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Technical Efficiency and Its Determinants: A DEA and Tobit Analysis of Indian Public Sector Banks (2015–16 to 2024–25)

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ABSTRACT

This paper examines the technical efficiency of Indian Public Sector Banks during 2015–16 to 2024–25 using a two-stage Data Envelopment Analysis (DEA)–Tobit regression framework. In the first stage, DEA estimates overall technical efficiency (CCR), pure technical efficiency (BCC), and scale efficiency (SE), while the second stage employs Tobit regression to identify the determinants of bank efficiency. The DEA results indicate a gradual improvement in bank efficiency over the study period. The BCC model identifies more efficient banks than the CCR model, suggesting that scale inefficiency, rather than managerial inefficiency, was the primary source of inefficiency. Furthermore, the scale efficiency results indicate that banks progressively moved towards their optimal scale of operation. The Tobit regression results reveal that Bank Size [Ln (Total Assets)] has a significant negative effect on efficiency, whereas Capital Adequacy Ratio (CAR), Net NPA Ratio, Return on Assets (ROA), and Cost-to-Income Ratio (CIR) do not have statistically significant effects. Overall, the findings suggest that improving resource utilization and operating at an optimal scale are essential for enhancing the efficiency and long-term performance of Indian Public Sector Banks.

Keywords: Data Envelopment Analysis (DEA), Tobit Regression, Technical Efficiency, Public Sector Banks, Total Deposits, Operating Expenses, Loans and Advances, Investments, Bank Size, Capital Adequacy Ratio (CAR), Return on Assets (ROA), Net Non-Performing Assets (Net NPA).

1. Introduction

The banking sector plays a crucial role in the economic development of any country by mobilizing savings, providing credit, facilitating investment, and supporting business activities. A sound and efficient banking system promotes capital formation, facilitates financial intermediation, and contributes to sustainable economic growth. In India, Public Sector Banks (PSBs) have traditionally been the backbone of the banking system due to their extensive branch network, large customer base, and significant contribution to financial inclusion. These banks play an important role in implementing government initiatives, extending credit to priority sectors, and ensuring the availability of banking services across both urban and rural regions. Over the past decade, the Indian banking industry has witnessed several structural and regulatory changes, including bank mergers, the implementation of the Insolvency and Bankruptcy Code (IBC), technological advancements, and the rapid expansion of digital banking services. At the same time, increased competition from private sector banks and financial technology (FinTech) firms has transformed the operating environment of commercial banks. While these developments have strengthened the banking sector, they have also increased the need for banks to improve their operational efficiency, optimize resource utilization, and maintain long-term financial sustainability.

Efficiency has become an important indicator of bank performance because it reflects how effectively banks transform their inputs into financial outputs. An efficient banking system not only improves profitability but also strengthens financial stability and supports sustainable economic growth. In the case of Public Sector Banks, assessing technical efficiency is particularly important as they continue to operate under increasing competitive pressure while fulfilling various social and developmental responsibilities. In addition, rising operating costs, changing customer expectations, stricter regulatory requirements, and continuous technological innovation have made efficient resource management more critical than ever. Efficient utilization of resources enables banks to improve service quality, reduce operational costs, strengthen their competitive position, and enhance financial performance. Regular assessment of technical efficiency also helps identify operational strengths and weaknesses, thereby supporting informed managerial decisions and effective policy formulation. Furthermore, efficiency analysis provides valuable information to regulators in designing policies that encourage better resource allocation and improve the overall productivity of the banking sector. Therefore, evaluating the technical efficiency of Public Sector Banks can provide useful insights for policymakers, regulators, and bank management in improving operational performance and ensuring the sustainable growth of the banking industry.

In this context, the present study examines the technical efficiency of selected Indian Public Sector Banks during the period 2015–16 to 2024–25 using Data Envelopment Analysis (DEA). DEA is a widely accepted non-parametric technique for measuring the relative efficiency of decision-making units by considering multiple inputs and outputs simultaneously. Compared with conventional financial ratio analysis, DEA provides a more comprehensive assessment of operational performance by identifying efficient and inefficient banks relative to the best-performing institutions in the sample. To further examine the factors influencing technical efficiency, the study applies the Tobit regression model in the second stage of analysis. This approach enables the study not only to estimate efficiency scores but also to identify the bank-specific factors associated with variations in technical efficiency. The findings of the study are expected to contribute to the existing literature on banking efficiency and provide useful insights for policymakers, bank management, and regulatory authorities in formulating appropriate strategies to improve operational performance and ensure the efficient utilization of resources in Indian Public Sector Banks.

