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CSR CONTRIBUTIONS FOR ENVIRONMENTAL SUSTAINABILITY: A COMPARISON OF PRIVATE BANKS IN EMERGING MARKET

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Abstract: *Over the years corporate social responsibility (CSR) has become a source of competitive advantage for firms including banks. CSR is one of the important aspects of a private bank's contribution to society apart from its functionality. The extant literature shows a scantiness of research concerning the assessment of the efficiency of banks in CSR expenditure towards environmental sustainability. The current work fills the gap in the literature by providing a multi-objective assessment framework to measure and compare the leading private banks based on their efficiency in CSR vis-à-vis environmental sustainability. This paper aims to study the ideal and actual contribution of the Indian private banking sector toward environmental sustainability and other sectors. This is done by using data from 10 private sector banks over 7 financial years and comparing their efficiencies over time using optimization techniques like Data Envelopment Analysis. To study the change in CSR contribution over time, the Malmquist Index has been used. City Union and HDFC have shown the highest contribution towards environmental sustainability as a part of their CSR acts consistently over the years irrespective of the income generated. The outcome of the present paper shall enable the decision-makers to formulate of the appropriate policies.*

Key words: *CSR, Data Envelopment Analysis (DEA), Efficiency, Malmquist Index, Environmental sustainability, Banking.*

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1. Introduction

CSR is the spending of a business towards social welfare and environmental issues from the income generated. Being an emerging economy, India became the first nation to formally mandate corporate social responsibility in April 2014. Indian Companies Act contains section 135 which requires businesses with a certain level of sales and profit to devote a minimum of 2% of their mean revenue over the previous three years to CSR. The private banks of India also fall under this rule. On the humanitarian ground CSR stands as a direct reflection of the Key Performance Indicators (KPIs) of these private banks like profit, income or average net profit. CSR helps the business organizations including banks to earn reputations from the society (Ruiz & García, 2021) and has a positive impact on the efficiency (Belasri et al., 2020). CSR activities are intended to extend benefits to the major stakeholders like employees, customers, society or communities and environment. Subsequently, a mutually beneficial linkage gets created among the firms such as banks and the major stakeholders. As a result, the firms become able to enjoy the competitive advantage(Eyasu & Arefayne, 2020). From the perspective of the banks, Ben Abdallah et al.(2020)observed a bidirectional causal interrelationship between business stability and soundness and banks' CSR efforts toward sustainable development. Several studies have used the MCDM technique combined with other methods like TOPSIS (Technique for order of performance by similarity to ideal solution) and Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) for portfolio optimization and IPO ranking (Biswas & Joshi, 2023; Gupta et al., 2023). While other studies have implemented the three tools of Markowitz model, DEA and intuitionistic fuzzy set (IFS) for portfolio selection and a new combined Markowitz and the cross DEA model have been suggested.

Environmental sustainability has been a major issue in the 21st Century. We are struggling to improve the conditions of our planet so that we may assure our own survival (Dabic-Miletic & Simic, 2023). The companies are expected to contribute in more than sufficient amounts towards this cause. The sectors that CSR can be contributed towards are several like Education, Rural Development etc. Especially, after COVID-19 struck we expect more contributions towards the Health Care sector. Keeping in line with the social and environmental changes, businesses are expected to play a proactive role to support the activities pertaining to sustainable development (Aslaksen et al., 2021). Among the major stakeholders of the firms, environment is of central importance. Firms respond to the environmental concerns at organizational level (by interacting and collaborating with other firms) and at individual level (by addressing the needs of the society and people toward achieving sustainable development goals) (Pogutz, 2009). Environmental sustainability of the firms entails the practices and decisions pertaining to management of processes and resources, design of the products and services to protect the environment and maintain the ecosystem for generations to come (Cowan et al., 2010; Donald S., 2009; Pane Haden et al., 2009; Biswas et al., 2023a). Research conducted by Badi & Abdulshahed (2021) suggested a set of indicators to evaluate the sustainability of the iron and steel industry in Libya using a rough AHP model. A new study aims to analyze the performance evaluation relates to the supply chain of petrochemical companies using the network DEA and Malmquist index; subsequently testing their efficiencies over time (Bazargan et al., 2023). Quite reasonably decisions related to the environmental concern has become an important cornerstone of the overall CSR strategies of the corporate. The firms integrate environmental accountability and social responsibility in their business model to effectively formulate and execute CSR activities for achieving sustainable development goals (Shahzad et al., 2020; Williamson et al., 2006). Businesses need a structure they address the sustainability challenge in order to recognize both possibilities and dangers, develop, implement, and improve their sustainable development strategies to be more environmentally conscious (Baumgartner, 2014). Orlitzky et al. (2011) examined three theoretical perspectives on strategic corporate social responsibility. Strategic CSR is defined as voluntary CSR initiatives that improve a company's reputation and competitiveness. CSR promotes firms execute their operations in a way that makes them morally successful. We can state that effective CSR procedures can develop a socially sustainable organization. It is our responsibility to assess this aspect in India's private banking industry. An orientation of the business activities toward environmental sustainability and CSR practices helps the firms to win the competition, attract and retain motivated talents, gain the trust of the investors and customers, meet the regulatory and statutory requirements and build a strong connectivity with the community (De Roeck & Delobbe, 2012; Debnath et al., 2018; Jamali & Karam, 2018; Lyon & Maxwell, 2007; Nguyen et al., 2021; Pamucar & Biswas, 2023).

In this context, the present work aims to carry out a comparative study of CSR of the Indian private banking segment focusing on their contributions towards environmental sustainability. The study has been conducted on the top 10 private banks having the largest market capital during the period FY 2014-15 to FY 2020-21 i.e., from the year India has mandated CSR. The researchers intend to find answers to the following research questions.

RQ 1. How can an effective model be formulated to compare the CSR efficiencies of the banks?

RQ 2. To what extent do the private banks differ in their CSR efficiencies vis-à-vis environmental sustainability?

Since gauging the efficiency in CSR performance requires to consider a number of variables, its becomes a problem of multi-criteria decision making (MCDM) that posits the requirement to satisfy a number of criteria or constraints to figure out the best possible alternatives and/or optimize the constraints to arrive at a best possible solution (Sahoo & Goswami, 2023; Mzili et al., 2023; Chatterjee & Chakraborty, 2023). In the current work the model has been formulated using a widely used and robust operations research (OR) method such as DEA. DEA is a nonparametric method which can be defined as a mathematical programming model that, when applied to observable data, offers a mechanism to derive empirical estimations of relations like the frontier of production efficiency, which form the basis of contemporary economics. It is a method for measuring multiple inputs and outputs that compares the effectiveness of various decision-making units (Charnes et al., 1978). It was improved upon and another model to comprehend the Pure Technical Efficiency (PTE) and Scale Efficiency (SE) with respect to the efficient frontier was developed (Banker et al., 1984). The present work employs DEA to calculate the efficiencies of the private banks based on their yearly revenue and CSR expenditure. Further the Malmquist Productivity Index measure has been used to study the improvement or deterioration in CSR expenditure. DEA allows the analysts to compare the other DMUs with the most efficient ones in the group i.e., the benchmark; but lacks the ability to rank these benchmarks. Super Efficiency is a technique that allows us to rank these fully efficient DMUs (Andersen & Petersen, 1993). The Malmquist Productivity Index is a bilateral measure based on the concept of production function(Färe et al., 1998). This allows to compare the technologies of two economies (Caves et al., 1982).

The motivation of the current work stems from the findings of literature review which shows that there is a scantiness of past studies conducted to compare the banks on the basis of their CSR vis-à-vis environmental sustainability .There have been past study comparing the performance of private and public sector banks in India on a five-year time horizon using a Multi-Criteria Decision Making (MCDM) technique where Entropy is used for weight selection (Laha & Biswas, 2019). With respect to the concerns for sustainability there is a study conducted by Hafsal et al. (2020) which attempted to examine the effect of the non-performing assets (NPA) on overall banking efficiency. The authors utilized a two-stage DEA model. However, Hafsal et al. (2020) did not specifically consider environmental sustainability in connection with sustainability to compare the banks. Ecer & Pamucar (2022) felt the indubitable importance of contributions of the banks toward sustainable development for sectoral as well as economic growth of the nation. The researchers had compared the banks with a newly developed Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) and Dombi Bonferroni (DOBI) framework while considering various attributes of triple bottom line. The researchers have noted electricity consumption as one of the major drivers for attaining sustainability for banking sector. Concerning the banking sector this kind of study is quite rare. However, Ecer & Pamucar (2022) did not consider environmental sustainability in conjunction with CSR to assess the efficiency of the banks. Our work therefore extends this study. Thus, it may be surmised that apparently no study exists on comparing the CSR contribution of the private Indian banks with respect to environmental conservation which is of paramount importance in today's time where environmental degradation and sustainability are subjects of utter eminence. DEA has been widely used in comparing bank performance(Antunes et al., 2022; Mahmoudabadi & Emrouznejad, 2019; Moutinho et al., 2021; Wang et al., 2019). But it is seen that the application of DEA in evaluating CSR efficiency towards environmental sustainability is apparently limited.

