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A DATA-DRIVEN ANALYSIS OF POST-MERGER PERFORMANCE EFFICIENCY IN INDIAN BANKS: A PARETO–KOOPMANS AND MACHINE LEARNING-BASED FRAMEWORK

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Abstract

This study aims to empirically analyse the behaviours of Indian domestic banks following the 2020 post-merger scenario. It assesses their productive performance using a generalised Pareto-Koopmans (PK) technical efficiency measure. To define the banking technology set in India, a variant of the intermediation approach was used, involving three inputs and three outputs. This research advances the literature on bank performance measurement by applying the PK efficiency technique to address limitations found in traditional input- and output-oriented radial measures. Given technological differences, efficiency was evaluated using a bank-specific frontier. The study particularly focuses on performance improvements in both small and large banks during the post-financial crisis and post-merger periods, covering 2011 to 2023. It also compares the BCC input and output-oriented methods with the PK efficiency scores using panel data from 30 Indian banks. Results from the radial (BCC) approach suggest that banks are highly efficient, but efficiency scores slightly decline under the non-radial (PK) measure. PK scores reveal significant improvement potential for non-public sector banks. The disaggregated PK model also identified two key sources of inefficiency: labour and physical capital. Regression analysis shows that CAR, NPA, and bank size significantly impact performance.

Keywords- *PK Efficiency, Technical Efficiency, Radial Measures, Non-Radial Measures, Data Envelopment Analysis,*

Introduction

Background and Context:

Economic growth is shaped by numerous factors, with the financial system among the most crucial. The size and efficiency of the financial system significantly influence economic development. Specific indicators, such as stock market capitalisation and the turnover ratio of stocks, exhibit a clear, positive, yet nonlinear relationship with GDP growth dynamics. (Mariusz Prochniak1, Katarzyna Wasiak2, 2016)
The Indian financial system is essential to the country's economic growth, with banks playing a pivotal role (Sufian, 2011).

The banking industry underwent a significant transformation following the 1992 reforms, which welcomed international and private players into the market (Kumar & Gulati, 2010; Mukherjee et al., 2002; Ghosh, 2016). Thereafter, the industry has seen a series of significant reforms driven by technological advancements and a commitment to inclusive development.

Banks act as financial intermediaries, channelling funds to vital sectors such as agriculture, infrastructure, and small businesses. Banks play a crucial role in promoting financial inclusion, particularly in rural areas, thanks to digital banking innovations.

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In India, banks act as a financial backbone, safeguarding assets, enabling fund transfers, and advising entrepreneurs. Their broader functions encompass financing SMEs, promoting entrepreneurship, and fostering growth through innovative schemes and specialised financial services. (BeenaArya et al., 2023)

Since the 1992 economic reforms, India's banking sector has experienced significant transformation and modernisation. The liberalisation policies welcomed private and foreign banks, boosting competition and efficiency. Advances in technology—such as digital banking, mobile wallets, and fintech innovations—have profoundly enhanced customer experience and access. Initiatives like Pradhan Mantri Jan Dhan Yojana have expanded banking services to previously underserved groups. Together, these developments have fostered a vibrant and inclusive banking landscape, contributing to India's economic growth.

Despite these improvements, the banking sector continues to face considerable challenges, particularly amid ongoing economic downturns and the additional strain of the COVID-19 pandemic.

The reforms and challenges of the Indian Banking industry were analysed (Kalyan Nalla Bala, 2017) to identify issues such as limited access in remote areas, rising customer expectations due to IT advancements, and competition from the entry of foreign banks. These factors present both opportunities and hurdles for sustainability.

Given these challenges, decision-makers, researchers, and academics need to analyse and distinguish the behaviour of traditional banking institutions in India. Accurately measuring bank performance has become a crucial priority. Past studies have examined various performance metrics (Spokeviciute et al., 2019; Mercan et al., 2003; Haslem et al., 1999; Avkiran, 2006), indicating that a strong financial sector can promote economic partnerships. However, many of these studies primarily focus on advanced economies (Avkiran, 2011; Shawtari et al., 2015; Repkova, 2014).

Problem Statement:

Multiple studies have evaluated the performance of Indian banking systems using various methodologies to assess banks' fiscal health comprehensively. Methods such as MADM, CAMEL, Financial Ratio Analysis, DEA, and AHP have been employed (Saini, N., Khanduja, D., 2019; Suresh, K. et al., 2023; Neesha, 2025; Budhedeo, Shradha H., 2018; Subramanyam, T., 2023; Kumar, Pawan et al., 2020).

Earlier research (Saha & Ravisankar, 2000; Bhattacharya et al., 1997; Mukherjee et al., 2002) examined various performance-related issues, and subsequent studies (Kumar & Gulati, 2010; Bhatia & Mahendru, 2015; Roy, 2014; Goyal et al., 2019) followed suit in India. Despite this, many of these works have notable limitations. This study aims to fill that experimental gap and contribute fresh insights into the functioning of the Indian banking system.

On review of these earlier studies, the following gaps were observed:
1. Lack of an advanced performance measurement approach to evaluate the banking performance of India
2. Absence of studies tracking efficiency trends over extended periods.
3. Study on combined PSB and PVB banks of India
4. Lack of focus on technological advancements impacting banking operations
5. Neglect of dynamic market conditions and their influence on bank performance

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These gaps highlight areas for further investigation to enhance understanding and improve banking practices.

Research Objectives and Contribution:

This study assesses the behaviour and productivity results of Indian banks post-2020 merger using PK measures. It examines differences in technological efficiency, identifies inefficiencies in labour and physical capital, and compares BCC and PK efficiency scores. The research also explores improvements in small and large banks after the financial crisis and mergers, considering factors such as capital adequacy ratios, non-performing assets, and bank size that affect overall performance.

