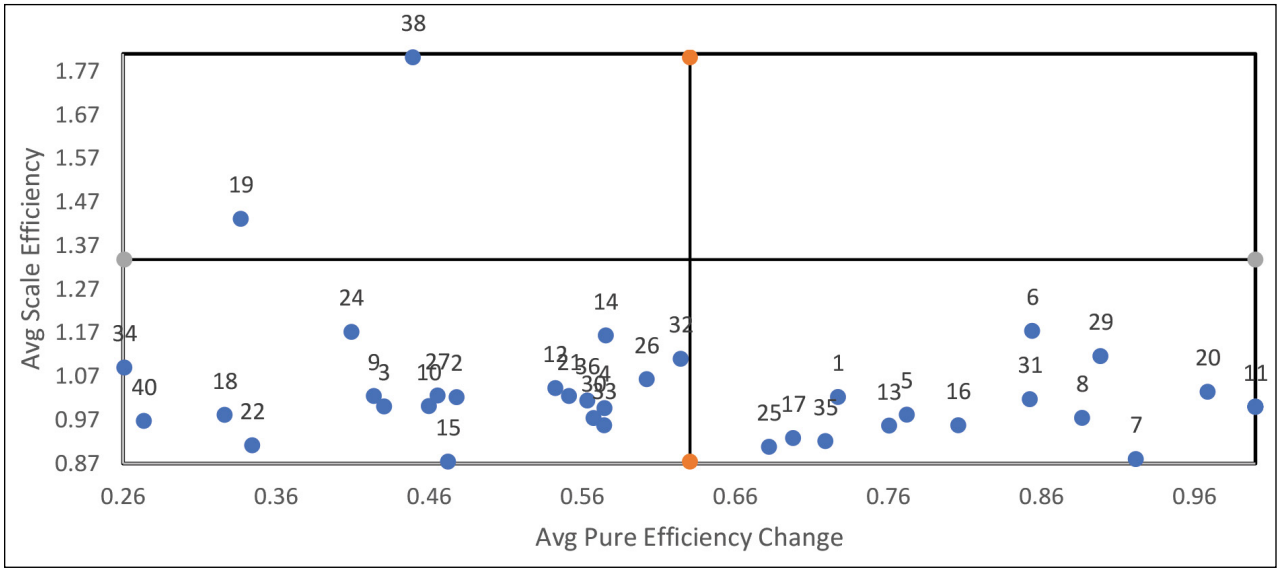


Figure 4. Scale efficiency v/s pure technical efficiency.

achieve high efficiency in terms of technical and scale operations. This could be because the firms could not improve their technical efficiency by increasing their scale of operations and achieving technical efficiency simultaneously. This could also be because firms need time to improve their scale of operations and technical efficiency. The capital-intensive nature of manufacturing organisations leads to a delay in achieving the optimum scale of operations. Also, the reorganisation process leads to a delay in achieving the optimum or desired levels of efficiency.

5. Conclusion

Evaluating performance is vital for businesses across all industries. It is not just about assessing their effectiveness and accomplishments but also about comparing themselves to their competitors. This benchmarking process allows them to understand where they stand in the market.

The firms facing financial distress look for ways to overcome it. Inefficiency on the financial front leads to inefficiency in the working and operations of the firm. Financial restructuring of firms is a change in the debt-equity component of the firm and is one of the measures that help firms overcome financial distress. The impact of economic restructuring on the firm's operational efficiency can identify the success of the process. This study applies the MI to evaluate the firms' productivity, using multiple inputs and producing multiple outputs over time.

The total factor productivity growth of the firms restructured through NCLT has been measured over three years post-reorganisation of the firm. Over time, the changes have been studied concerning technological change and changes in technical efficiency. Technical efficiency, also known as the catching-up effect, represents progress towards the production's efficient frontier. On the other hand, technological change, referred to as frontier shift, signifies innovation and investment. Considering the above findings, several valuable managerial insights and implications have been explored within the manufacturing sector.

The overall productivity of all the firms under study has shown a downward trend, as shown in Table 3. This can be attributed to the firm's technical efficiency, which has shown a similar downward trend three years after reorganisation. The technical efficiency change was 0.7361 in the first-year post-reorganisation and was further reduced to 0.6305 in the second year and to 0.5703 in the third year. The technical efficiency change can be decomposed into pure technical efficiency and change in the scale efficiency of the firm. While the pure technical efficiency has improved over the years, the scale efficiency has spiralled down. This reflects that as the firm comes out of the resolution process, there is an improvement in the utilisation of the scales of production. After that, the firms do not look for upgrades in the scale of the business, which, on the whole, leads to a marked decrease in the factor productivity of the firm, scaling down from 1.3224 to 0.8829 in three years.