2. Literature Review

The efficiency of the banking sector has been widely examined using Data Envelopment Analysis (DEA) and its extensions. Earlier studies on Indian banks primarily focused on measuring technical efficiency by adopting different approaches, such as the production approach, intermediation approach, and value-added approach. Das and Ghosh (2006) employed DEA and Tobit regression to analyse the efficiency of Indian scheduled commercial banks and reported that medium-sized public sector banks performed relatively better than other banks. Similarly, Bodla and Bajaj (2010) evaluated private sector banks using an input-oriented CCR DEA model and found that only a limited number of banks were fully efficient, while most banks exhibited operational inefficiencies.

Subsequent studies extended the efficiency analysis by comparing public and private sector banks and incorporating different DEA models. Karimzadeh (2012) reported that public sector banks outperformed private sector banks during the study period, whereas Narayanasamy and Muthulakshmi (2014) observed that bank efficiency was positively associated with return on assets and negatively associated with non-performing assets. Baidya and Mitra (2012) also assessed the technical efficiency of Indian public sector banks using DEA and the Andersen–Petersen Super-Efficiency model, highlighting considerable variation in efficiency among banks.

More recent studies have focused on the impact of regulatory reforms, technological developments, and bank consolidation on efficiency. Sangeetha (2020) examined the technical efficiency and productivity of Indian public sector banks using DEA and the Malmquist Productivity Index and concluded that although most public sector banks operated efficiently, there remained scope for improving productivity and resource utilization. Following the consolidation of public sector banks, Rekha Rao Subraveti and Niranjan Reddy (2022) analysed the post-merger efficiency of twelve public sector banks and identified employee expenses and total operating expenses as major sources of inefficiency. Kundu and Banerjee (2024) further compared the operational efficiency of public and private sector banks and reported that private sector banks were relatively more efficient, although larger and older public sector banks demonstrated better operational performance. Similarly, Arora et al. (2025) found that rising non-performing assets adversely affected bank efficiency, while Das et al. (2025) reported that post-merger operational performance varied considerably across banks despite improvements in scale efficiency.

Overall, the existing literature suggests that DEA has become one of the most widely accepted methods for evaluating banking efficiency and that Tobit regression is commonly employed to identify the determinants of efficiency. However, the findings across studies remain mixed, particularly regarding the relative performance of public sector banks and the factors influencing their efficiency. Moreover, much of the existing evidence relates to earlier periods or focuses on specific reforms such as bank mergers. These observations provide the basis for the present study, which evaluates the technical efficiency of selected Indian Public Sector Banks during 2015–16 to 2024–25 using DEA and further examines its determinants through the Tobit regression model.

3. Research Gap

The existing literature has extensively examined the efficiency of Indian banks using Data Envelopment Analysis (DEA) under different approaches and models, including CCR, BCC, SBM, and the Malmquist Productivity Index. While several studies have focused on public sector banks, private sector banks, or comparative analyses, most of them have covered periods ending before or immediately after the public sector bank mergers of 2020. Consequently, there is limited evidence on the efficiency performance of Indian public sector banks over a more recent and extended period.

Furthermore, although a few studies have integrated DEA with second-stage regression techniques to examine the determinants of bank efficiency, comprehensive evidence for the post-merger and post-pandemic period remains limited. Therefore, the present study addresses these gaps by evaluating the technical efficiency of 12 Indian Public Sector Banks over the period 2015–16 to 2024–25 using Data Envelopment Analysis (DEA) and subsequently employing Tobit regression to identify the determinants of bank efficiency. The study is expected to provide updated empirical evidence on the efficiency and its determinants in the contemporary Indian banking sector.

4. Research Methodology

This study adopts a quantitative research design to evaluate the technical efficiency of 12 selected Indian Public Sector Banks and to identify the factors influencing their efficiency over the period 2015–16 to 2024–25. A two-stage analytical framework has been employed. In the first stage, Data Envelopment Analysis (DEA) is used to estimate the technical efficiency of the selected banks. In the second stage, the Tobit regression model is applied to examine the determinants of technical efficiency. This two-stage approach provides a comprehensive assessment by measuring the efficiency levels of Public Sector Banks and identifying the factors responsible for variations in their technical efficiency.