This research offers valuable additions to the finance literature in several ways. First, it uses an extensive dataset of 30 banks, allowing comparisons between private and public banks across different divisions, unlike earlier studies that mainly focused on government-owned banks (Gulati & Kumar, 2010). Additionally, our analysis spans a longer period from 2011 to 2023. Lastly, we utilise an expanded version of the PK technique to deliver a comprehensive assessment of the Indian banking sector.
While past studies have applied DEA to assess Indian domestic banks (Saha & Ravisankar, 2000; Mukherjee et al., 2002; Bhattacharya et al., 1997; Goyal et al., 2019; Staub et al., 2010; Avkiran, 2011; Kumar & Gulati, 2010), this work considers, the first study to utilize the PK technical approach for evaluating Indian banks' performance.

This study enhances knowledge of Indian banking performance measurement by utilising the Pareto-Koopmans (PK) efficiency technique, which addresses the limitations of radial measures. It incorporates an extended dataset (2011-2023) and evaluates efficiency on bank-group-specific frontiers, highlighting improvements following the financial crisis and merger periods. The research compares BCC and PK scores, reveals inefficiencies in labour and capital, and identifies areas for improvement, especially in non-public-sector banks. Additionally, it examines the performance differences between private and public banks, offering valuable insights for targeted policy reforms.

This study is crucial for academics, policymakers, and banking professionals, as it introduces the Pareto-Koopmans (PK) efficiency technique to address the limitations of radial measures in evaluating bank performance. It provides insights into inefficiencies in labour and physical capital, and examines variations in efficiency post-merger and during financial crises. Comparing public and private banks highlights areas for improvement. The findings guide policymakers in formulating effective strategies, assist academics in enriching the literature, and help banking professionals optimise performance for sustainable growth.

Methodology Overview:

This study employs advanced efficiency models, specifically the Pareto-Koopmans (PK) technique, to assess the performance of Indian banks following mergers. It compares input-output efficiencies using data from 30 banks and identifies areas of inefficiency, such as labour and capital. The approach provides thoughtful insights into improving productivity across bank groups.
The Pareto-Koopmans (PK) technical efficiency measure is particularly well-suited for evaluating Indian banks compared to previous approaches, as it addresses the limitations of radial measures. Unlike input- and output-oriented measures, PK considers both dimensions simultaneously, offering a holistic view of bank efficiency. Combined with regression analysis, PK provides a robust framework for understanding complex influences like capital adequacy, NPAs, and bank size.

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Structure of the Paper:

The structure of this paper is organised as follows: Section 2 reviews the existing literature; Section 3 details the methodology and data sources, including the models used for efficiency score assessment; Section 4 presents our findings using the PK and BCC models for both public and private banks, accompanied by an individual-level analysis; and Section 5 concludes with the main implications of our results.

Review of Literature

Bank efficiency has dominated mainstream finance research as the core that underlies and conditions economic stability and growth. Various methodologies have been employed to evaluate and compare bank efficiency, including Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), and Principal Component Analysis (PCA). Farrell (1957) was the first to argue that the efficiency frontier approach should be used to estimate bank efficiency using multiple inputs. From there, Rhodes et al. (1978) developed Data Envelopment Analysis, a non-parametric method for measuring the efficiency of relative decision-making units, which revolutionised the measurement of research efficiency. Banker et al. (1984) extended DEA by developing the BCC model, which not only estimates technical inefficiencies but also identifies scale inefficiencies. The overall efficiency analysis was further enhanced with the increased precision achieved. Berger and Humphrey (1997) present a comprehensive international survey of financial institution efficiency, focusing on key determinants of effectiveness and providing guidance for further research to better understand efficiency in the financial sector. Saha et al. (2000) utilised DEA to rate Indian commercial banks within a strict framework, measuring their relative performance and efficiency. Sathye rated banks in India as an emerging economy in 2003, using a non-parametric approach to clarify operational performance and competitive dynamics within the banking industry. Sufian (2007) applied DEA window analysis to examine changing efficiency trends in the commercial banking groups of Singapore, detailing the performance variation of these institutions over time using a non-stochastic frontier approach. Gupta et al. (2008) analysed the dynamics of productive efficiency in Indian banks to highlight trends and patterns that support the changing scene of the banking sector. Kumar (2008) studied the efficiency-profitability nexus in Indian public sector banks, which disclosed a significant relationship between operational efficiency and financial performance for the banking sector. Kumar et al. (2011) applied a progressive time-weighted mean approach of DEA to benchmark Indian banks for the post-reform period, highlighting changes in efficiency and performance indicators over time.

Chortareas et al. (2013) investigate the link between financial freedom and bank efficiency in the European Union, offering empirical evidence on how regulatory environments affect banking performance. Tandon et al. (2014) assessed the technical, pure technical, and scale efficiencies of Indian banks using DEA (Data Envelopment Analysis), providing insights into their operational performance. Tzeremes (2015) utilised the conditional directional distance function to examine how specific factors influence efficiency dynamics in Indian banking, deepening our understanding of external influences on bank performance. Stoica et al. (2015) studied the impact of internet banking on Romanian banks' efficiency using DEA and PCA, finding that digital banking adoption is positively associated with operational efficiency. Their findings enhance our understanding of the role of technological advancements in improving financial performance, offering practical insights for industry professionals and researchers. Jain et al. (2016) applied decision tree analysis to identify key factors in DEA, thereby improving data-driven bank efficiency measurement in India. Goyal et al. (2018) used the meta-frontier directional distance function DEA to evaluate efficiency and technology gaps in the Indian banking sector, revealing performance differences among banking groups. Drab et al. (2018) compared the efficiency of banks in the Visegrad countries using comparative metrics to examine regional factors and practices that affect performance. This study

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contributes to a broader understanding of banking efficiency in Central and Eastern Europe, emphasising regional dynamics and operational practices.

Kaya, N. (2018) reviews bank efficiency across country groups using Data Envelopment Analysis and uses meta-regression to identify factors affecting technical efficiency. It finds that while study year and country income levels do not affect efficiency, factors like the number of banks, observations, publication year, and countries studied do have a significant impact.

Vo. X.V. and Nguyen, H.H. (2018), use a combination of Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to measure the efficiency of Vietnamese banks. The DEA identifies the most efficient banks, while SFA accounts for random errors and inefficiencies, providing a more accurate assessment of efficiency.