The companies included in this study are those that experienced financial distress and underwent restructuring through the NCLT. Hence our results show that despite changes to their capital structure, restructured firms require time to return to their normal operational routines. The delayed positive returns from restructurings may indicate the initially high costs incurred, where these costs are temporarily offset by the organisation's ability to adjust to the required scale of change. However, these benefits are quickly outpaced due to the episodic nature of restructuring. The observed negative returns in most cases suggest that the indirect costs, such as disruptions to established routines and complementarities, may indeed exceed the advantages gained from organisational adjustments. The return lag could be attributed to the organisation's inability to sustain and return to regular operations during this transitional period. Additionally,

Table 3. Average values of various components post reorganisation.

Year(s) after reorganisation	Total factor Productivity (MI)	Technical Efficiency Change (E)	Technological Change (T)	Pure Technical Efficiency (PT)	Scale Efficiency (S)
One year	0.7206	0.7361	0.9751	0.5923	1.3224
Two years	0.6945	0.6305	1.1167	0.6982	0.909
Three years	0.6465	0.5703	1.1749	0.6487	0.8829

while technological innovation created new production opportunities, many firms were unable to capitalise on these advancements fully

This implies that firms need to work on achieving the optimum scale of production, which is a significant component in assessing the firm's overall factor productivity.

The technological change has been positive and has shown an upward trend, moving from 0.9751 to 1.1167 and 1.1749 over three years, reflecting the technological advancements embraced by the decision-making units.

5.1 Contribution of Research

This study introduces efficiency indices, including total factor productivity as well as technical and technological change indices. However, their use has been somewhat limited, as has the broader application of DEA models combined with the MI. The majority of research on non-parametric efficiency measures has focused on the financial sector, particularly on banks, insurance companies, non-banking financial institutions, and financial cooperative societies. In contrast, the application of these methods to non-financial firms remains relatively underexplored.

No recovery period in firms after the Tribunal's reorganisation has been examined. Monitoring efficiency measures across various industries was particularly insightful, as it traced the recovery and pinpointed factors that aided in enhancing the efficiency measures.

The study offers valuable insights into the factors driving changes in firm efficiency, enabling management to explore the underlying causes of operational performance variations. This understanding can help determine whether improvements in efficiency are necessary through technological advancements or adjustments to the firm's scale parameters. Additionally, policymakers can gain a clearer perspective on whether restructuring was a more effective decision than liquidation in the context of firm recovery.

5.2 Limitations of the Study

This study significantly enriches the existing knowledge on efficiency measures by employing a non-parametric approach. However, it is essential to note some limitations. The DEA methodology only quantifies relative efficiency and does not pinpoint the causes of inefficiency. As a result, we could only identify those units that exhibit inefficiency and require further scrutiny. The inefficiency index is solely relative to the most efficient frontier. Further studies are required to identify the factors that can improve the overall efficiency of the firms.

Additionally, the dataset utilised in this study is restricted to 40 companies, as only firms that have undergone restructuring through the NCLT were considered. The study aimed to evaluate the post-restructuring performance of these firms. However, the application of DEA in this analysis is limited by its focus on manufacturing companies.

5.3 Areas of Future Research

Future research could explore the factors contributing to variations in efficiency scores among firms, specifically considering differences in firm size and age groups. Additionally, as more companies undergo restructuring through the NCLT, the dataset can be expanded, potentially yielding more robust and comprehensive results.

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7. Appendix

Table A1. Malmquist index Score of 40 manufacturing firms 3 Years post-restructuring.

Company	Company Name	Industry group	MI(Year 1)	MI(Year 2)	MI(Year 3)
1	Sree Metaliks Ltd.	Sponge iron	0.744	0.810	0.702
2	Shirdi Industries Ltd.	Wood and wood products	0.606	0.418	0.378
3	Trinity Auto Components Ltd.	Castings and forgings	0.485	0.487	0.447
4	Raj Oil Mills Ltd.	Vegetable oils and products	0.544	0.606	0.555
5	Ved Cellulose Ltd.	Paper and newsprint	0.862	0.743	0.777
6	Tata Steel B S L Ltd. [Merged]	Steel	1.000	1.000	1.000
7	Ellora Paper Mills Ltd.	Paper and newsprint	1.000	1.000	1.000
8	Paragon Steels Pvt. Ltd.	Steel	0.957	0.743	1.000
9	Cosmic Ferro Alloys Ltd.	Diversified manufacturing	0.373	0.519	0.338
10	Sun Paper Mill Ltd.	Paper and newsprint	0.496	0.513	0.421
11	Ultratech Nathdwara Cement Ltd.	Cement	1.000	1.000	1.000