4.1 Data and Sample

The study is based on a balanced panel dataset comprising 12 Indian Public Sector Banks for the period 2015–16 to 2024–25. Secondary data have been sourced from the CMIE ProwessIQ database, a widely used source of standardized financial information on Indian banking institutions. The study period encompasses major structural and regulatory developments in the Indian banking sector, including the implementation of the Insolvency and Bankruptcy Code (IBC), the consolidation of Public Sector Banks, and the expansion of digital banking services. The use of a balanced panel dataset facilitates a consistent evaluation of the technical efficiency of the selected banks throughout the study period.

4.2 Measurement of Efficiency Using Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA), originally developed by Charnes, Cooper, and Rhodes (1978) and later extended by Banker, Charnes, and Cooper (1984), is a non-parametric linear programming technique used to evaluate the relative efficiency of homogeneous Decision-Making Units (DMUs). Unlike parametric approaches, DEA does not require the specification of a functional form for the production process. Instead, it constructs an efficient frontier from the observed data and measures the relative efficiency of each DMU by comparing multiple inputs and outputs simultaneously. In the present study, each selected Indian Public Sector Bank is treated as a Decision-Making Unit (DMU).

The study adopts an input-oriented DEA model based on the intermediation approach, which considers banks as financial intermediaries that transform deposits and operating expenses into earning assets. The input-oriented approach is considered appropriate because bank management has greater control over the utilization of inputs than over the generation of outputs. Consequently, the analysis focuses on identifying the proportional reduction in inputs required to achieve efficiency while maintaining the existing level of outputs.

DEA can be formulated in two mathematically equivalent forms: the Multiplier (Primal) Model and the Envelopment (Dual) Model. The Multiplier Model determines the optimal weights assigned to inputs and outputs for each DMU to maximize its relative efficiency score. The Envelopment Model, on the other hand, constructs the efficient frontier by enveloping the observed data and evaluates each DMU relative to that frontier. Although both formulations produce identical efficiency scores under the same assumptions, the present study employs the input-oriented Envelopment (Dual) Model because it provides a computationally efficient framework for estimating efficiency and is the formulation most commonly adopted in empirical DEA studies. In addition, the Envelopment formulation facilitates the identification of benchmark (reference) DMUs and the estimation of target input reductions for inefficient banks.

To evaluate the efficiency of the selected Public Sector Banks, the study estimates both the CCR and BCC models under different returns-to-scale assumptions.

Overall Technical Efficiency (OTE): Estimated using the CCR (Charnes, Cooper, and Rhodes) model under the assumption of Constant Returns to Scale (CRS). This measure captures the overall efficiency of a bank by incorporating both managerial performance and scale efficiency.

Pure Technical Efficiency (PTE): Estimated using the BCC (Banker, Charnes, and Cooper) model under the assumption of Variable Returns to Scale (VRS). It measures managerial efficiency after removing the influence of scale effects.

Scale Efficiency (SE): Calculated as the ratio of Overall Technical Efficiency (OTE) to Pure Technical Efficiency (PTE). It indicates whether a bank is operating at its most productive or optimal scale.

The input-oriented CCR envelopment model is expressed as follows:

$$\min \theta$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \; i = 1, \dots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \; r = 1, \dots, s$$

$$\lambda_j \geq 0, \; j = 1, \dots, n$$

Where:

- θ= Technical efficiency score
- x_{ij}= Quantity of input $i$used by DMU j
- y_{rj}= Quantity of output $r$produced by DMU j
- λ_j= Intensity variable
- m= Number of inputs
- s= Number of outputs
- n= Number of Decision-Making Units (DMUs)

The BCC model is obtained by incorporating the following convexity constraint into the CCR model:

$$\sum_{j=1}^{n} \lambda_j = 1$$

Finally, Scale Efficiency (SE) is computed as:

$$SE = \frac{OTE}{PTE}$$

Where:

- **SE =** Scale Efficiency
- **OTE =** Overall Technical Efficiency
- **PTE =** Pure Technical Efficiency

The efficiency scores obtained from the DEA model range from 0 to 1, where a score of 1 indicates that a bank lies on the efficient frontier and is considered relatively efficient, whereas a score of less than 1 indicates the presence of technical inefficiency.

4.3 Selection of Input and Output Variables

The input and output variables used in this study are selected based on the intermediation approach, which considers banks as financial intermediaries that mobilize deposits and transform them into earning assets. This approach has been widely adopted in the banking efficiency literature and is considered appropriate for evaluating the operational performance of commercial banks. Accordingly, the following input and output variables are used in the DEA model.