Ofori-Sasu et al. (2019) used DEA to examine the relationship between funding structure and technical efficiency in Ghanaian banks, highlighting how financing strategies influence banking performance. Hassan investigated how regulatory policies impact performance efficiency in banks, providing a detailed analysis of different regulatory frameworks and their effects on banking operations. His work clarifies the trade-offs and advantages of various regulatory approaches, deepening the understanding of their influence on banking performance and operational efficiency.

Nguyen et al. (2020) applied a non-parametric method to evaluate the benefits of bank mergers in Vietnam, addressing a gap by analysing how mergers affect bank efficiency. Their findings inform policy decisions regarding consolidation and enhance comprehension of the advantages and challenges of banking mergers in Vietnam. Rezaeiani and Foroughi introduced a novel ranking method for efficient decision-making units in data envelopment analysis, using a reference frontier share to improve the robustness of efficiency assessments.

Boubaker et al. (2020) use a fuzzy multi-objective two-stage DEA approach to compare the efficiency of U.S. commercial banks affiliated with single-bank and multi-bank holding companies from 1994 to 2018. It finds that multi-bank holding company affiliates are generally more efficient, benefiting from parent resources. However, this relationship has an inverted U shape, indicating an optimal number of subsidiaries for maximum efficiency.

Kumar. A et al. (2020) utilise Window DEA to analyse the efficiency of private sector banks in India from 2005 to 2017, revealing that banks with higher efficiency scores also exhibit greater variability, thereby reinforcing the notion that higher efficiency is associated with greater risk.

Wang et al. (2021) introduced a decision support model that uses advanced analytical methods to assess technological progress and productivity gains in Vietnamese commercial banks. Their findings highlight how technological innovations influence banking productivity, offering a potential roadmap for boosting operational efficiency in the financial industry. Boďa and Piklova (2021) present evidence from a banking case study, analysing how input-output specifications affect efficiency scores in DEA. Their work underscores the importance of methodological sensitivity in relative-efficiency analysis and suggests ways to improve the accuracy and reliability of DEA evaluations. Maji and Hussain (2021) explore the relationships among technical efficiency, intellectual capital efficiency, and overall bank performance in India's emerging markets. Their results show that leveraging intellectual capital can enhance technical efficiency, providing insights for optimising bank performance amid evolving financial environments. Their research also sheds light on liberalisation policies and banking efficiency, deepening the understanding of regulatory impacts on financial institutions. Jelassi and Delhoumi (2021) used a two-stage Data Envelopment Analysis to identify the factors influencing technical efficiency in Tunisian banks. Their study examines the internal and external determinants of efficiency and illustrates how various factors affect bank performance in the Tunisian context.

Goswami (2022) models NPL and examines convergence among banks in India across different crisis periods. His research offers a thorough analysis of how financial crises influence bank performance, risk profiles, and the behaviour of NPLs, as well as regulatory responses in a challenging financial environment. It serves as a valuable resource for analysing bank performance

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under financial stress. While not explicitly addressed, it offers insightful, nuanced perspectives on how these factors affect operational efficiency.

Achi. A (2022) highlights that substantial global research has focused on measuring banking-sector efficiency using Data Envelopment Analysis (DEA). As studies specifically analysing Algerian banks are limited, he studied the efficiency of Algerian banks using partial least squares (PLS) regression and found that deposit-producing efficiency is positively influenced by bank size and age. In contrast, revenue-earning efficiency is negatively impacted by these factors.

Wanke et al. (2022) analyse the development and application of a robust DEA model that incorporates multiple scenarios to assess the efficiency of bank branches under uncertain, variable conditions, explicitly addressing the limitations of traditional DEA models.

López-Penabad, M.C., et al. (2022) examine the U-shaped relationship between corporate social performance (CSP) and bank efficiency, revealing that banks with very high or low CSP levels are the most efficient, with environmental factors having a minimal impact. This study employs Data Envelopment Analysis (DEA) and truncated regression models to assess bank efficiency and its relationship with Corporate Social Performance. The research employs DEA-WEI models to address measurement challenges and offers a multidimensional framework for assessing the impact of CSP on bank efficiency.

Horvat, A.M. (2022) utilises an output-focused Data Envelopment Analysis (DEA) model with variable returns to evaluate the technical efficiency of banks in the Western Balkans. This method considers loans and investments as inputs, while net interest income, net non-interest income, and net income serve as outputs. The study examines data from 79 banks across five countries over five years to track changes in their technical efficiency.

Boubaker et al. (2022) utilisent une nouvelle analyse inverse de données (InvDEA) pour évaluer l'efficacité de 49 banques islamiques dans 10 pays au cours de la pandémie de COVID-19. This approach calculates the ideal inputs required to sustain a specific efficiency level, accounting for output variations resulting from the pandemic's effects. It emphasises banks with diminished efficiency, aiming to improve their performance and overall efficiency.

Omrani et al. (2022) present a novel mixed-integer network DEA (MI-NDEA) model to evaluate the efficiency of 45 Agribank branches in West Azerbaijan Province, Iran. The model includes various extensions to the conventional DEA model, such as those that incorporate shared inputs, integer variables, and undesirable outputs.

Mateev et al. (2022) explore how efficiency and market competition influence bank performance in the MENA region, especially during the COVID-19 pandemic. They compare Islamic and conventional banks, finding that efficiency enhances financial stability but also raises risk appetite. Conventional banks experience more significant profitability effects than Islamic banks.

Mirzaei.A et al (2022) evaluate the stock performance of 426 banks from 48 countries during the early COVID-19 crisis, finding that Islamic banks outperformed conventional banks by 10-13%. It attributes this difference to higher pre-crisis efficiency, as measured by non-parametric Data Envelopment Analysis (DEA), which significantly explains the crisis stock returns for Islamic banks but not for conventional banks.