The major contributions of the present work are as follows. First, the current work provides a robust framework for measuring CSR efficiency vis-à-vis environmental sustainability for private banks in the emerging economy like India. Second, a DEA framework with Malmquist Productivity Index is utilized to make comparison of the increase or decrease of CSR performance of given banks over time.

The rest of the ongoing paper is structured as follows. In section 2 some of the recent applications of DEA in assessing banking performance and related areas have been discussed. Section 3 explains the methodology while in section 4 key findings are highlighted. Section 5 presents a brief discussion on the implications of the work. Section 6 provides the concluding remarks and showcases some of the future scopes for further research.

2. Related work

A plethora of work has used DEA for evaluating banking performance and addressing related issues. In fact, the use of DEA in banking sector is age old. The study by Sherman & Gold (1985) uses the DEA method to compare the efficiency of efficient and inefficient bank branches. They came to an agreement that DEA is a useful supplement to other techniques measuring banking efficiency after taking into account the services rendered as outputs and the resources utilized to deliver these services as inputs. From 1986 to 1991, in the beginning of the present phase of liberalization, the organizational effectiveness of 70 Indian commercial banks was evaluated using DEA. The fluctuation in the predicted efficiency ratings was then explained using a parametric strategy known as stochastic frontier analysis. Private sector banks and foreign banks operating in India were determined to be less effective than public sector banks. They discovered that the performance of foreign banks had been improving over time, the performance of private Indian banks had just been stagnant whereas, the performance of Indian public banks had been declining with time (Bhattacharyya et al., 1997). DEA has been used before to study 27 Indian Public Sector Banks for the year of 2004-05, a single financial year. The findings suggest an 88.5% overall technical efficiency with 7 banks identified to be the benchmarks (S. Kumar & Gulati, 2008). Inefficient scale rather than purely technical factors is the main reason why private banks have fared better than public sector banks in our country, as previously mentioned (N. Kumar & Singh, 2015).

In this section a brief summary of some of the recently published work on applications of DEA in banking sector is highlighted.

For example, Lee et al. (2017) conducted a study on Korean banks. The study discovered that the performance gap between special banks and smaller lenders is statistically significant. The authors of this research recommend using the MSBM model rather than the Banker, Charles, and Cooper (BCC) model since the MSBM model can cope with negative data. Work on measuring CSR using fuzzy network process was performed by Debnath et al.(2018a) . Deverakonda & Munipalle (2019) examined the contrast in performance of foreign banks and domestic counterparts in India. The underlying intention of the researchers was to figure out the effect of entry of the foreign banks on domestic banking sector. The study utilized DEA as tool. The authors observed that the entry of foreign banks had intensified the competition but domestic banks showed better performance over the study period 2005 to 2013. Mahmoudabadi & Emrouznejad (2019) followed three aspects such as production, intermediation and social welfare to carry out a multistage comparison of the branches of a commercial bank in Iran. The authors applied a network slacks-based measure (SBM) DEA method. The study of Wang et al. (2019) also used SBM based DEA method to carry out a comparative analysis of bank performance on a global platform. The study considered asset, liability and capitalization as inputs and revenue as the output. Owusu Kwateng et al.(2019) diversified the strand of literature by using bootstrap analysis-based DEA method along with machine learning models to discern the effect of internet used banking on banking performance in Ghana. Nandy & Singh, (2020) inspected farm efficiency using Machine Learning and DEA to predict the impact of environmental factor on the farms' output level.

Jomthanachai et al. (2021) used DEA with ML algorithms to examine the risk management that included cross-efficiency DEA with ANN to forecast the risk level. Moutinho et al. (2021) investigated the relationship of the bank performance with the intellectual capital efficiency. The authors used DEA for performance-based ranking of the banks. Using fractional regression approach the study demonstrated a positive effect of performance on intellectual capital efficiency. Cvetkoska & Fotova Čiković (2021) applied an output-oriented BCC DEA model to compare a set of Macedonian and Croatian banks on the basis of their expenses (as inputs) and revenues (as outputs). Maradin et al. (2021) set the context of their study as Islamic banking. The authors utilized Malmquist total factor productivity index with DEA to compare the operational performance of the banks. The study of Lartey et al. (2021) put forth a three staged network DEA model to assess efficiency of the banks given the risk exposure and financial performance. (Li et al., 2021) considered deposits as flexible measure to compare the Chinese banks over a period of 2014-2018 using a two-stage DEA approach.

Antunes et al. (2022) conducted a longitudinal study on banking performance in China. The study was designed in two stages wherein the efficiencies of the banks were derived at the first stage using DEA approach and the second stage applied neural network-based model to delve into the interrelationship of bank specific measures with efficiency. The study revealed a consistent improvement in the efficiency, varying level of volatility across the various categories of banks such as foreign, state-owned and rural commercial and a different impact on efficiency for the traditional and non-traditional banks. Omrani et al. (2023) proposed a mixed-integer network DEA framework to compare the relative efficiencies of banks on the dimensions like profit, productivity, internet banking and overall performance. Bayiley (2022) took help of DEA-based Malmquist productivity index and GMM dynamic models to assess total factor productivity of Ethiopian banks and carried out a classification into three categories such as regressive, stable, and progressive. The researcher considered constant returns to scale for the variables related to income and expense. Corporate governance and bank productivity were examined using a two-phase model that combined DEA and random forest regression (Thaker et al., 2022). Current research presented by Biswas et al. (2023) used multi-criteria decision making (MCDM) framework to compare BRICS (developing nations) and G7 countries (developed nations) on the basis of their energy efficiency vis-à-vis ES. Same methodology was used by Puška et al. (2023) to establish the level of economic freedom in the Balkan countries where again Entropy technique assigned the designated weights.

2.1. Research gap and novelty of the study

It is apparent that no such study exists on comparing the CSR contribution of the private Indian banks with respect to environmental conservation which is of paramount importance in today's time where environmental degradation and sustainability are subjects of utter eminence. The novelty of this research lies in adoption of the DEA approach to assess effectiveness in the Indian private banking sector, considering CSR as a major parameter. Businesses are becoming more aware of concerns related to society and the environment. A company executes a CSR plan in order to lessen harm, engage in moral business customs, be accountable along an international supply chain, engage in philanthropy, and create a self-directed method for managing its staff. Hence, we have tried to incorporate the aspect of environmental sustainability into this research by considering it as an independent output variable to increase the social impact of the study. The goal of business sustainability is to maximize the long-term benefits to the economy, society, and the environment; which is imperative to business management. Sustainable development attempts to leave systems with the capacity to endure. A sustainable company strategy has three components: social, economic, and environmental. In the twenty-first century, environmental sustainability is the most imperative among these. Businesses that damage environmental systems deny future generation's access to the same environmental value, which makes them unsustainable.

3. Materials and methods

In this section a description of the research methodology is provided. This study takes into account 10 Indian private sector banks as the DMUs for the Data Envelopment Analysis. These 10 banks are selected based on their large market capital. The input variable for this study is yearly income of banks and two output variables are CSR expenditure in the sector of Environmental Sustainability and CSR expenditure in all other sectors combined. The data has been collected for the time period of the financial years commencing from 2014-15 to 2020-21. The CSR data has been collected from the site (csr.gov.in), which is a public site hosted by the govt. of

India. The income data has been taken from the publicly available data at moneycontol.com. The variables have been scaled using mean normalization before any methodologies were applied. The 10 banks used for the study are as given below in Table 1:

Table 1. List of banks

S/L	Name of the Bank	S/L	Name of the Bank
A1	HDFC Bank	A6	IDBI Bank
A2	ICICI Bank	A7	Yes Bank
A3	Kotak Mahindra Bank	A8	Federal Bank
A4	Axis Bank	A9	City Union Bank
A5	IndusInd Bank	A10	Karur Vyasa Bank

The primary investigative method of this study involves Envelopment Analysis. Initially we have fitted both input and output-oriented CRS and VRS models to the given data year wise. In many time periods we observe more than one bank give an efficiency score of 1; in order to break this ambiguity and conclude which is the best among them we have employed the super- efficiency technique. One important aspect to note here is though we have obtained results for all the models possible, however, our interpretations are based on Input oriented approach because the sole focus is how much more the firms have contributed towards protection of environment through CSR for a minimum level of earning. Also, as our data is comprised of 7 years (2014 to 2021) we have used the Malmquist Productivity Index to provide a comparative analysis over years with respect to its output generation. MPI helps us to inspect which banks have increased its productivity in terms of CSR and sustainability with time.