12	G B Global Ltd.	Diversified cotton textile	0.445	0.734	0.426
13	Bansal Steel and Power Ltd.	Steel	0.929	0.859	0.626
14	Amalgam Steel and Power Ltd.	Other ferrous metal products	0.783	0.710	0.471
15	Bafna Pharmaceuticals Ltd.	Drugs and pharmaceuticals	0.449	0.444	0.402
16	Swadisht Oils Pvt. Ltd.	Vegetable oils and products	1.000	0.866	0.711
17	Alok Industries Ltd.	Diversified cotton textile	0.581	0.822	0.853
18	Star Agro Marine Exports Pvt. Ltd.	Marine foods	0.421	0.396	0.435
19	Danalakshmi Paper Mills Pvt. Ltd.	Paper and newsprint	1.000	0.316	0.345
20	S P S Steels Rolling Mills Ltd.	Sponge iron	1.000	1.000	1.000
21	Calyx Chemicals and Pharmaceuticals Ltd.	Drugs and pharmaceuticals	0.325	0.697	0.584
22	Maiyas Beverages and Foods Pvt. Ltd.	Cocoa products and confectionery	0.272	0.278	0.259
23	Tehri Iron and Steel Casting Ltd.	Steel	1.000	1.000	1.000
24	Allied Strips Ltd.	Steel	0.535	0.503	0.379
25	Deccan Chronicle Holdings Ltd.	Media-print	1.000	0.850	0.467
26	Uttam Strips Ltd.	Steel	0.326	0.668	0.771
27	Orchid Pharma Ltd.	Drugs and pharmaceuticals	0.504	0.499	0.451
28	Olive Lifesciences Pvt. Ltd.	Other agricultural products	1.000	1.000	1.000
29	Patanjali Foods Ltd.	Vegetable oils and products	1.000	1.000	1.000
30	M I C Electronics Ltd.	Other electronics	1.000	0.562	0.327
31	Bhushan Power and Steel Ltd.	Steel	1.000	1.000	0.994
32	Sunstar Overseas Ltd.	Other agricultural products	0.950	0.686	0.466
33	Icomm Tele Ltd.	Other ferrous metal products	0.324	0.621	0.711
34	New Phaltan Sugar Works Ltd.	Sugar	0.402	0.196	0.263
35	Shaifali Rolls Ltd.	Castings and forgings	0.577	0.841	0.857
36	A R G L Ltd.	Agricultural machinery	0.544	0.575	0.570
37	Logic Eastern India Pvt. Ltd.	Communication equipment	1.000	1.000	1.000
38	Era T and D Ltd.	Other ferrous metal products	1.000	0.662	0.530
39	Tantia Constructions Ltd.	Infrastructural construction	1.000	1.000	1.000
40	F M Hammerle Textiles Ltd.	Cloth	0.392	0.156	0.346
Average Score			**0.7206**	**0.6944**	**0.721**

Table A2. Technical efficiency scores of companies using constant returns to scale.

Company	Company Name	TE(CRS)			Avg. Technical Efficiency
1	Sree Metaliks Ltd.	0.791	0.726	0.594	0.704
2	Shirdi Industries Ltd.	0.713	0.415	0.365	0.498
3	Trinity Auto Components Ltd.	0.436	0.455	0.401	0.431
4	Raj Oil Mills Ltd.	0.559	0.603	0.555	0.572
5	Ved Cellulose Ltd.	0.856	0.711	0.711	0.759
6	Tata Steel B S L Ltd. [Merged]	1.000	1.000	0.744	0.915
7	Ellora Paper Mills Ltd.	1.000	0.608	0.726	0.778