Shaddady and Alnori (2023) investigate the relationship between environmental, social, and governance (ESG) practices and bank efficiency, adopting ten fundamental financial indicators across 11 listed banks in Saudi Arabia from 2016 to 2021. They find that ESG activities generally enhance bank efficiency. It also highlights that the positive impact is most pronounced in social and governance practices, with environmental factors playing a minor but still beneficial role.

In another study of Chinese banks, Antunes, J et al. (2023) highlight that earlier research on banking efficiency mainly used methods such as Data Envelopment Analysis (DEA), Bootstrapped DEA, Network DEA, and stochastic frontier analysis (SFA) to evaluate different efficiency aspects, including technical, scale, and cost efficiency. However, these studies often neglected the effects of serial data and the complex, nonlinear relationships between efficiency and other bank-specific

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factors. To address this, the study adopts a more comprehensive approach combining DEA with the SSRP model. The findings indicate that Chinese banks improved their cost efficiency from 2010 to 2015. However, their efficiency became inconsistent thereafter, with state-owned banks performing best and rural commercial banks worst by 2018.

Istaiteyeh et al. (2024) discuss how Data Envelopment Analysis (DEA) has become a widely used method for evaluating bank efficiency globally. It highlights that DEA can effectively handle multiple inputs and outputs, making it a preferred tool for efficiency analysis in the banking sector.

Kolahdoozi. Let al. (2024) utilise the MSORM model to assess group efficiency in the banking sector, effectively handling negative data and providing valuable insights into performance variations and evaluation methods.

Kiani-Ghalehno. R. and Mahmoodirad.A (2024) utilise a hybrid algorithm integrating decision-making techniques, statistical analysis, and Data Envelopment Analysis to assess bank branch performance amid uncertain data. Their findings indicate that efficiency rankings fluctuate with variations in fuzzy number ranges, yet strong correlations persist.

Methodological Foundation

This study employs Data Envelopment Analysis (DEA) to assess the performance of Indian commercial banks, specifically calculating PK efficiency scores, which are considered one of the most advanced non-radial measures (K.S. Khati and D. Mukherjee, 2020). Unlike previous foundational works by Charnes, Cooper, and Rhodes (1978), Banker et al. (1984), and Ray (2004), this research does not rely on the traditional DEA models.

The CCR model operates under constant returns to scale (CRS), while the BCC model assumes variable returns to scale (VRS); neither adequately captures proportional changes in inputs or outputs of a Decision Making Unit (DMU). To address this, we apply the input directed VRS Technical Efficiency score corresponding to DMU_0 by solving the subsequent Linear Programming formulation:

$$\min \theta$$

$$\text{s.t.} \sum_{j=1}^{N} \lambda j Yrj \geq \theta Y_{r0} \forall \ r = 1, 2, \dots, m$$

$$\sum_{j=1}^{N} \lambda j Xij \leq \theta X_{i0} \forall \ i = 1, 2, \dots, n$$

$$\sum_{j=1}^{N} \lambda j = 1$$

$$\lambda_j \geq 0 \ \forall \ j = 1, 2, \dots, N. \qquad (1)$$

In the above model, m and n represent the number of outputs and inputs, respectively, while N denotes the number of Decision Making Units. It is also specified that $\theta*$ must equate with TEio, for which the prior need is to obtain the optimal value of θ^*.

Comparably, by the following DEA model, the 0th decision-making unit's output-oriented score can be computed.

$$\max Ø$$

$$\text{s.t.} \sum_{j=1}^{N} \lambda j Yrj \geq Ø Y_{r0} \forall \ r = 1, 2, \dots, m$$

$$\sum_{j=1}^{N} \lambda j Xij \leq Ø X_{i0} \forall \ i = 1, 2, \dots, n$$

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$$\sum_{j=1}^{N} \lambda j = 1$$

$\lambda_j \geq 0\ \forall$ j = 1, 2, …, N. (2)

Based on the above BCC model framework, we can measure efficiency by maximising the fractional expansion of all outputs at a specified level of given inputs. All the input and output bundles are denoted by X and Y, respectively. The fraction at which all outputs can be expanded to achieve the efficiency score is denoted by Φ. Φ^* reflects the optimal blend for this model, through which TEi0 must equate to $1/\varphi^*$.

Unlike input- and output-oriented measures, PK considers both dimensions simultaneously, offering a holistic view of bank efficiency. The Pareto-Koopmans (PK) efficiency technique addresses the limitations of radial measures. Whether output-oriented or input-oriented, a radial decision-making unit primarily exhibits slack. That is why it is essential to frame a model free of any non-zero slacks by integrating both output and input inefficiency bundles (Charnes et al., 1985). By solving the following LP model, the PK measure attempts to calculate an efficiency score free from biases by determining the ratio of average input efficiency to average output efficiency.

$$\Gamma = \min \frac{\frac{1}{n}\sum_i \theta i}{\frac{1}{m}\sum_r \text{Ø}r}$$

s.t. $\sum_{j=1}^{N} \lambda j Yrj \geq \text{Ø}_r Y_{r0} \forall r = 1, 2,.. \ldots, m$

$\sum_{j=1}^{N} \lambda j Xij \leq \theta X_{i0} \forall i = 1, 2, \ldots\ldots, n$

$\theta_i \leq 1\ \forall\ i = 1, 2, \ldots\ldots, n$

$\sum_{j=1}^{N} \lambda j = 1$; $\lambda_j \geq 0\ \forall j = 1, 2, \ldots, N$ (3)

The above equation represents the proportions (Ør, θi) by simultaneously boosting output and reducing input to achieve efficiency. λj Represents a decision-making unit that performs efficiently from the perspective of orientation, encompassing both combined output and input approaches. The above non-linear model can be approximated by a linear form, as described below (Ray, 2004).

$\tilde{\Gamma} \approx 1 + \frac{1}{n}\sum_i \theta i - \frac{1}{m}\sum_r \text{Ø}r$ (4)

$\min \tilde{\Gamma} = \frac{1}{n}\sum_i \theta i - \frac{1}{m}\sum_r \text{Ø}r$ (5)

The favourable worth of θ^* and Φ^* we determine by solving the revised expression. In the decision criterion of the original equation (3), by substituting the favourable values of θ∗ and Φ∗, the PK efficiency score, Γ*, is obtained.