3.1. Data Envelopment Analysis (DEA): Concept of Efficiency

Efficiency tells how well a firm utilizes its input resources for production. Technical effectiveness and resource allocation effectiveness can be separated out of this. DEA helps us to measure these by building an Efficient Production Frontier using available Decision-Making Units (DMUs) keeping the input(s) in x-axis and output(s) in y-axis. All units operating on the frontier cannot increase production without adding more inputs or decrease use of inputs without reducing production.

3.1.1. CCR Model (Constant Return to Scale)

The efficiency of each DMU is determined under this model as the greatest ratio of the sum of all weighted outputs to the sum of all weighted inputs. When an increase in input leads to an equi-proportional increase in output it is known as constant return to scale. Under this model efficiency is defined as follows:

$$Efficiency = \frac{Sum\ of\ \ weighted\ outputs}{Sum\ of\ \ weighted\ inputs} \tag{1}$$

The weights in the ratio are calculated under the restriction that equivalent ratios for all DMUs must be less than or equal to one when numerous inputs and outputs are reduced to a single effective input and a single effective output without the pre-assigned weights. As a result, the weights of the effective input-output ratio depend on the efficiency score. We can resolve the linear programming model below to calculate the relative efficiency score of a particular DMUA if there are n DMUs, each with m sources and s outcomes.

$$\max\left(\theta = \frac{\sum_{j=1}^{s} u_j y_{jr}}{\sum_{i=1}^{m} v_i x_{ir}}\right) \tag{2}$$

Subject to

$$\frac{\sum_{j=1}^{s} u_j y_{jr}}{\sum_{i=1}^{m} v_i x_{ir}} \leq 1;\ r = 1, 2 \ldots n$$

Where,

$$u_j \geq 0;\ j = 1, 2 \ldots s;\ v_i \geq 0;\ i = 1, 2 \ldots m$$

x_{ir} is the quantity of i^{th} input utilized by the r^{th} decision making units (DMU); non-negative

y_{jr} is the quantity of j^{th} output produced by the r^{th} DMU; non-negative

v_i is the weight imposed on i^{th} input

u_j is the weight imposed on j^{th} output

The above stated LP model, (1) is an input-oriented DEA model, meaning it seeks to maximize the proportional reduction in inputs while maintaining the same level of outputs. Similarly, there exists an output-oriented model that seeks to maximize the proportional increase in outputs while using the same level of inputs. The following LP model describes the output-oriented CRS DEA model:

$$\min\left(\theta = \frac{\sum_{i=1}^{m} v_i x_{ir}}{\sum_{j=1}^{s} u_j y_{jr}}\right) \tag{3}$$

Subject to

$$\frac{\sum_{i=1}^{m} v_i x_{ir}}{\sum_{j=1}^{s} u_j y_{jr}} \geq 1;\ r = 1, 2 \ldots n$$

Where,

$$u_j \geq 0;\ j = 1, 2 \ldots s;\ v_i \geq 0;\ i = 1, 2 \ldots m$$

3.1.2. BCC Model (Variable Return to Scale)

This model was developed to comprehend the pure technical efficiency (PTE) as well as the scale efficiency (SE) with respect to the efficient frontier. PTE is the measure of how far a DMU is from operating at the efficient frontier. SE is the measure of how much a can firm reduce its use of inputs if it operates at CRS. If a DMU is functioning at diminishing, increasing, or constant returns to scale, the BCC model can detect. The absence of a proportional increase (or drop) in output with an increase (or decrease) in input is known as a variable return to scale. The input-focused BCC model has the following form:

$$\begin{aligned}
&\max \sum_{j=1}^{s} \mu_j y_{ir} + \mu_0 \\
&S.T \\
&\sum_{j=1}^{s} \mu_j y_{ir} - \sum_{i=1}^{m} v_i x_{ir} + \mu_0 \leq 0 \\
&\sum_{i=1}^{m} v_i x_{ir} = 1
\end{aligned} \tag{4}$$

Where, $\mu_j \geq 0;\ j = 1, 2 \ldots s;\ v_i \geq 0;\ i = 1, 2 \ldots m;\ \mu_0 \in \mathbb{R}, \mu_0\ is\ \ free$

The output-oriented BCC model is described by the linear programming model given below:

$$\begin{aligned}
&\max \sum_{j=1}^{s} v_j x_{ir} + v_0 \\
&S.T \\
&\sum_{j=1}^{s} \mu_j y_{ir} - \sum_{i=1}^{m} v_i x_{ir} + v_0 \leq 0 \\
&\sum_{j=1}^{s} \mu_j y_{ir} = 1
\end{aligned} \tag{5}$$

Where, $\mu_j \geq 0;\ j = 1, 2 \ldots s;\ v_i \geq 0;\ i = 1, 2 \ldots m;\ v_0 \in \mathbb{R}, v_0\ is\ \ free$

We must note that in the BCC model, $\mu_j = tu_j;\ v_i = tv_i;\ t = \left(\sum_{i=1}^{m} v_i x_{ir} \right)^{-1}$

From the above LP models (1), (2), (3) & (4) we can conclude all efficiency scores are between 0 and 1. Where a score of 1 indicates 100% efficiency of a DMU and a score below 1 indicating relative inefficiency (which increases the more it is closer to 0).

Most of the DMUs with Efficiency 1 are chosen as the benchmark for comparison. While DMUs that are both on the CRS and VRS frontier are operating at optimal scale and have no scale or non-scale inefficiency.

3.2. Super Efficiency (Ranking the Benchmarks)

Since the scores of all efficient units are 1, we are unable to differentiate and compare between highly efficient DMUs. This problem is solved by using the method of super efficiency. This method allows a fully efficient DMU, A to achieve an efficiency score more than 1 by removing the A-th constraint from the model. The input-oriented CRS super efficiency model is given below:

$$\max \sum_{j=1}^{s} u_j y_{jA}$$

Subject to

$$\sum_{i=1}^{m} v_i x_{ir} - \sum_{j=1}^{s} \mu_j y_{jr} \geq 0;\ r = 1, 2 \ldots n;\ r \neq A \tag{6}$$

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

Where, $u_j \geq 0;\ j = 1, 2 \ldots s;\ v_i \geq 0;\ i = 1, 2 \ldots m$

Unfortunately, the VRS model of Super efficiency poses a problem of infeasibility in certain cases. This is due to the creation of a new efficiency frontier excluding the DMU A being evaluated. If the DMU A has extremely small (or large) input (or output) then it is unable to project on the efficiency surface no matter its increase (or decrease) in input (or output), hence the efficiency score becomes infeasible.

3.3. Malmquist Productivity Index (MPI) (Comparing the efficiencies across time)

Originally it was built for comparing 2 economies based on the ideas of Professor Sten Malmquist. It is used to measure change in productivity over 2 different time periods for DMUs (Färe et al., 1998). The contemporaneous MPI considers both "Frontier Shift" effect i.e., Technological Change (TC) as well as "Catching Up" effect i.e., Technical Efficiency Change (TEC) based on the benchmark(s) of the contemporary time and assumes that all DMUs operate under the same and unaltered technology in each time period. The TC captures the change in technology over time (i.e., how much more or less is produced for the same input) compared to the best practice technology. Technological change helps us to capture if the production frontier is moving outwards with time. The TEC captures how far the observed productivity is from maximum possible productivity or whether the firms are getting closer to the production frontier over time.

The following formula gives us the MPI:

$$MPI = TEC \times TC \tag{7}$$

$$TEC = SEC \times PTEC \tag{8}$$

This decomposition of Technical Efficiency change is possible only under VRS. SEC denotes scale efficiency change and PTEC denotes the pure technical efficiency change. SEC measures how closer a particular DMU gets towards the efficient frontier under the assumption of CRS under the ideal condition. PTEC is comparison of efficiencies under VRS assumption over two consecutive time periods given the same DMU. Any empirical estimation of this decomposition of the Malmquist productivity change index should be treated with caution, since it mixes VRS and CRS efficiencies in the estimation of its components.