Input Variables

Total Deposits: represent the primary source of funds mobilized by banks and reflect their ability to attract financial resources for lending and investment activities.

Operating Expenses: include administrative, personnel, and other operating costs incurred in carrying out banking operations. These expenses represent the resources consumed in the intermediation process.

Output Variables

Loans and Advances: represent the principal earning assets of banks and constitute their core lending activity. They indicate the bank's ability to convert mobilized funds into productive credit.

Investments: include investments in government securities and other approved financial instruments that generate income and contribute to the overall earning capacity of banks.

4.4 Second Stage: Tobit Regression Analysis

Following the estimation of efficiency scores using Data Envelopment Analysis (DEA), a second-stage Tobit regression model is employed to examine the bank-specific determinants of technical efficiency. The DEA efficiency scores obtained in the first stage serve as the dependent variable in the Tobit model. Since these efficiency scores are bounded between 0 and 1, the use of Ordinary Least Squares (OLS) regression may produce biased and inconsistent estimates. Therefore, the Tobit regression model, originally proposed by Tobin (1958), is employed to account for the censored nature of the dependent variable and to obtain consistent estimates of the relationship between technical efficiency and its determinants.

The explanatory variables included in the model are Bank Size [Ln (Total Assets)], Return on Assets (ROA), Capital Adequacy Ratio (CAR), Net Non-Performing Assets (Net NPA) Ratio, and Cost-to-Income Ratio (CIR). Bank Size is measured as the natural logarithm of Total Assets [Ln (Total Assets)] to reduce skewness, minimize the influence of extreme observations, improve the stability of the Tobit regression estimates, and facilitate comparison across banks of different sizes. The remaining explanatory variables are used in their original form.

The latent Tobit regression model estimated in the study is specified as follows:

$$TE_{it}^{*} = \beta_0 + \beta_1 LnTA_{it} + \beta_2 ROA_{it} + \beta_3 CAR_{it} + \beta_4 NNPA_{it} + \beta_5 CIR_{it} + \varepsilon_{it}$$

Where,

$$TE_{it} = \begin{cases} 0, & \text{if } TE_{it}^{*} \leq 0, \\ TE_{it}^{*}, & \text{if } 0 < TE_{it}^{*} < 1, \\ 1, & \text{if } TE_{it}^{*} \geq 1. \end{cases}$$

Where:

- TE_{it}^{*}= Latent (unobserved) technical efficiency score
- TE_{it}= Observed DEA technical efficiency score
- $LnTA$= Natural Logarithm of Total Assets (Bank Size)
- ROA= Return on Assets
- CAR= Capital Adequacy Ratio
- $NNPA$= Net Non-Performing Assets Ratio
- CIR= Cost-to-Income Ratio
- β_0= Intercept
- $\beta_1 - \beta_5$= Regression coefficients

- ε_{it}= Random error term
- i= Selected Public Sector Banks
- t= Financial year (2015–16 to 2024–25)

The latent variable TE_{it}^{*}represents the underlying technical efficiency of a bank, whereas the observed DEA technical efficiency score $(TE_{it})$is bounded between 0 and 1. The Tobit model estimates the effect of bank-specific characteristics on technical efficiency while explicitly accounting for the censored nature of the dependent variable. The model is estimated in R using the AER package through the Maximum Likelihood Estimation (MLE) method. Statistical significance is assessed at the 1%, 5%, and 10% significance levels.

5. Data Analysis and Interpretation

Table 1. Overall Technical Efficiency of Selected Public Sector Banks under Constant Returns to Scale (CRS) during the Period 2015–16 to 2024–25

Year	No. of Banks	No. of Efficient Banks	Mean CCR Efficiency (M)	Standard deviation (SD)	Coefficient of variation (CV %)
2015-16	12	2	0.932	0.046	4.95
2016-17	12	2	0.946	0.057	6.12
2017-18	12	3	0.924	0.063	6.89
2018-19	12	5	0.957	0.051	5.42
2019-20	12	2	0.948	0.046	4.86
2020-21	12	6	0.966	0.038	4.01
2021-22	12	5	0.958	0.041	4.34
2022-23	12	4	0.965	0.035	3.67
2023-24	12	6	0.976	0.035	3.62
2024-25	12	5	0.970	0.040	4.16

Source: Author's computation using DEAFrontier.