$\Gamma^* = \frac{\frac{1}{n}\sum_i \theta i*}{\frac{1}{m}\sum_r \text{Ø}r*}$ (6)

When Ør* and θi* equal 1, the decision-making unit is considered PK efficient, with efficiency ranging from 0 to 1.

Data Source and Statistical Model

Given the widespread acceptance of the intermediate approach in assessing bank performance, this study aims to employ a modified intermediation approach to explain the established mechanisms of Indian banks. The three inputs used are Loanable funds, Physical Capital, and Labour. The three outputs are other Incomes, Advances and Investment. Except for labour, all these variables are expressed in millions of rupees, as described by Kumar (2008).

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In this study, we focus only on public and non-public sector banks to evaluate their performance during the pre- and post-merger periods. Between PSBs and PVBs, there are technological differences, so we treat them separately to calculate efficiencies using bank-group-specific frontiers rather than standard frontiers. The study period spans 13 years, from 2011 to 2023. The data were collected from a sample of 12 public and 18 private banks that were operational throughout the study period. The various issues of Statistical Tables Relating to Banks in India, published by the Reserve Bank of India (RBI), were used as the data source. After reviewing the relevant empirical literature, we have identified six variables for use in the second-stage regression.

Data Analysis & Interpretations

This study primarily compares the two technical efficiency scores for government- and privately owned banks. It uses the Pareto-Koopmans measure, an advanced technique, rather than input- and output-oriented BCC scores. The analysis begins with an overall discussion of the technical efficiency scores for private and public sector banks. It then examines these scores at an individual bank level. Finally, second-phase regression analysis identifies the factors influencing PK scores.

Table-1

Outline of TE Ratings for Government-owned banks														
Years*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*2020*	*2021*	*2022*	*2023*	All Years
BCC efficiency (Input-oriented)														
Mean	0.9953	0.9956	0.997	0.998	0.998	0.99	0.99	0.9897	0.991	0.99	0.99	1	0.9894	0.996
Median	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Standard deviation	0.0131	0.0095	0.008	0.007	0.006	0.02	0.03	0.0255	0.027	0.026	0.034	1	0.0196	0.013
Banks on the frontier	9	9	10	11	10	9	9	10	9	10	10	10	9	
BCC efficiency (Output-oriented)														
Mean	0.9953	0.9956	0.997	0.998	0.998	0.99	0.991	0.9897	0.991	0.99	0.99	1	0.9896	0.996
Median	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Standard deviation	0.0132	0.0095	0.008	0.007	0.006	0.02	0.026	0.0252	0.027	0.025	0.033	0.01	0.0193	0.012
Banks on the frontier	9	9	10	11	10	9	9	10	9	10	10	10	9	
PK efficiency														
Mean	.94657	.967479	.978	.956	.983	.93	.961	0.9608	0.956	0.969	0.968	0.97	0.9529	0.961
Median	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Standard deviation	0.11308	0.082323	0.064	0.086	0.041	0.13	0.087	0.0915	0.085	0.073	0.082	0.07	0.0895	0.085
Banks on the frontier	9	9	9	9	10	9	9	10	9	10	10	10	9	

Source: The authors

Table 2: Summary of PK Efficiency scores obtained by individual Government Owned Banks

Name	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*2020*	*2021*	*2022*	*2023*
Bank Of Baroda	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Bank Of India	1.000	0.970	1.000	1.000	1.000	0.648	0.837	0.761	0.748	0.788	0.729	0.819	0.756
Bank Of Maharashtra	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Canara Bank	1.000	1.000	1.000	1.000	1.000	0.705	0.970	1.000	0.875	0.845	1.000	1.000	1.000
Central Bank Of India	0.628	0.716	0.777	1.000	1.000	1.000	0.728	0.769	1.000	1.000	1.000	1.000	1.000
Indian Bank	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Indian Overseas Bank	0.880	0.923	0.965	0.891	0.913	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Punjab And Sind Bank	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Punjab National Bank	0.851	1.000	1.000	0.839	0.880	0.768	1.000	1.000	1.000	1.000	0.890	0.817	0.797
State Bank Of India	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
UCO Bank	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.848	1.000	1.000	1.000	0.882
Union Bank Of India	1.000	1.000	1.000	0.742	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Source: The authors

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Table 3

Grouping based on the efficiency of Public Sector Banks

PK Efficiency	*2011*	*2023*
< 0.5		
.501-0.6		
0.601-0.700	CBI	
0.701-0.800		Bank of India PNB
.801-0.90	Indian Overseas PNB	UCO
0.901-1.00	Bank of Baroda Bank of India Bank of Maharashtra Canara Bank Indian Bank Punjab and Sind Bank State Bank of India UCO Bank Union Bank of India	Bank of Baroda Bank of Maharashtra Canara Bank Central Bank of India Indian Bank Indian Overseas Bank Punjab and Sind Bank State Bank of India Union Bank of India

Source: The authors

In Table 1, the technical efficiency scores, using both radial and non-radial measures, are displayed for banks under Government ownership. The outcome is optimistic, aligning with other studies that public sector banks are highly competent. The average efficiency scores appear to be very high across years, i.e., above 0.95, regardless of orientation type. The mean PK efficiency annual results are also tremendous and do not reflect any further scope for improvement. Except for 2011 and 2016, the annual mean PK efficiency scores of PSBs are above 0.95 throughout the entire study period. Over time, the mean score is lower than the median score. The number of banks on the frontier is the same in both the initial and terminal years. Examining the mean and median values reveals that the efficiency scores exhibit a negatively skewed distribution, indicating that several banks are very close to the PK efficiency frontier. The standard deviations of technical productiveness, as measured by BCC input- and output-oriented scores, are lower than those of PK scores.