4. Results

In this section a summary of the key findings is presented. DEA has been applied to all units for each financial year, under VRS with both input and output orientation. Both orientations have been applied to check which units can reduce income yet maintain CSR outputs as well as which units can increase their CSR outputs at the current income levels. Hence, we obtain 7 DEA plots (Figure1-7) and two 10×7 efficiency matrices for input and output of the 10 DMUs over 7 years as given in Tables 2 and 3. The X-axis represents the input variable (Income) and the Y-axis represents the output. The red dotted line on each graph indicates the CRS and the black plot shows the VRS.

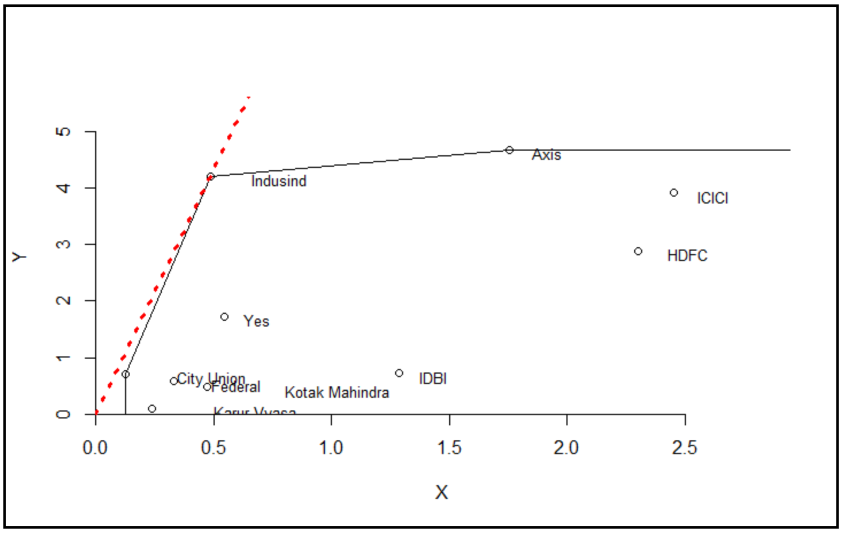

Figure 1. DEA plot of financial year 2014-15

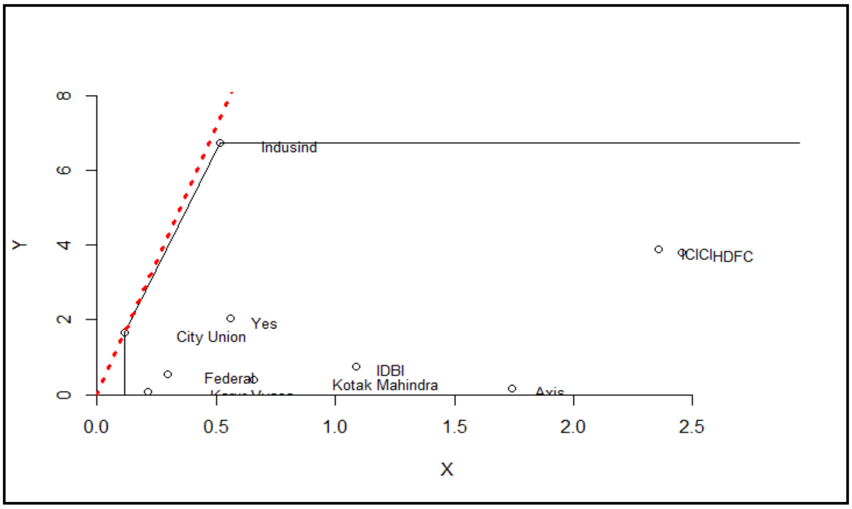

Figure 2. DEA plot of financial year 2015-16

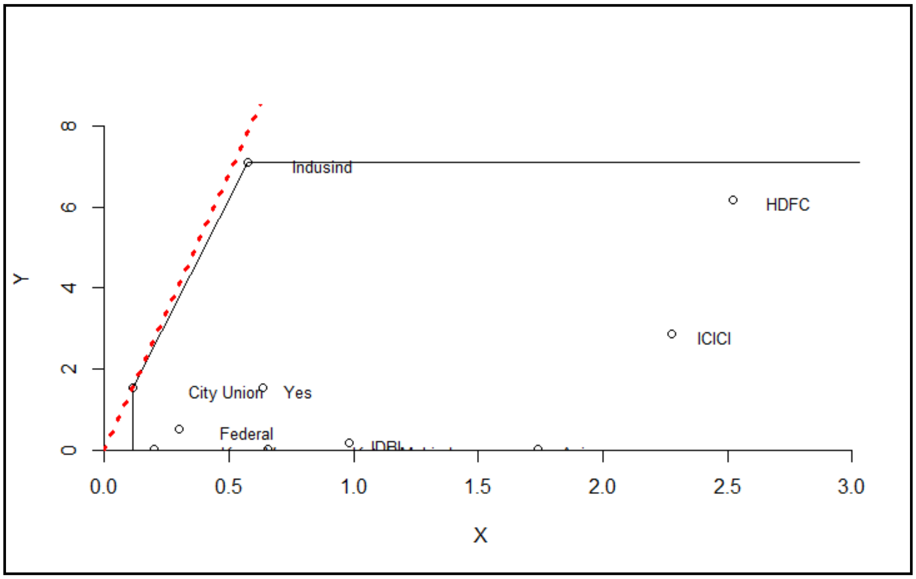

Figure 3. DEA plot of financial year 2016-17

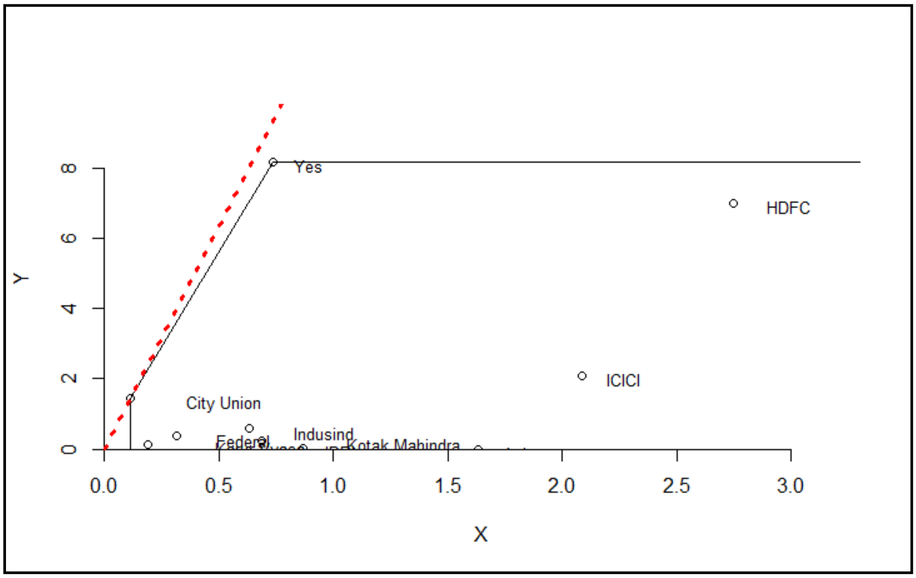

Figure 4. DEA plot of financial year 2017-18

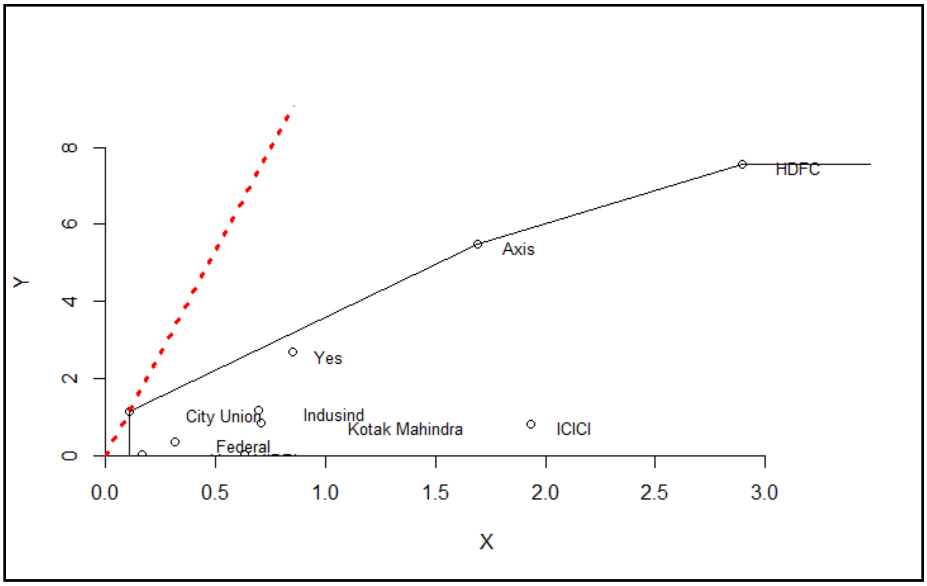

Figure 5. DEA plot of financial year 2018-19

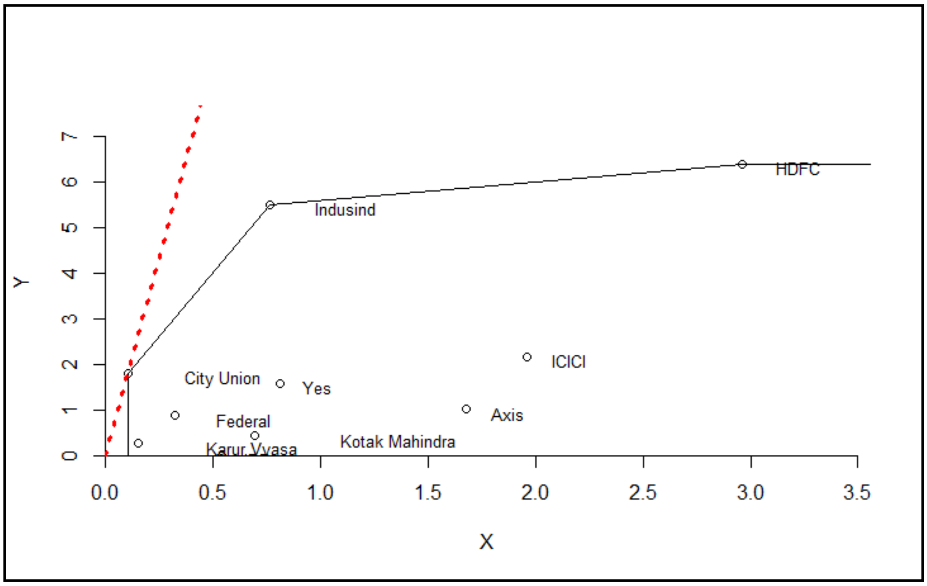

Figure 6. DEA plot of financial year 2019-20

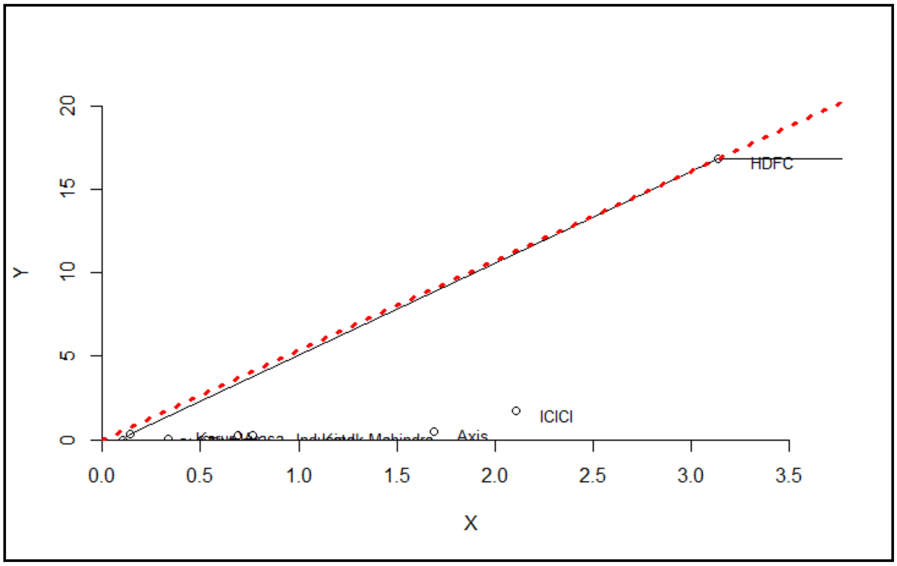

Figure 7. DEA plot of financial year 2020-21

The following two tables (Table 2 and 3) give the input-oriented and output-oriented efficiency scores of the ten selected banks over the seven financial years of our study period.

Table 2. Input-oriented Efficiency Scores

	Period						
DMU	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21
A1	0.6787	0.8853	1.0000	1.0000	1.0000	1.0000	1.0000
A2	1.0000	1.0000	0.5637	0.4328	0.2062	0.3410	0.3876
A3	0.4387	0.3327	0.1727	0.2615	0.2925	0.3735	0.2995
A4	1.0000	0.0842	0.0650	0.0693	1.0000	0.0647	0.1874
A5	1.0000	1.0000	1.0000	0.3103	0.4089	1.0000	0.2927
A6	0.1528	0.1503	0.1152	0.1310	0.1688	0.1917	0.1971
A7	0.8676	1.0000	0.6202	1.0000	0.8180	0.3117	0.2070
A8	0.8867	0.7785	0.7195	0.5910	0.6463	0.8018	0.3793
A9	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
A10	0.5192	0.5454	0.5711	0.5962	0.6316	0.6786	1.0000

Table 3. Output-oriented Efficiency Scores

	Period						
DMU	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21
A1	0.8598	0.9560	1.0000	1.0000	1.0000	1.0000	1.0000
A2	1.0000	1.0000	0.5466	0.4087	0.1663	0.3659	0.3566
A3	0.2792	0.2498	0.0198	0.1571	0.3165	0.3072	0.1795
A4	1.0000	0.0530	0.0042	0.0000	1.0000	0.1994	0.1353
A5	1.0000	1.0000	1.0000	0.2118	0.4546	1.0000	0.1842
A6	0.1654	0.1440	0.0260	0.0107	0.0031	0.0000	0.0001