Table 1 presents the Overall Technical Efficiency (CCR) scores of the selected Public Sector Banks under the assumption of Constant Returns to Scale (CRS) during the period 2015–16 to 2024–25. The results indicate that the selected banks maintained a relatively high level of overall technical efficiency throughout the study period. The mean CCR efficiency score ranged from 0.924 in 2017–18 to 0.976 in 2023–24, increasing from 0.932 in 2015–16 to 0.970 in 2024–25. Although the average efficiency declined slightly in 2017–18, this may be associated with continued asset-quality stress and high NPAs among Public Sector Banks. Following the Asset Quality Review (AQR), increased recognition of stressed advances as NPAs led to higher provisioning requirements and pressure on bank performance. The gross NPA ratio of PSBs reached 14.6% in 2017–18, compared with 11.7% in the previous year (Ministry of Finance, 2018; RBI, 2018).

The number of fully efficient banks also showed a positive trend during the study period. Only two banks achieved full efficiency in 2015–16, 2016–17, and 2019–20, whereas the number increased to six banks in 2020–21 and 2023–24. Although the average efficiency score declined slightly in 2017–18, the subsequent years witnessed a steady recovery, indicating improvements in operational efficiency and resource utilisation.

The values of the standard deviation (SD) and coefficient of variation (CV) further reveal that variation in efficiency across banks gradually declined over the study period. The SD decreased from 0.063 in 2017–18 to 0.035 in 2022–23 and 2023–24, while the CV fell from 6.89% to 3.62% over the same period. The declining dispersion indicates increasing consistency in efficiency levels across the selected banks. Overall, the CCR results suggest a steady improvement in technical efficiency, although the mean CCR efficiency remained below unity, indicating that some banks continued to operate below the efficient frontier.

Table 2. Pure Technical Efficiency of Selected Public Sector Banks under Variable Returns to Scale (VRS) during the Period 2015–16 to 2024–25

Year	No. of Banks	No. of Efficient Banks	Mean BCC Efficiency (M)	Standard deviation (SD)	Coefficient of variation (CV %)
2015-16	12	4	0.966	0.040	4.17
2016-17	12	7	0.970	0.051	5.30
2017-18	12	6	0.954	0.050	5.30
2018-19	12	6	0.971	0.044	4.60
2019-20	12	8	0.980	0.035	3.59
2020-21	12	7	0.972	0.037	3.86
2021-22	12	7	0.967	0.042	4.36
2022-23	12	5	0.973	0.031	3.25
2023-24	12	8	0.979	0.033	3.34
2024-25	12	9	0.979	0.039	3.93

Source: Author's computation using DEAFrontier.

Table 2 presents the Pure Technical Efficiency (BCC) scores of the selected Public Sector Banks under the assumption of Variable Returns to Scale (VRS) during the period 2015–16 to 2024–25. The results indicate that the selected banks maintained a relatively high level of pure technical efficiency throughout the study period. The mean BCC efficiency score ranged from 0.954 in 2017–18 to 0.980 in 2019–20, remaining above 0.95 in every year. Although the average efficiency declined slightly in 2017–18, this may be attributed to the asset-quality stress and high level of NPAs discussed earlier. The subsequent recovery in efficiency indicates improvements in managerial and operational practices.

The number of fully efficient banks exhibited a gradual improvement over the study period. Only four banks were fully efficient in 2015–16, whereas the number increased to seven banks in 2016–17, 2020–21, and 2021–22, reached eight banks in 2019–20 and 2023–24, and further increased to nine banks in 2024–25. The increasing number of banks operating on the efficiency frontier indicates an improvement in managerial efficiency over time.

The standard deviation (SD) and coefficient of variation (CV) further provide evidence regarding the consistency of pure technical efficiency across banks. The SD declined from 0.051 in 2016–17 to 0.031 in 2022–23, while the CV decreased from 5.30% to 3.25% over the same period. The lower dispersion in the later years suggests greater uniformity in managerial efficiency among the selected Public Sector Banks.

Overall, the BCC results indicate that the selected Public Sector Banks achieved relatively high levels of pure technical efficiency throughout the study period. The consistently high mean BCC scores, together with the increasing number of fully efficient banks and lower dispersion in later years, suggest improvements in managerial performance and resource utilisation. However, the mean BCC efficiency remained below unity, indicating scope for further improvement among relatively less efficient banks.