8	Paragon Steels Pvt. Ltd.	0.955	0.681	0.961	0.865
9	Cosmic Ferro Alloys Ltd.	0.443	0.517	0.326	0.429
10	Sun Paper Mill Ltd.	0.517	0.501	0.368	0.462
11	Ultratech Nathdwara Cement Ltd.	1.000	1.000	1.000	1.000
12	G B Global Ltd.	0.511	0.730	0.426	0.556
13	Bansal Steel and Power Ltd.	0.940	0.686	0.547	0.725
14	Amalgam Steel and Power Ltd.	0.795	0.709	0.470	0.658
15	Bafna Pharmaceuticals Ltd.	0.383	0.436	0.401	0.407
16	Swadisht Oils Pvt. Ltd.	1.000	0.629	0.697	0.776
17	Alok Industries Ltd.	0.645	0.464	0.444	0.517
18	Star Agro Marine Exports Pvt. Ltd.	0.332	0.312	0.313	0.319
19	Danalakshmi Paper Mills Pvt. Ltd.	1.000	0.274	0.292	0.522
20	S P S Steels Rolling Mills Ltd.	1.000	1.000	1.000	1.000
21	Calyx Chemicals and Pharmaceuticals Ltd.	0.385	0.690	0.551	0.542
22	Maiyas Beverages and Foods Pvt. Ltd.	0.401	0.276	0.199	0.292
23	Tehri Iron and Steel Casting Ltd.	1.000	1.000	1.000	1.000
24	Allied Strips Ltd.	0.565	0.494	0.359	0.472
25	Deccan Chronicle Holdings Ltd.	1.000	0.598	0.292	0.630
26	Uttam Strips Ltd.	0.425	0.667	0.717	0.603
27	Orchid Pharma Ltd.	0.553	0.449	0.390	0.464
28	Olive Lifesciences Pvt. Ltd.	1.000	1.000	1.000	1.000
29	Patanjali Foods Ltd.	1.000	0.941	0.972	0.971
30	M I C Electronics Ltd.	1.000	0.503	0.165	0.556
31	Bhushan Power and Steel Ltd.	1.000	0.694	0.579	0.758
32	Sunstar Overseas Ltd.	0.963	0.686	0.444	0.698
33	Icomm Tele Ltd.	0.394	0.527	0.625	0.515
34	New Phaltan Sugar Works Ltd.	0.456	0.184	0.241	0.294
35	Shaifali Rolls Ltd.	0.542	0.774	0.639	0.652
36	A R G L Ltd.	0.586	0.564	0.561	0.571
37	Logic Eastern India Pvt. Ltd.	1.000	1.000	1.000	1.000
38	Era T and D Ltd.	1.000	0.575	0.390	0.655
39	Tantia Constructions Ltd.	1.000	1.000	1.000	1.000
40	F M Hammerle Textiles Ltd.	0.301	0.138	0.344	0.261
Average Score 0.736			**0.630**	**0.570**	**0.646**

Table A3. Change in efficiency of companies due to pure technological change.

Company	Company Name	Pure Technological Change			Avg. Pure Technological Change
1	Sree Metaliks Ltd.	0.940	1.115	1.182	1.079
2	Shirdi Industries Ltd.	0.850	1.007	1.036	0.964
3	Trinity Auto Components Ltd.	1.113	1.071	1.114	1.099
4	Raj Oil Mills Ltd.	0.973	1.005	1.000	0.993