A7	0.8554	1.0000	0.5745	1.0000	0.8664	0.3345	0.0001
A8	0.8303	0.6864	0.6081	0.4396	0.5007	0.7510	0.1120
A9	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
A10	0.0703	0.1532	0.0491	0.2225	0.0469	0.1405	1.0000

Since multiple efficient banks were found for all 7 years, Super Efficiency Ranking technique was applied and another 2 super efficiency matrices were obtained as given in Table 4 and 5 below.

Table 4. Input-oriented Super Efficiency Scores

	Period						
DMU	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21
A1	0.6787	0.8853	Inf	Inf	Inf	Inf	Inf
A2	Inf	Inf	0.5637	0.4328	0.2062	0.3410	0.3876
A3	0.4387	0.3327	0.1727	0.2615	0.2925	0.3735	0.2995
A4	Inf	0.0842	0.0650	0.0693	Inf	0.0647	0.1874
A5	Inf	Inf	Inf	0.3103	0.4089	Inf	0.2927
A6	0.1528	0.1503	0.1152	0.1310	0.1688	0.1917	0.1971
A7	0.8676	1.4351	0.6202	Inf	0.8180	0.3117	0.2070
A8	0.8867	0.7785	0.7195	0.5910	0.6463	0.8018	0.3793
A9	2.2264	2.4909	2.5587	2.4634	4.5203	3.4957	1.3703
A10	0.5192	0.5454	0.5711	0.5962	0.6316	0.6786	1.5598

Table 5. Output-oriented Super Efficiency Scores

	Period						
DMU	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21
A1	0.8598	0.9560	2.0800	3.2776	9.1725	4.8166	30.6681
A2	1.0331	1.1197	0.5466	0.4087	0.1663	0.3659	0.3566
A3	0.2792	0.2498	0.0198	0.1571	0.3165	0.3072	0.1795
A4	1.3942	0.0530	0.0042	0.0000	2.4783	0.1994	0.1353
A5	3.9040	4.2192	4.7528	0.2118	0.4546	2.7676	0.1842
A6	0.1654	0.1440	0.0260	0.0107	0.0031	0.0000	0.0001
A7	0.8554	1.4976	0.5745	5.8866	0.8664	0.3345	0.0001
A8	0.8303	0.6864	0.6081	0.4396	0.5007	0.7510	0.1120
A9	Inf	Inf	Inf	Inf	Inf	Inf	Inf
A10	0.0703	0.1532	0.0491	0.2225	0.0469	0.1405	3.1626

In the input-oriented study, we find City Union Bank to be the most efficient until the financial year 2019-20 after which in 2020-21 Karur Vyasa Bank becomes the most efficient with a score of 1.55. There are banks that show infeasibility (i.e., efficiency equivalent to infinity) which should indicate very high CSR output proportional to their income. Hence, taking the infeasible units into account we have HDFC being the best performer whose efficiency although not 1 but has improved in the first 2 years then remained constant at infinity. Hence, if the other banks are to perform efficiently using proportionately less input but contributing more to CSR, they should follow the operating procedures of City union or HDFC Bank. The output-oriented study shows City Union Bank efficiency to be infeasible throughout, while HDFC Bank remains the best feasible performer since 2018-19.