Table 3. Scale Efficiency of Selected Public Sector Banks during the Period 2015–16 to 2024–25

Year	No. of Banks	No. of Scale-Efficient Banks	Mean Scale Efficiency (M)	Standard deviation (SD)	Coefficient of variation (CV %)
2015-16	12	2	0.965	0.038	3.97
2016-17	12	2	0.964	0.044	4.56
2017-18	12	3	0.968	0.034	3.53
2018-19	12	5	0.986	0.023	2.37
2019-20	12	2	0.967	0.039	4.00
2020-21	12	6	0.992	0.018	1.77
2021-22	12	5	0.991	0.016	1.58
2022-23	12	4	0.992	0.012	1.19
2023-24	12	6	0.997	0.007	0.67
2024-25	12	5	0.984	0.029	2.94

Source: Author's computation using DEAFrontier.

Table 3 presents the Scale Efficiency (SE) scores of the selected Public Sector Banks during the period 2015–16 to 2024–25. Scale efficiency measures whether banks operate at an optimal scale by comparing overall technical efficiency under the CCR model with pure technical efficiency under the BCC model. The results indicate that the selected Public Sector Banks maintained a high level of scale efficiency throughout the study period. The mean scale efficiency score ranged from 0.964 in 2016–17 to 0.997 in 2023–24, indicating that most banks operated relatively close to their optimal scale. Overall, the mean scale efficiency improved from 0.965 in 2015–16 to 0.984 in 2024–25, although the highest value of 0.997 was recorded in 2023–24.

The number of scale-efficient banks also showed an overall positive trend during the study period. Only two banks were scale-efficient in 2015–16, 2016–17, and 2019–20, whereas five banks achieved scale efficiency in 2018–19, 2021–22, and 2024–25, and six banks reached the efficiency frontier in 2020–21 and 2023–24. This trend indicates that a larger proportion of Public Sector Banks operated at or close to their optimal scale in the later years. The standard deviation (SD) and coefficient of variation (CV) further indicate that differences in scale efficiency across banks gradually narrowed over time. The SD declined from 0.044 in 2016–17 to 0.007 in 2023–24, while the CV decreased from 4.56% to 0.67% over the same period. The lower dispersion observed in the later years suggests greater consistency in scale efficiency among the selected Public Sector Banks.

Overall, the scale efficiency results indicate a general improvement in the operating scale of the selected Public Sector Banks throughout the study period. The increase in mean scale efficiency, together with the rise in the number of scale-efficient banks and the decline in inter-bank variation, suggests that the selected banks increasingly operated closer to their optimal scale. These findings, when considered alongside the CCR and BCC results, suggest that improvements in both managerial efficiency and scale efficiency contributed to the overall enhancement of bank efficiency during the study period.

Table 4. Benchmark Banks under the CCR and BCC Models

Year	CCR Benchmark Bank(s)	BCC Benchmark Bank(s)
2015-16	SBI and UCO Bank	SBI, UCO Bank, Bank of Maharashtra, Punjab & Sind Bank
2016-17	SBI, Bank of Baroda	SBI, Bank of Baroda, Union Bank of India, Indian Bank, UCO Bank, Punjab & Sind Bank
2017-18	SBI, Bank of Baroda, Indian Bank	SBI, UCO Bank, Bank of Baroda, Canara Bank, Indian Bank, Punjab & Sind Bank
2018-19	SBI, Bank of Baroda, Bank of Maharashtra, Indian Bank, UCO Bank	SBI, Bank of Baroda, UCO Bank, CBI, Indian Bank, Bank of Maharashtra, Punjab & Sind Bank
2019-20	Indian Bank, UCO Bank	SBI, Bank of Baroda, CBI, Punjab National Bank, Indian Bank, UCO Bank, Punjab & Sind Bank
2020-21	SBI, UCO Bank, Bank of Baroda, Indian Bank, Bank of Maharashtra	SBI, UCO Bank, Bank of Baroda, Indian Bank, Bank of Maharashtra, Punjab & Sind Bank
2021-22	SBI, UCO Bank, Bank of Baroda, Bank of Maharashtra, Punjab & Sind Bank	SBI, Bank of Baroda, Union Bank of India, UCO Bank, CBI, Bank of Maharashtra, Punjab & Sind Bank
2022-23	Bank of Baroda, CBI, Bank of Maharashtra, Punjab & Sind Bank	SBI, Bank of Baroda, CBI, Bank of Maharashtra, Punjab & Sind Bank
2023-24	Indian Bank, Indian Overseas Bank,	SBI, Bank of Baroda, CBI, Indian

	Punjab & Sind Bank, Bank of Baroda, CBI, Bank of Maharashtra	Bank, Indian Overseas Bank, Bank of India, Bank of Maharashtra, Punjab & Sind Bank
2024-25	Bank of Baroda, Indian Overseas Bank, Bank of Maharashtra, CBI, Indian Bank	SBI, Bank of Baroda, CBI, Punjab National Bank, Indian Bank, Bank of India, Indian Overseas Bank, Bank of Maharashtra, Punjab & Sind Bank

Source: Author's computation based on DEAFrontier benchmark output.