5	Ved Cellulose Ltd.	1.008	1.044	1.092	1.048
6	Tata Steel B S L Ltd. [Merged]	1.000	1.000	1.343	1.114
7	Ellora Paper Mills Ltd.	1.000	1.644	1.378	1.341
8	Paragon Steels Pvt. Ltd.	1.002	1.092	1.041	1.045
9	Cosmic Ferro Alloys Ltd.	0.841	1.004	1.036	0.960
10	Sun Paper Mill Ltd.	0.959	1.024	1.144	1.042
11	Ultratech Nathdwara Cement Ltd.	1.000	1.000	1.000	1.000
12	G B Global Ltd.	0.870	1.005	1.000	0.959
13	Bansal Steel and Power Ltd.	0.988	1.252	1.145	1.128
14	Amalgam Steel and Power Ltd.	0.985	1.002	1.001	0.996
15	Bafna Pharmaceuticals Ltd.	1.173	1.019	1.001	1.064
16	Swadisht Oils Pvt. Ltd.	1.000	1.377	1.019	1.132
17	Alok Industries Ltd.	0.902	1.771	1.923	1.532
18	Star Agro Marine Exports Pvt. Ltd.	1.269	1.268	1.389	1.309
19	Danalakshmi Paper Mills Pvt. Ltd.	1.000	1.152	1.180	1.111
20	S P S Steels Rolling Mills Ltd.	1.000	1.000	1.000	1.000
21	Calyx Chemicals and Pharmaceuticals Ltd.	0.845	1.009	1.060	0.971
22	Maiyas Beverages and Foods Pvt. Ltd.	0.677	1.005	1.301	0.995
23	Tehri Iron and Steel Casting Ltd.	1.000	1.000	1.000	1.000
24	Allied Strips Ltd.	0.947	1.018	1.058	1.007
25	Deccan Chronicle Holdings Ltd.	1.000	1.423	1.598	1.340
26	Uttam Strips Ltd.	0.767	1.002	1.076	0.948
27	Orchid Pharma Ltd.	0.912	1.112	1.156	1.060
28	Olive Lifesciences Pvt. Ltd.	1.000	1.000	1.000	1.000
29	Patanjali Foods Ltd.	1.000	1.063	1.028	1.031
30	M I C Electronics Ltd.	1.000	1.116	1.980	1.365
31	Bhushan Power and Steel Ltd.	1.000	1.441	1.717	1.386
32	Sunstar Overseas Ltd.	0.986	1.000	1.050	1.012
33	Icomm Tele Ltd.	0.823	1.178	1.136	1.046
34	New Phaltan Sugar Works Ltd.	0.880	1.065	1.091	1.012
35	Shaifali Rolls Ltd.	1.064	1.086	1.341	1.164
36	A R G L Ltd.	0.928	1.019	1.016	0.988
37	Logic Eastern India Pvt. Ltd.	1.000	1.000	1.000	1.000
38	Era T and D Ltd.	1.000	1.150	1.360	1.170
39	Tantia Constructions Ltd.	1.000	1.000	1.000	1.000
40	F M Hammerle Textiles Ltd.	1.303	1.129	1.003	1.145
Average Score		**0.975**	**1.117**	**1.175**	**1.089**

Table A4. Change in efficiency of companies due to pure efficiency change.

Company	Company Name	Pure efficiency Change (TE(VRS))			Avg. Pure Efficiency Change
1	Sree Metaliks Ltd.	0.541	0.848	0.792	0.727
2	Shirdi Industries Ltd.	0.551	0.485	0.398	0.478
3	Trinity Auto Components Ltd.	0.415	0.466	0.410	0.431
4	Raj Oil Mills Ltd.	0.534	0.603	0.587	0.575
5	Ved Cellulose Ltd.	0.841	0.723	0.753	0.772
6	Tata Steel B S L Ltd. [Merged]	0.562	1.000	1.000	0.854
7	Ellora Paper Mills Ltd.	0.766	1.000	1.000	0.922
8	Paragon Steels Pvt. Ltd.	0.949	0.712	1.000	0.887
9	Cosmic Ferro Alloys Ltd.	0.368	0.558	0.346	0.424
10	Sun Paper Mill Ltd.	0.492	0.506	0.381	0.460
11	Ultratech Nathdwara Cement Ltd.	1.000	1.000	1.000	1.000
12	G B Global Ltd.	0.404	0.731	0.493	0.543
13	Bansal Steel and Power Ltd.	0.760	0.882	0.640	0.761
14	Amalgam Steel and Power Ltd.	0.505	0.709	0.513	0.576
15	Bafna Pharmaceuticals Ltd.	0.383	0.500	0.534	0.472
16	Swadisht Oils Pvt. Ltd.	1.000	0.712	0.705	0.806
17	Alok Industries Ltd.	0.373	0.852	0.869	0.698
18	Star Agro Marine Exports Pvt. Ltd.	0.304	0.331	0.344	0.326
19	Danalakshmi Paper Mills Pvt. Ltd.	0.422	0.285	0.304	0.337
20	S P S Steels Rolling Mills Ltd.	0.907	1.000	1.000	0.969
21	Calyx Chemicals and Pharmaceuticals Ltd.	0.313	0.732	0.609	0.551
22	Maiyas Beverages and Foods Pvt. Ltd.	0.267	0.403	0.363	0.344
23	Tehri Iron and Steel Casting Ltd.	1.000	1.000	1.000	1.000
24	Allied Strips Ltd.	0.368	0.495	0.365	0.409
25	Deccan Chronicle Holdings Ltd.	0.699	0.859	0.489	0.682
26	Uttam Strips Ltd.	0.321	0.690	0.796	0.602
27	Orchid Pharma Ltd.	0.393	0.532	0.472	0.466
28	Olive Lifesciences Pvt. Ltd.	1.000	1.000	1.000	1.000
29	Patanjali Foods Ltd.	0.696	1.000	1.000	0.899
30	M I C Electronics Ltd.	1.000	0.534	0.169	0.567
31	Bhushan Power and Steel Ltd.	0.563	1.000	0.995	0.853
32	Sunstar Overseas Ltd.	0.682	0.746	0.446	0.624
33	Icomm Tele Ltd.	0.319	0.684	0.720	0.574
34	New Phaltan Sugar Works Ltd.	0.353	0.185	0.244	0.261
35	Shaifali Rolls Ltd.	0.524	0.828	0.805	0.719