To compare the change in productivity across time we used the contemporaneous MPI as shown in Table 6 below. All "Mean" calculated in the following tables refer to geometric mean. The input and output oriented MPI have the same values. Also, the TC values are the same for both (Table 7). This indicates no matter the orientation, DEA is always based upon the appropriate utilization of input variables. No bank has shown absolute constant growth in productivity over their previous year. HDFC and Karur Vyasa has shown an overall productivity growth of 13% and 32 % from 2015-16 till 2020-21. There has been a sudden spike in the growth of Axis bank in the year 2018-19, the year when Axis Bank was the benchmark. Similarly, there has been a huge improvement for Kotak Mahindra Bank in the year 2017-18. In the year 2020-21 Yes Bank has shown considerable downfall in productivity over all the years and banks.

All such changes can be attributed to SEC or PTEC (Table 8-11). For input and output orientations the overall technical efficiency change (TEC) is the same but the SEC and PTEC vary hugely, when the PTEC changes the SEC adjusts naturally and vice versa to maintain the same scores for input and output-oriented TEC. Also, after calculating the variance in the average PTEC and SEC, we find PTEC to be less variant as compared to SEC.

Table 6. Malmquist Productivity Index (MPI) for both input and output orientations

	Period						
DMU	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21	Mean
A1	0.0540	0.1067	0.0003	202719.8882	0.2310	1.5001	0.7083
A2	2.5199	0.9476	0.9434	0.8235	1.6548	0.0107	0.5660
A3	1.2582	0.8336	0.7611	1.0914	1.5657	0.1366	0.7558
A4	1.2930	1.5851	1.0689	1.0278	0.8347	1.1311	1.1339
A5	1.3267	0.7659	0.7962	0.4156	1.7538	1.1698	0.9400
A6	1.3998	0.1821	0.5543	0.2550	0.0015	4.6110	0.2495
A7	1.5240	0.9442	0.2201	1.6822	2.3595	0.1382	0.7470
A8	2.5947	0.2739	5.3702	0.1502	6.8312	1.4082	1.3292
A9	1.2371	0.0780	8.5300	1.5961	1.1334	0.5987	0.9810
A10	1.6825	0.5525	1.5627	0.4305	0.7342	0.0001	0.1897

Table 7. Technological Change (TC) for both input and output orientations.

	Period						
DMU	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21	Mean
A1	1.3242	1.0418	1.0261	0.8383	1.5266	0.5303	0.9933
A2	1.7490	0.9476	0.9434	0.8235	1.6548	0.4466	0.9918
A3	1.3329	0.9802	1.0569	1.0113	0.8950	1.1189	1.0575
A4	1.3242	1.0417	1.0689	1.0278	0.8347	1.1311	1.0615
A5	1.3242	1.0418	1.0716	1.0280	0.8678	1.1025	1.0644
A6	1.4853	0.9542	1.0287	1.0142	1.1787	0.1854	0.8284
A7	1.6021	0.9598	0.9825	0.9700	1.0900	0.6589	1.0086
A8	1.4810	1.0212	1.0605	1.0022	1.0807	0.2297	0.8580
A9	1.3667	1.0382	1.0716	0.9872	0.9154	1.0747	1.0671
A10	1.3733	0.9675	0.9820	0.8720	1.1369	0.3394	0.8718

Table 8. PTEC for input oriented MPI

	Period					
DMU	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21
A1	0.0842	0.7722	1.0659	14.4230	0.0647	2.8959
A2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
A3	0.8779	0.9243	0.8214	1.0935	1.2407	0.4731
A4	1.3044	1.1296	1.0000	1.0000	1.0000	1.0000
A5	1.0000	0.5637	0.7678	0.4763	1.6540	1.1368
A6	0.9836	0.7662	1.1374	1.2882	1.1358	1.0281
A7	1.0000	1.0000	0.3103	1.3180	2.4454	0.2927
A8	1.0505	1.0472	1.0439	1.0595	1.0744	1.4736
A9	0.7585	0.5191	1.5138	1.1188	1.2768	0.8020
A10	1.1526	0.6202	1.6123	0.8180	0.3810	0.6641

Table 9. SEC for input oriented MPI

	Period					
DMU	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21
A1	0.4841	0.1327	0.0003	16767.1229	2.3385	0.9769
A2	1.4408	1.0000	1.0000	1.0000	1.0000	0.0240
A3	1.0752	0.9201	0.8768	0.9869	1.4100	0.2581
A4	0.7486	1.3471	1.0000	1.0000	1.0000	1.0000
A5	1.0019	1.3041	0.9676	0.8489	1.2218	0.9334
A6	0.9582	0.2491	0.4737	0.1951	0.0011	24.1886
A7	0.9512	0.9838	0.7220	1.3159	0.8852	0.7167
A8	1.6678	0.2562	4.8509	0.1415	5.8835	4.1598
A9	1.1934	0.1447	5.2582	1.4451	0.9697	0.6946
A10	1.0629	0.9206	0.9870	0.6035	1.6949	0.0005

Table 10. PTEC for output oriented MPI

	Period					
DMU	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21
A1	0.0530	0.0801	0.0007	349654.6871	0.1994	0.6786
A2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
A3	0.8267	0.8859	0.7229	1.1389	1.5001	0.1492
A4	1.1119	1.0460	1.0000	1.0000	1.0000	1.0000
A5	1.0000	0.5466	0.7477	0.4069	2.1999	0.9747
A6	0.8706	0.1807	0.4123	0.2846	0.0027	10.3800
A7	1.0000	1.0000	0.2118	2.1467	2.1995	0.1842
A8	2.1779	0.3205	4.5320	0.2110	2.9938	7.1149
A9	0.8947	0.0794	7.9200	2.0154	0.9707	0.5841
A10	1.1690	0.5745	1.7406	0.8664	0.3861	0.0003

Table 11. SEC for output oriented MPI

	Period					
DMU	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21
A1	0.7693	1.2792	0.4510	0.6916	0.7589	4.1687
A2	1.4408	1.0000	1.0000	1.0000	1.0000	0.0240
A3	1.1418	0.9600	0.9962	0.9476	1.1662	0.8185
A4	0.8782	1.4548	1.0000	1.0000	1.0000	1.0000
A5	1.0019	1.3449	0.9936	0.9937	0.9186	1.0886
A6	1.0825	1.0561	1.3068	0.8834	0.4568	2.3959
A7	0.9512	0.9838	1.0578	0.8079	0.9841	1.1386
A8	0.8045	0.8371	1.1173	0.7102	2.1115	0.8615
A9	1.0118	0.9462	1.0050	0.8022	1.2755	0.9537
A10	1.0480	0.9939	0.9142	0.5698	1.6725	1.1115

5. Research Implications

This work compares the expenditure towards CSR of top 10 banks which can be thought of as the representation of the market of private banking in India. These banks have been chosen based on their market capital (Private Banks which have the topmost 10 market caps in India). We know that CSR is an essential marker for the contribution of private companies towards social welfare. Private Banking is an industry widely trusted upon by the mass and hence to study if such an industry is doing enough to hold on to their social responsibility to set an ideal benchmark to the other organizations in terms of CSR can be looked upon as a motive of this research. Nowadays, investors and industrialists are much more aware of responsible investment. This involves considering environmental, social issues when making investment decisions and influencing companies or assets accordingly. Banking industry sets a bar for other firms in terms of social responsibility and investment stature hence it must exhibit positive impact through its turnover intentions to lead by strong example. This study can be extended further to study numerous private sector banks and other private sector industry in India. Our paper has been primarily based upon the technique of DEA and super efficiency. Also, this comprises the unique use of Malmquist Productivity Index to make comparison of the increase or decrease of CSR performance of given banks over time.

This research has sensible implication for the decision makers of private sector banks in India where they can comply with the changing regulations w.r.t. CSR and follow the best practices of other banks as many organizations have a notion that spending in CSR leads to wasting of funds rather than following the good practices followed by them and doing better for years to come and at the end our study will give a positive impression on the investor who chose socially responsible investing which gives more weight to social change over return on investment.