Table 4 presents the benchmark banks identified under the CCR and BCC models during the period 2015–16 to 2024–25. The results indicate that the benchmark banks varied across the study period, reflecting changes in the efficiency frontier. Under the CCR model, SBI, UCO Bank, Bank of Baroda, Indian Bank, and Bank of Maharashtra emerged as the key benchmark banks in different years. In contrast, the BCC model identified a broader set of benchmark banks, including SBI, Bank of Baroda, UCO Bank, Indian Bank, Bank of Maharashtra, Punjab & Sind Bank, CBI, Union Bank of India, Bank of India, and Canara Bank. Among these, SBI emerged as the most frequently referenced benchmark bank throughout the study period, indicating its consistent position on the efficient frontier. Overall, the benchmark analysis suggests that these efficient banks served as best-practice reference institutions, providing valuable managerial guidance for improving the operational efficiency of relatively inefficient Public Sector Banks.

Table 5. Tobit Regression Results for the Selected Public Sector Banks during the Period 2015–16 to 2024–25

Variables	Coefficient	Std. Error	z-value	p-value
(Intercept)	1.186	0.182	6.504	<0.001
Ln(Total Assets)	-0.016	0.007	-2.288	0.022
CAR	0.005	0.004	1.194	0.232
Net NPA Ratio	0.004	0.003	1.017	0.308
ROA	0.000	0.010	0.048	0.961
Cost Income Ratio (CIR)	-0.001	0.001	-1.062	0.288
Error Distribution				
Log(scale)	-2.761	0.085	-32.337	<0.001

Source: Author's computation using R.

Table 4 presents the results of the Tobit regression model estimated to identify the determinants of technical efficiency of the selected Public Sector Banks during the period 2015–16 to 2024–25. The DEA technical efficiency score is used as the dependent variable, while Bank Size [Ln(Total Assets)], Capital Adequacy Ratio (CAR), Net NPA Ratio, Return on Assets (ROA), and Cost Income Ratio (CIR) are included as explanatory variables. The Tobit model is employed because the DEA efficiency scores are bounded between 0 and 1.

The results indicate that Bank Size [Ln(Total Assets)] is the only variable with a statistically significant effect on technical efficiency. The estimated coefficient is −0.016 and is significant at the 5 percent level ($p = 0.022$), indicating a negative relationship between bank size and technical efficiency. This suggests that larger Public Sector Banks tended to exhibit slightly lower technical efficiency than relatively smaller banks, possibly because increases in bank size are accompanied by greater organizational complexity and coordination costs.

The estimated coefficients of CAR, Net NPA Ratio, and ROA are positive, whereas the coefficient of the Cost Income Ratio is negative. However, none of these variables is statistically significant, as their p-values exceed 0.05. Therefore, the study does not provide sufficient statistical evidence to conclude that capital adequacy, asset quality, profitability, or operating cost efficiency significantly influence technical efficiency. Overall, the Tobit regression results indicate that Bank Size is the only significant determinant of technical efficiency, while the remaining explanatory variables do not exhibit a statistically significant relationship with the technical efficiency of the selected Public Sector Banks.

Table6. Descriptive Statistics of the Input and Output Variables Used in the DEA Model

Variable	Mean (M)	Standard Deviation (SD)	Min.	Max.	Coefficient of Variation (CV)	Skewness	Kurtosis
Total Deposits	100851.110	122705.729	12060.1	621229.5	121.670	2.636	6.790
Operating expenses	7119.682	8794.890	872	47390.3	123.529	2.739	7.495
Loans & advances	71719.806	91170.565	7878.9	484165	127.1204	2.665	7.095
Investment	32467.042	42420.700	3302.2	201381	130.657	2.811	7.328

Source: Author's computation using R.