The discussion then shifts to individual bank-level observations. During the study period, P&S Bank, BOB, BOM, Indian Bank, and the State Bank of India consistently remained at the frontier. BOI has been below the frontier for nine years and had the lowest score among banks in 2023. In 2011, the Central Bank of India recorded the lowest score but achieved a perfect score of 1.000 by the end of the period. The State Bank of India maintained its efficiency throughout the post-financial crisis period and during the mergers of Indian public sector banks in 2011 and 2017. Punjab National Bank's score declined slightly after merging with Oriental Bank of Commerce and United Bank of India in 2020, to 0.797. Conversely, Canara Bank achieved a higher PK score after its 2020 merger with Syndicate Bank, reaching 1.000. Similarly, Canara Bank, Union Bank of India, Indian Bank, and Bank of Baroda secured a maximum PK score of 1.000 during the post-merger period of 2020. Overall, there is considerable variation in bank performances across the period. The efficient allocation of nationalised banks is summarised in Table 3 for 2011 and 2023.

Table 4 presents the overall technical efficiency (OTE) scores of non-public sector banks obtained through the BCC and Pareto-Koopmans models. In terms of BCC input and output orientation, banks are found to be highly efficient, but such efficiency scores slightly dropped under the PK model. However, the reduction rate is more than that identified for public sector banks. The mean

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PK efficiency score was lowest in 2011, at 0.854, and rose to 0.854 in 2023. The number of banks on the frontier was 9 in the initial year and rose to 13 in the last year. Similar to the observation on public sector banks, the allocation of banks appears to be very close to the PK perimeter. The standard deviation figure represents PK scores, which exhibit greater dispersion than BCC technical efficiency scores.

Table-4

Aggregate technical efficiency performance of Private Banks														
Years	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*2020*	*2021*	*2022*	*2023*	Over the entire period
Efficiency under input minimisation (BCC)														
Mean	0.9708	0.9782	0.9834	0.9866	0.9637	0.9868	0.9891	0.9852	0.9859	0.9709	0.9754	0.978	0.9823	0.9893
Median	0.9983	1	1	1	1	1	1	1	1	1	1	1	1	1
Standard deviation	0.0411	0.0344	0.0272	0.0264	0.0502	0.0222	0.0233	0.0278	0.0262	0.0459	0.0424	0.0495	0.0325	0.0224
Banks on the frontier	9	11	10	11	11	12	13	12	12	10	11	13	13	
Output-oriented BCC efficiency														
Mean	0.9718	0.9778	0.9833	0.9854	0.9609	0.9864	0.9889	0.985	0.9858	0.9706	0.9751	0.978	0.9824	0.9891
Median	0.9983	1	1	0.9891	1	1	1	1	1	1	1	1	1	1
Standard deviation	0.0391	0.0354	0.027	0.0295	0.0558	0.0227	0.0235	0.0277	0.0266	0.0464	0.0428	0.0497	0.0322	0.0227
Banks on the frontier	8	11	10	11	11	12	13	12	12	10	11	13	13	
Pareto-Koopmans efficiency														
Mean	0.76133	0.86041	0.841	0.86446	0.83351	0.87061	0.89944	0.86501	0.8791	0.80406	0.85052	0.89935	0.87453	0.8541
Median	0.89615	1	1	1	1	1	1	1	1	1	1	1	1	0.99201
Standard Deviation	0.28987	0.19221	0.20626	0.20024	0.22762	0.20319	0.17928	0.20671	0.18697	0.2538	0.20712	0.17136	0.21717	0.21091
Banks on Frontier	9	11	10	11	11	12	13	12	12	10	11	13	13	

Source: The authors

Table 5: Summary of PK Efficiency scores obtained by individual Private Sector Banks

Name	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Axis Bank Ltd	1	1	1	1	1	1	1	1	1	0.718	0.759	1	1
City Union Bank Ltd	0.641	0.763	0.942	0.795	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CSB Bank Ltd	0.434	0.561	0.491	0.557	0.495	1.000	1.000	0.605	1.000	1.000	1.000	1.000	1.000
DCB Bank Ltd	0.725	1.000	0.587	1.000	1.000	1.000	1.000	1.000	0.611	0.463	0.567	0.568	0.502
Dhanlaxmi Bank Ltd	0.435	0.539	1.000	0.423	0.390	0.515	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Federal Bank Ltd	0.596	1.000	0.639	0.718	0.734	0.594	0.667	0.707	1.000	1.000	1.000	1.000	1.000
HDFC Bank Ltd.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ICICI Bank Limited	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.752	0.662	1.000	0.774	1.000
Indusind Bank Ltd	0.792	0.776	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Jammu & Kashmir Bank Ltd	1.000	0.492	0.555	0.473	0.473	0.484	0.427	0.386	0.476	0.207	0.376	1.000	0.382
Karnataka Bank Ltd	0.476	0.648	0.742	0.824	0.640	0.595	1.000	0.613	0.633	0.543	0.699	0.627	0.608
KarurVysya Bank Ltd	0.580	0.709	0.680	0.770	1.000	0.882	0.762	0.705	0.788	0.802	0.695	1.000	1.000
Kotak Mahindra Bank Ltd.	1.000	1.000	1.000	1.000	1.000	1.000	0.739	1.000	1.000	0.569	1.000	1.000	1.000
Nainital Bank Ltd.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
RBL Bank Ltd	1.000	1.000	1.000	1.000	0.702	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
South Indian Bank Ltd	0.024	1.000	0.502	1.000	0.568	0.600	0.594	0.554	0.564	0.509	0.646	0.616	0.525
Tamilnad Mercantile Bank Ltd	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Yes Bank Ltd.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.567	0.604	0.724