36	A R G L Ltd.	0.541	0.569	0.580	0.563
37	Logic Eastern India Pvt. Ltd.	1.000	1.000	1.000	1.000
38	Era T and D Ltd.	0.277	0.628	0.444	0.449
39	Tantia Constructions Ltd.	1.000	1.000	1.000	1.000
40	F M Hammerle Textiles Ltd.	0.299	0.138	0.383	0.274
Average Score		**0.592**	**0.698**	**0.649**	**0.646**

Table A5. Efficiency changes due to change in scale of operations.

Company	Company Name	Scale Change			Avg. Scale Efficiency
1	Sree Metaliks Ltd.	1.461	0.856	0.749	1.022
2	Shirdi Industries Ltd.	1.295	0.855	0.917	1.022
3	Trinity Auto Components Ltd.	1.049	0.975	0.978	1.001
4	Raj Oil Mills Ltd.	1.047	1.000	0.945	0.997
5	Ved Cellulose Ltd.	1.018	0.983	0.944	0.982
6	Tata Steel B S L Ltd. [Merged]	1.778	1.000	0.744	1.174
7	Ellora Paper Mills Ltd.	1.306	0.608	0.726	0.880
8	Paragon Steels Pvt. Ltd.	1.007	0.956	0.961	0.975
9	Cosmic Ferro Alloys Ltd.	1.205	0.926	0.943	1.025
10	Sun Paper Mill Ltd.	1.050	0.990	0.965	1.002
11	Ultratech Nathdwara Cement Ltd.	1.000	1.000	1.000	1.000
12	G B Global Ltd.	1.266	0.999	0.864	1.043
13	Bansal Steel and Power Ltd.	1.237	0.778	0.855	0.957
14	Amalgam Steel and Power Ltd.	1.575	1.000	0.916	1.164
15	Bafna Pharmaceuticals Ltd.	1.000	0.872	0.751	0.874
16	Swadisht Oils Pvt. Ltd.	1.000	0.884	0.989	0.957
17	Alok Industries Ltd.	1.730	0.545	0.510	0.928
18	Star Agro Marine Exports Pvt. Ltd.	1.091	0.942	0.911	0.981
19	Danalakshmi Paper Mills Pvt. Ltd.	2.370	0.963	0.961	1.431
20	S P S Steels Rolling Mills Ltd.	1.103	1.000	1.000	1.034
21	Calyx Chemicals and Pharmaceuticals Ltd.	1.227	0.944	0.904	1.025
22	Maiyas Beverages and Foods Pvt. Ltd.	1.501	0.685	0.549	0.912
23	Tehri Iron and Steel Casting Ltd.	1.000	1.000	1.000	1.000
24	Allied Strips Ltd.	1.534	0.997	0.984	1.172
25	Deccan Chronicle Holdings Ltd.	1.432	0.695	0.598	0.908
26	Uttam Strips Ltd.	1.322	0.966	0.901	1.063
27	Orchid Pharma Ltd.	1.407	0.844	0.826	1.026
28	Olive Lifesciences Pvt. Ltd.	1.000	1.000	1.000	1.000
29	Patanjali Foods Ltd.	1.436	0.941	0.972	1.116
30	M I C Electronics Ltd.	1.000	0.943	0.979	0.974

31	Bhushan Power and Steel Ltd.	1.776	0.694	0.582	1.017
32	Sunstar Overseas Ltd.	1.414	0.920	0.997	1.110
33	Icomm Tele Ltd.	1.234	0.770	0.868	0.957
34	New Phaltan Sugar Works Ltd.	1.291	0.992	0.987	1.090
35	Shaifali Rolls Ltd.	1.035	0.934	0.794	0.921
36	A R G L Ltd.	1.084	0.992	0.967	1.014
37	Logic Eastern India Pvt. Ltd.	1.000	1.000	1.000	1.000
38	Era T and D Ltd.	3.611	0.917	0.878	1.802
39	Tantia Constructions Ltd.	1.000	1.000	1.000	1.000
40	F M Hammerle Textiles Ltd.	1.006	0.998	0.899	0.968
Average Score		**1.322**	**0.909**	**0.883**	**1.038**