Table 5 presents the descriptive statistics of the input and output variables used in the DEA model for the selected Public Sector Banks. The results indicate considerable variation across the variables, as reflected by the relatively high standard deviations and coefficients of variation, suggesting noticeable differences in the scale of operations among the sample banks. All variables exhibit positive skewness, indicating that a few banks reported relatively higher values than the majority of the sample. Furthermore, the kurtosis values exceed three for all variables, indicating leptokurtic distributions with relatively heavier tails. Overall, the descriptive statistics reveal substantial heterogeneity in the operational characteristics of the selected Public Sector Banks, highlighting the diversity in their resource base and business activities during the study period.

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Table 7. Descriptive Statistics of the Variables Used in the Tobit Regression Model

Variables	Mean	Standard Deviation (SD)	Min.	Max.	Coefficient of Variation (CV)	Skewness	Kurtosis
Ln(Total Assets)	11.214	0.948	9.512	13.557	8.454	0.458	-0.116
CAR	13.91	2.58	9.04	20.5	18.547	0.163	-0.774
Net_NPA	4.392	3.434	0.2	15.3	78.176	0.897	0.350
ROA	0.065	0.928	-3.000	1.800	1427.600	-1.108	1.336
Cost_Income	83.762	5.567	67.600	101.200	6.647	0.005	0.952

Source: Author's computation using R.

Table 6 presents the descriptive statistics of the variables used in the Tobit regression model for the selected Public Sector Banks during the period 2015–16 to 2024–25. The results indicate moderate variation in ln(Total Assets), CAR, and the Cost-to-Income Ratio, whereas Net NPA and particularly ROA exhibit relatively higher variability, as reflected by their coefficients of variation. The skewness values suggest that most variables are approximately symmetric, while ROA exhibits negative skewness (−1.108), which may be attributed to the presence of some negative ROA observations, resulting in a longer left tail of the distribution. The kurtosis values indicate no substantial departure from normality. Overall, the descriptive statistics suggest that the explanatory variables are suitable for the Tobit regression analysis.

6. Conclusion

This study examined the technical efficiency of 12 Indian Public Sector Banks during the period 2015–16 to 2024–25 using a two-stage Data Envelopment Analysis (DEA)–Tobit regression framework. Following the intermediation approach, Total Deposits and Operating Expenses were considered as input variables, while Loans and Advances and Investments were treated as output variables. The findings indicate a gradual improvement in the efficiency performance of the selected Public Sector Banks throughout the study period.

The DEA results show that the mean overall technical efficiency under the CCR model improved steadily, accompanied by an increase in the number of technically efficient banks over time. The BCC model consistently reported higher efficiency scores and a greater number of efficient banks than the CCR model, indicating that scale inefficiency, rather than managerial inefficiency, remained the primary source of overall technical inefficiency. The Scale Efficiency analysis further revealed that the selected banks progressively moved towards their optimal scale of operation. Moreover, the benchmark analysis identified several efficient Public Sector Banks as best-practice reference institutions, with SBI emerging as the most frequently referenced benchmark bank during the study period. These benchmark banks provide valuable guidance for relatively inefficient banks in improving resource utilization and operational performance.

The Tobit regression analysis revealed that Bank Size [Ln (Total Assets)] has a statistically significant negative effect on technical efficiency, suggesting that expansion in asset size alone does not necessarily improve bank efficiency. In contrast, Capital Adequacy Ratio (CAR), Net NPA Ratio, Return on Assets (ROA), and Cost-to-Income Ratio (CIR) were found to have no statistically significant influence on technical efficiency.

Overall, the findings suggest that improving technical efficiency in Indian Public Sector Banks depends more on achieving an optimal scale of operation and efficiently utilizing available resources than on merely expanding the size of operations. Accordingly, bank management should focus on strengthening operational efficiency, improving resource allocation, and maintaining an appropriate scale of operations to achieve sustainable performance improvements. The findings also provide useful insights for policymakers and banking regulators in designing strategies to enhance the operational efficiency, competitiveness, and long-term sustainability of Public Sector Banks.

Although the study provides important evidence on the efficiency performance of Indian Public Sector Banks, it is limited to a sample of 12 banks and employs the conventional DEA–Tobit framework. Future research may extend the analysis by including private sector and foreign banks, incorporating macroeconomic and institutional variables, or applying advanced frontier techniques such as Bootstrap DEA, the Malmquist Productivity Index, or Stochastic Frontier Analysis to provide a more comprehensive understanding of banking efficiency dynamics.

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The author(s) declare that it is not applicable.

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