Source: The authors

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Table-6

Grouping based on the efficiency of Public Sector Banks

PK Efficiency	*2011*	2023
< 0.5	CSB Bank Limited Dhanlaxmi Bank Limited Karnataka Bank Ltd South Indian Bank Ltd	J&K Bank Ltd
0.501-0.600	Federal Bank Ltd KarurVysya Bank Ltd	DCB Bank Limited South Indian Bank Ltd
0.601-0.700	City Union Bank Limited	Karnataka Bank Ltd
0.701-0.800	DCB Bank Limited Indusind Bank Ltd	Yes Bank Ltd.
0.801-0.900		
0.901-1.00	Axis Bank Limited HDFC Bank Ltd. ICICI Bank Limited Jammu & Kashmir Bank Ltd Kotak Mahindra Bank Ltd. Nainital Bank Ltd RBI Bank Ltd Tamilnad Mercantile Bank Ltd Yes Bank Ltd.	Axis Bank Limited City Union Bank Limited CSB Bank Limited Dhanlaxmi Bank Limited Federal Bank Ltd HDFC Bank Ltd. ICICI Bank Limited Indusind Bank Ltd KarurVysya Bank Ltd Kotak Mahindra Bank Ltd. Nainital Bank Ltd RBI Bank Ltd Tamilnad Mercantile Bank Ltd

Source: The authors

The following discussion is on individual bank-level observations. Over the study period, HDFC Bank Ltd., Nainital Bank Ltd., and Tamil Nadu Mercantile Bank Ltd. consistently maintained their position on the frontier. Jammu & Kashmir Bank Ltd. Operated below the frontier for 11 years and obtained a minimum score of 0.207 in the year 2020. Karnataka Bank Ltd. could take a position on the frontier only in 2017. Karur Vysya Bank Ltd. has continuously improved its efficiency score, rising from 0.580 (2011) to 1.000 (2023). Over the study period, South Indian Bank Ltd. obtained a minimum score of 0.024 in 2011. A wide variation is observed in the bank's performance throughout the study period, while most banks remain on the frontier for at least 1 year. For the initial and terminal years, the lowest PK scores were recorded by South Indian Bank Ltd (0.024) and Jammu & Kashmir Bank Ltd (0.382). Table 6 summarises the grouping of private sector banks on PK efficiency scores through the years 2011 and 2023.

Table 7PK Efficiency score obtained by large and small Public Sector Banks

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Large Government-Owned Banks	0.950	1.000	1.000	0.946	0.960	0.923	1.000	1.000	1.000	1.000	0.963	0.939	0.932
Small Government-Owned Banks	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
All Government-Owned Banks	0.955	0.987	0.994	0.912	0.966	0.961	1.000	1.000	0.975	1.000	0.982	0.970	0.946

Source: The authors

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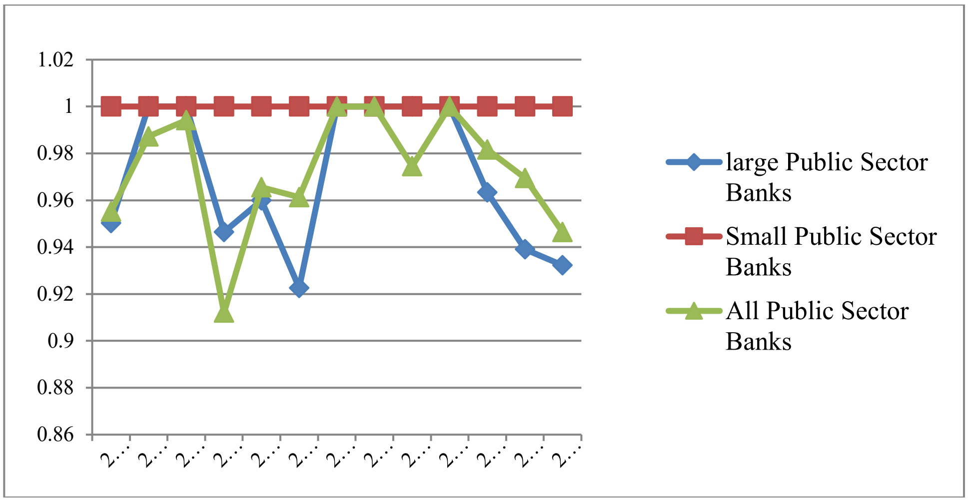

Figure 1 (Source: The authors)

Table 8PK Efficiency score obtained by large and small Private Sector Banks

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Large Privately Owned Banks	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.917	0.793	0.920	0.925	1.000
Small Privately Owned Banks	0.908	1.000	0.862	1.000	0.901	1.000	1.000	1.000	0.870	0.821	0.856	0.856	0.834
All Privately Owned Banks	.761	.860	.841	.864	.834	.871	.899	.865	.879	.804	.851	.899	.875

Source: The authors

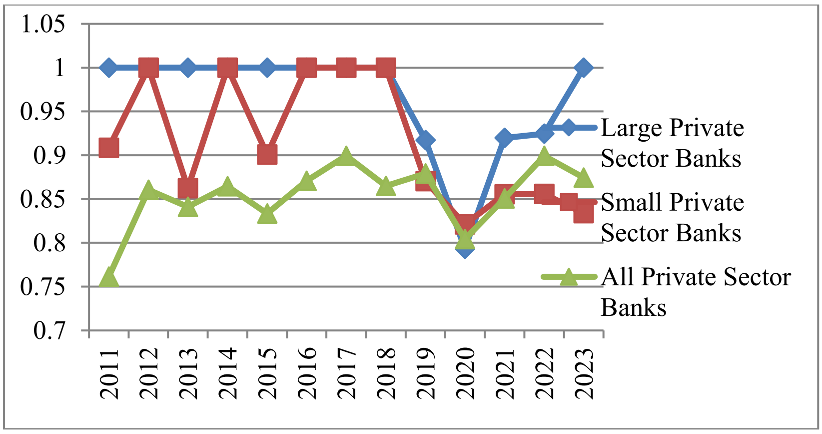

Figure 2 (Source: The authors)

The subsequent analysis examines the association between PK efficiency and the bank's size. To examine these banks, they are divided into two groups—large and small banks—based on their size in 2011. In the public sector, three small banks—BOM, P&S Bank, and Indian Bank —and PNB, SBI, and BOB are the most significant undertakings. For private sector banks, minor banks include RBL, DCB, and Nainital, while large banks include HDFC, ICICI, and Axis. Table 7 and Figure 1 depict the performance of both categories of banks within the Public sector. A fair performance is consistently observed among small banks. In contrast, large PSBs performed below the overall mean in 2016, 2021, 2022, and 2023, with a slight variation in average PK score. Table 8 and Figure 2 present the performance of private sector banks, including both large and small banks, based on the mean annual PK effectiveness rating. During the analysis period, both categories of private-sector banks exhibited higher mean efficiency scores than the overall group average. A large bank maintains an efficiency score closer to 1.000, except during the 2020 post-merger period. In contrast, variation in PK efficiency scores was evident across small banks throughout the study period, and small banks' scores exceeded those of large banks in 2020.