6. Conclusion and Future Scope

Research on CSR has become more significant to understand their involvement in giving back to the society but CSR spending by the banking sector is still not talked about. Our study on these top ten private banks for the last seven financial years indicate that seven out of the top ten banks have at least once (if not for the whole period) have become the benchmark for CSR contributions. Considering the fact that these ten banks are the largest by market capital, we can come to the conclusion that other banks including those not considered in this research should follow the example of banks like City Union or HDFC as they have performed well for the studied period in all aspect. This also implies that City Union and HDFC have shown highest contribution towards environment sustainability as a part of their CSR act consistently over the years irrespective of the income generated. In this regard, we must also mention IndusInd, ICICI and Axis banks as under the input-oriented model, these banks also exhibit efficiency of 1 for considerable number of years thus setting benchmarks. The comparison of improvement (or regress) in technology of these banks shows pure technical efficiency to be more stagnant than scale efficiency. The average of MPI values give us the idea that HDFC and Karur Vyasa have shown progress over the years. While Federal, HDFC, ICICI, Kotak Mahindra, and IndusInd have all shown Technological Change i.e., improvement in CSR output levels as compared to the benchmark.

Though we have tried to present comprehensive research in this study however there will remain some limitations of the models and methodology used. Firstly, CSR encompasses a wide range of social and environmental activities, and there is no universally accepted set of metrics to measure this effect. Secondly, comparing CSR performance across industries can be problematic due to their varying business models, priorities, and geographical locations. Thirdly, DEA models often focus solely on internal efficiencies and do not account for external factors that could influence CSR performance, such as regulatory environment, social norms, or global events. To overcome some of these limitations, researchers should exercise caution in the interpretation of results with qualitative assessments or other complementary methods to provide a more comprehensive view.

Further research on this subject can be done using more DMUs (both private and public sector banks) and the non-radial and slack based models of DEA. We can use the Global Malmquist Index which takes into account all DMUs from all periods to form a global benchmark. A future work may be planned to apply the present framework for comparing the CSR efficiencies of the firms belonging to other sectors like auto, FMCG and so on while focusing on the environmental sustainability. Next, a causal model may be developed to understand the effect of investment on environmental sustainability (as a part of CSR) on stock performance, financial stability and revenue generation by the firms. Nevertheless, the present work shall help the decision makers to understand how the current private banks can improve their CSR outputs and how banks are improving themselves to contribute towards social welfare.

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References

Andersen, P., & Petersen, N. C. (1993). A Procedure for Ranking Efficient Units in Data Envelopment Analysis. *Management Science*, *39*(10), 1261–1264. https://doi.org/10.1287/mnsc.39.10.1261

Antunes, J., Hadi-Vencheh, A., Jamshidi, A., Tan, Y., & Wanke, P. (2022). Bank efficiency estimation in China: DEA-RENNA approach. *Annals of Operations Research*, *315*(2), 1373–1398. https://doi.org/10.1007/s10479-021-04111-2

Aslaksen, H. M., Hildebrandt, C., & Johnsen, H. Chr. G. (2021). The long-term transformation of the concept of CSR: towards a more comprehensive emphasis on sustainability. *International Journal of Corporate Social Responsibility*, *6*(1), 11. https://doi.org/10.1186/s40991-021-00063-9

Badi, I., & Abdulshahed, A. (2021). Sustainability performance measurement for Libyan Iron and Steel Company using Rough AHP. *Journal of Decision Analytics and Intelligent Computing*, *1*(1), 22–34. https://doi.org/10.31181/jdaic1001202222b

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9), 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

Baumgartner, R. J. (2014). Managing Corporate Sustainability and CSR: A Conceptual Framework Combining Values, Strategies and Instruments Contributing to Sustainable Development. *Corporate Social Responsibility and Environmental Management*, *21*(5), 258–271. https://doi.org/10.1002/csr.1336

Bayiley, Y. T. (2022). Assessing Bank Performance Using Malmquist Productivity Index Approach and One-Step System GMM Dynamic Panel Data Model. *Open Journal of Business and Management*, *10*(02), 798–821. https://doi.org/10.4236/ojbm.2022.102045

Bazargan, A., Najafi, S. E., Lotfi, F. H., Fallah, M., & Edalatpanah, S. A. (2023). Presenting a productivity analysis model for Iran oil industries using Malmquist network analysis. *Decision Making: Applications in Management and Engineering*, *6*(2), 251–292. https://doi.org/10.31181/dmame622023705

Belasri, S., Gomes, M., & Pijourlet, G. (2020). Corporate social responsibility and bank efficiency. *Journal of Multinational Financial Management*, *54*, 100612. https://doi.org/10.1016/j.mulfin.2020.100612

Ben Abdallah, S., Saïdane, D., & Ben Slama, M. (2020). CSR and banking soundness: A causal perspective. *Business Ethics: A European Review*, *29*(4), 706–721. https://doi.org/10.1111/beer.12294

Bhattacharyya, A., Lovell, C. A. K., & Sahay, P. (1997). The impact of liberalization on the productive efficiency of Indian commercial banks. *European Journal of Operational Research*, *98*(2), 332–345. https://doi.org/10.1016/S0377-2217(96)00351-7

Biswas, S., Datta, D., & Kar, S. (2023). Energy Efficiency and Environmental Sustainability: A Multi-Criteria based Comparison of BRICS and G7 Countries. In *Emerging Technology and Management Trends in Environment and Sustainability: Proceedings of the International Conference, EMTES-2022* (1st ed., Vol. 1, pp. 107–125). Taylor and Francis. https://doi.org/10.4324/9781003356233

Biswas, S., & Joshi, N. (2023). A Performance based Ranking of Initial Public Offerings (IPOs) in India. *Journal of Decision Analytics and Intelligent Computing*, *3*(1), 15–32. https://doi.org/10.31181/10023022023b

Biswas, S., Gupta, S., Upadhyay, A., Bandyopadhyay, G., & Shaw, R. (2023a, April). A New Grey Correlational Compromise Ranking Approach for Portfolio Selection for Investment in ESG Stocks. In International Conference on Advances in Computing and Data Sciences (pp. 566-580). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-37940-6_46

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). Multilateral Comparisons of Output, Input, and Productivity Using Superlative Index Numbers. *The Economic Journal*, *92*(365), 73. https://doi.org/10.2307/2232257

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chatterjee, S., & Chakraborty, S. (2023). A Multi-criteria decision making approach for 3D printer nozzle material selection. *Reports in Mechanical Engineering*, 4(1), 62–79. https://doi.org/10.31181/rme040121042023c

Cowan, D. M., Dopart, P., Ferracini, T., Sahmel, J., Merryman, K., Gaffney, S., & Paustenbach, D. J. (2010). A cross-sectional analysis of reported corporate environmental sustainability practices. *Regulatory Toxicology and Pharmacology*, *58*(3), 524–538. https://doi.org/10.1016/j.yrtph.2010.09.004

Cvetkoska, V., & Fotova Čiković, K. (2021). Efficiency Analysis of Macedonian and Croatian Banking Sectors with DEA. *Economy, Business & Development: An International Journal*, *2*(2), 1–19. https://doi.org/10.47063/ebd.00003

Dabic-Miletic, S., & Simic, V. (2023). Smart and Sustainable Waste Tire Management: Decision-Making Challenges and Future Directions. *Decision Making Advances*, 1(1), 10–16. https://doi.org/10.31181/v120232

De Roeck, K., & Delobbe, N. (2012). Do Environmental CSR Initiatives Serve Organizations' Legitimacy in the Oil Industry? Exploring Employees' Reactions Through Organizational Identification Theory. *Journal of Business Ethics*, *110*(4), 397–412. https://doi.org/10.1007/s10551-012-1489-x

Debnath, A., Bandyopadhyay, A., Roy, J., & Kar, S. (2018). Game theory based multi criteria decision making problem under uncertainty: A case study on Indian tea industry. *Journal of Business Economics and Management*, *19*(1), 154–175. https://doi.org/10.3846/16111699.2017.1401553

Debnath, A., Roy, J., Chatterjee, K., & Kar, S. (2018a). Measuring Corporate Social Responsibility Based on Fuzzy Analytic Networking Process-Based Balance Scorecard Model. *International Journal of Information Technology & Decision Making*, *17*(04), 1203–1235. https://doi.org/10.1142/S0219622018500232

Deverakonda, S., & Munipalle, U. (2019). Impact of Foreign Bank Entry on the Domestic Bank Performance in India : A DEA approach. *Finance India*, *33*(1), 85–104.

Donald S., S. (2009). Green Management Matters Only if it Yieds More Green: An Economic/Strategic Perspective. *Academy of Management Perspectives*, *23*(3), 5–16. https://doi.org/10.5465/amp.2009.43479260

Ecer, F., & Pamucar, D. (2022). A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector. *Omega*, *112*, 102690. https://doi.org/10.1016/j.omega.2022.102690

Eyasu, A. M., & Arefayne, D. (2020). The effect of corporate social responsibility on banks' competitive advantage: Evidence from Ethiopian lion international bank S.C. *Cogent Business & Management*, *7*(1), 1830473. https://doi.org/10.1080/23311975.2020.1830473

Färe, R., Grosskopf, S., & Roos, P. (1998). Malmquist Productivity Indexes: A Survey of Theory and Practice. In *Index Numbers: Essays in Honour of Sten Malmquist* (pp. 127–190). Springer Netherlands. https://doi.org/10.1007/978-94-011-4858-0_4

Gupta, S., Bandyopadhyay, G., Biswas, S., & Mitra, A. (2023). An integrated framework for classification and selection of stocks for portfolio construction: Evidence from NSE, India. *Decision Making: Applications in Management and Engineering*, *6*(1), 774–803. https://doi.org/10.31181/dmame0318062021g

Hafsal, K., Suvvari, A., & Durai, S. R. S. (2020). Efficiency of Indian banks with non-performing assets: evidence from two-stage network DEA. *Future Business Journal*, *6*(1), 26. https://doi.org/10.1186/s43093-020-00030-z

Jamali, D., & Karam, C. (2018). Corporate Social Responsibility in Developing Countries as an Emerging Field of Study. *International Journal of Management Reviews*, *20*(1), 32–61. https://doi.org/10.1111/ijmr.12112

Jomthanachai, S., Wong, W. P., & Lim, C. P. (2021). An application of data envelopment analysis and machine learning approach to risk management. *IEEE Access*, *9*, 85978–85994. https://doi.org/10.1109/ACCESS.2021.3087623

Kumar, N., & Singh, A. (2015). *Measuring Technical and Scale Efficiency of Banks in India Using DEA*. *17*, 66–71. https://doi.org/10.9790/487X-17126671

Kumar, S., & Gulati, R. (2008). An Examination of Technical, Pure Technical, and Scale Efficiencies in Indian Public Sector Banks using Data Envelopment Analysis. In *Eurasian Journal of Business and Economics* (Vol. 1, Issue 2). https://www.ejbe.org/index.php/EJBE/article/view/11

Laha, S., & Biswas, S. (2019). A hybrid unsupervised learning and multi-criteria decision making approach for performance evaluation of Indian banks. *Accounting*, 169–184. https://doi.org/10.5267/j.ac.2018.11.001

Lartey, T., James, G. A., & Danso, A. (2021). Interbank funding, bank risk exposure and performance in the UK: A three-stage network DEA approach. *International Review of Financial Analysis*, *75*, 101753. https://doi.org/10.1016/j.irfa.2021.101753

Lee, Y. J., Joo, S.-J., & Park, H. G. (2017). An application of data envelopment analysis for Korean banks with negative data. *Benchmarking: An International Journal*, *24*(4), 1052–1064. https://doi.org/10.1108/BIJ-02-2016-0023

Li, D., Li, Y., Gong, Y., & Yang, J. (2021). Estimation of bank performance from multiple perspectives: an alternative solution to the deposit dilemma. *Journal of Productivity Analysis*, *56*(2–3), 151–170. https://doi.org/10.1007/s11123-021-00614-z

Lyon, T. P., & Maxwell, J. W. (2007). Corporate Social Responsibility and the Environment: A Theoretical Perspective. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1011793

Mahmoudabadi, M. Z., & Emrouznejad, A. (2019). Comprehensive performance evaluation of banking branches: A three-stage slacks-based measure (SBM) data envelopment analysis. *International Review of Economics & Finance*, *64*, 359–376. https://doi.org/10.1016/j.iref.2019.08.001

Maradin, D., Suljić Nikolaj, S., & Olgić Draženović, B. (2021). *Efficiency and Productivity of Islamic Banking Industry by Using DEA Method: A Literature Review* (pp. 205–217). https://doi.org/10.1007/978-3-030-82778-6_12

Moutinho, V., Vale, J., Bertuzi, R., Bandeira, A. M., & Palhares, J. (2021). A Two-Stage DEA Model to Evaluate the Performance of Iberian Banks. *Economies*, *9*(3), 115. https://doi.org/10.3390/economies9030115

Mzili, T., Mzili, I., Riffi , M. E., Pamucar, D., Kurdi, M., & Ali, A. H. (2023). Optimizing production scheduling with the spotted hyena algorithm: A novel approach to the flow shop problem. *Reports in Mechanical Engineering*, 4(1), 90–103. https://doi.org/10.31181/rme040116072023m

Nandy, A., & Singh, P. K. (2020). Farm efficiency estimation using a hybrid approach of machine-learning and data envelopment analysis: Evidence from rural eastern India. *Journal of Cleaner Production*, *267*, 122106. https://doi.org/10.1016/j.jclepro.2020.122106

Nguyen, H. T., Le, D. M. D., Ho, T. T. M., & Nguyen, P. M. (2021). Enhancing sustainability in the contemporary model of CSR: a case of fast fashion industry in developing countries. *Social Responsibility Journal*, *17*(4), 578–591. https://doi.org/10.1108/SRJ-03-2019-0108

Omrani, H., Oveysi, Z., Emrouznejad, A., & Teplova, T. (2023). A mixed-integer network DEA with shared inputs and undesirable outputs for performance evaluation: Efficiency measurement of bank branches. *Journal of the Operational Research Society*, *74*(4), 1150–1165. https://doi.org/10.1080/01605682.2022.2064783

Orlitzky, M., Siegel, D. S., & Waldman, D. A. (2011). Strategic Corporate Social Responsibility and Environmental Sustainability. *Business & Society*, *50*(1), 6–27. https://doi.org/10.1177/0007650310394323

Owusu Kwateng, K., Osei-Wusu, E. E., & Amanor, K. (2019). Exploring the effect of online banking on bank performance using data envelopment analysis. *Benchmarking: An International Journal*, *27*(1), 137–165. https://doi.org/10.1108/BIJ-06-2018-0154

Pamucar, D., & Biswas, S. (2023). A Novel Hybrid Decision Making Framework for Comparing Market Performance of Metaverse Crypto Assets. *Decision Making Advances*, 1(1), 49-62. http://dx.doi.org/10.31181/dma1120238

Pane Haden, S. S., Oyler, J. D., & Humphreys, J. H. (2009). Historical, practical, and theoretical perspectives on green management. *Management Decision*, *47*(7), 1041–1055. https://doi.org/10.1108/00251740910978287

Puška, A., Štilić, A., & Stojanović, I. (2023). Approach for multi-criteria ranking of Balkan countries based on the index of economic freedom. *Journal of Decision Analytics and Intelligent Computing*, *3*(1), 1–14. https://doi.org/10.31181/jdaic10017022023p

Ruiz, B., & García, J. A. (2021). Analyzing the relationship between CSR and reputation in the banking sector. *Journal of Retailing and Consumer Services*, *61*, 102552. https://doi.org/10.1016/j.jretconser.2021.102552

Sahoo, S. K., & Goswami, S. S. (2023). A Comprehensive Review of Multiple Criteria Decision-Making (MCDM) Methods: Advancements, Applications, and Future Directions. *Decision Making Advances*, 1(1), 25–48. https://doi.org/10.31181/dma1120237

Shahzad, M., Qu, Y., Javed, S. A., Zafar, A. U., & Rehman, S. U. (2020). Relation of environment sustainability to CSR and green innovation: A case of Pakistani manufacturing industry. *Journal of Cleaner Production*, *253*, 119938. https://doi.org/10.1016/j.jclepro.2019.119938

Sherman, H. D., & Gold, F. (1985). Bank branch operating efficiency. *Journal of Banking & Finance*, *9*(2), 297–315. https://doi.org/10.1016/0378-4266(85)90025-1

Pogutz, S. (2009). Sustainable Development, Corporate Sustainability, and Corporate Social Responsibility: The Missing Link. In Utting P. & Clapp J. (Eds.), *Corporate Accountability and Sustainable Development* (Vol. 1, pp. 35–60). Oxford University Press.

Thaker, K., Charles, V., Pant, A., & Gherman, T. (2022). A DEA and random forest regression approach to studying bank efficiency and corporate governance. *Journal of the Operational Research Society*, *73*(6), 1258–1277. https://doi.org/10.1080/01605682.2021.1907239

Wang, C.-N., Luu, Q.-C., Nguyen, T.-K.-L., & Day, J.-D. (2019). Assessing Bank Performance Using Dynamic SBM Model. *Mathematics*, *7*(1), 73. https://doi.org/10.3390/math7010073

Williamson, D., Lynch-Wood, G., & Ramsay, J. (2006). Drivers of Environmental Behaviour in Manufacturing SMEs and the Implications for CSR. *Journal of Business Ethics*, *67*(3), 317–330. https://doi.org/10.1007/s10551-006-9187-1