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Table-9

Efficiency summary by inputs and outputs														
	2011	*2012*	*201*3	*2014*	*201*5	*2016*	*2017*	*201*8	*2019*	*2020*	*202*1	*2022*	*2023*	Over the entire period
Group A: Government-owned banks														
Outputs														
Advances	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Investments	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Other Incomes	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Inputs														
Loanable Funds	0.595	0.803	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.751	1.00	1.00	1.00	0.934
Physical Capital	0.876	0.788	1	1	1	1	1	1	1	0.936	1	1	1	0.969
Labour	0.723	0.791	0.876	0.839	0.857	0.824	0.937	0.842	0.798	0.774	0.777	0.855	0.839	0.825
Efficiency summary by inputs and outputs														
	2011	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*2020*	*2021*	*2022*	*2023*	All Years
Group B: Privately Owned Banks														
Outputs														
Advances	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Investments	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Other Income	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Input parameters														
Loanable Funds	1	1	1	1	1	1	1	1	1	0.9972	1	1	1	1
Physical Capital	0.7302	0.86894	0.899	0.889	0.877	0.865	0.889	0.849	0.832	0.7834	0.761	0.86	0.858	0.843
Labour	0.9058	0.85891	0.828	0.925	0.91	0.956	0.977	0.919	0.926	0.9372	0.932	0.971	0.98	0.925

Source: The authors

Considering all the inputs and outputs at an aggregate level, the PK score can measure and compare the performance of decision-making units. However, in managerial terms, it is used to improve a unit's productivity, although it makes only a limited contribution. Therefore, dividing the overall efficiency score among individual input and output factors helps identify inefficient sources. Table 9 presents a detailed study of individual component-wise efficiencies derived from the average theta and average pie. Inputting a specific efficiency score helps a decision-making unit identify the extent to which input quantity should be used proportionately to enable that DMU to operate on the frontier at the required Pareto-efficient point. The bottom part of panel A indicates that, over the entire study period, the average input efficiency is lowest for labour. This implies an underutilization of 17.43%, as its average efficiency score is 0.8257. Loanable funds and physical capital show minimal room for improvement, as their average input efficiency scores are moderately high across all public sector banks. Panel B highlights the annual average input and output efficiency scores for all non-public sector banks. The average input efficiency score is the lowest for physical capital (0.843). It implies that physical capital can be increased by 15.7% to enable private-sector banks to operate efficiently at the frontier. The other inputs and loanable funds' annual average efficiency scores are very high, indicating limited scope for improvement in their utilisation. Across public and private sector banks, the annual average output efficiency score is very high, suggesting little scope for further improvement. Overall, regarding individual output and input banks, they are advised to improve efficiency by focusing on two factors: labour and physical capital.

Table-10

	Government-Owned Banks			Privately Owned Banks		
Regressor	Coefficients	Std. Error	Sig.	Coefficients	Std. Error	Sig.
DEPLIB	.004	0.006	0.590	0.017	0.010	0.142
Priority	.004	0.004	0.341	0.003	0.006	0.645
Manage	-.174	0.114	0.176	-0.264	0.145	0.120
CAR	.001	0.010	0.915	-0.017	0.007	0.041
NPA	-0.005	0.004	0.263	-0.058	0.020	0.030
SIZE	-0.004	0.033	0.913	0.126	0.039	0.017
Constant	0.882	0.753	0.286	-1.175	0.848	0.215
R Square	0.439			0.789		
Adjusted R Square	-0.122			0.579		
Std. Error of the Estimate	0.015			0.025		

Source: The authors

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Table 10 presents a summary of the factors affecting the PK efficiency score from second-stage regression. The coefficients for SIZE and NPA are negative for public sector banks, indicating that as size and NPA increase, PSB efficiency decreases. Conversely, private banks exhibit a positive and significant coefficient for size, indicating that as size increases, PK efficiency also increases. The NPA coefficient is unfavourable for both bank sections. It suggests NPA hurts banks' efficiency. The coefficient for CAR is positive for public sector banks, indicating that CAR positively influences their efficiency. In contrast, for private-sector banks, the relationship is reversed: CAR is found to negatively influence bank efficiency. DEPLIB, Priority, and Manage are found to be insignificant for both bank groups, suggesting they do not contribute to bank efficiency.

Conclusion

This work seeks to determine the performance efficiency of Indian banks by utilising a non-radial orientation-free measure. PK efficiency is a generalised and advanced measure compared to existing orientation-specific traditional DEA measures. This study evaluated a panel of 30 banks from 2011 to 2023 using Pareto-Koopmans' technical efficiency and compared it with existing BCC input- and output-focused technical efficiency scores. A set of three inputs and three outputs was selected to run PK & BCC technical efficiency calculations concerning two specific bank frontiers. The BCC technical efficiency scores indicated that banks are highly efficient; however, these scores decreased slightly under the PK model. The PK technical efficiency scores indicate considerable scope for improvement in private-sector banks. By dividing the overall efficiency score among individual resources and performance elements, the study helped identify inefficient sources of performance. Overall, banks are advised to improve their efficiency by focusing on two key factors: labour and physical capital. The study also attempted to examine factors affecting the PK efficiency score by using second-stage regression. NPA reduces the efficiency of both bank groups, while bank size positively influences the competence score of private banks. The capital adequacy ratio positively influences the efficiency of public sector banks, whereas the opposite is true for private banks. While the study has provided new insights into the performance of the Indian banking sector, it also offers scope for further analysis and improvement.

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