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The Role of Ownership and Reforms in Shaping Bank Efficiency in India: A Two-Stage Dea Approach

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ABSTRACT

This study employs imbalanced panel data for three categories of ownership to assess the effectiveness of India's commercial financial institutions. To achieve this objective, the Data Envelopment Analysis (DEA) approach is applied. The results reveal that international banks demonstrate superior input–output efficiency compared to both public and private sector banks in India. Analyzing the efficiency variations of commercial banks further indicates that, unlike the first phase of banking sector reforms, the second phase witnessed substantial heterogeneity in bank performance. Over time, reforms have contributed to greater variability in commercial banks' efficiency levels. Moreover, the findings suggest that inefficient utilization of inputs in public and private sector banks calls for corrective measures to enhance productivity. The second-stage analysis shows that non-performing assets adversely affect efficiency scores, whereas total assets, return on assets, ownership structure, and the capital adequacy ratio exert a positive influence. Overall, foreign banks operate more efficiently than their public and private counterparts, largely due to relatively flexible regulations and more effective resource allocation practices..

Keywords: Banking Efficiency, Banking Sector Reforms, Data Envelopment Analysis, Two-Stage approach

JEL Classification: C23, E44, G21, G29

I. Introduction

Commercial banks play an essential role in emerging economies by leading in developing their financial intermediation and financial markets. Commercial banks are the fastest-growing financial intermediaries in India. In India, they dominate in providing financial services such as financial intermediation, deposit mobilisation, credit deployment, and investment services to achieve specificsocial objectives. In India's Post-independence period, banks played a critical part in the country's socio-economic development. Its role in developing agriculture, industry and businesses is paramount and has ushered in economicprogress.Then, the rationalisation of 14 commercial banks in 1969 brought about 70 percent of the banking business under the public sector's direct control, ownership and management. Since then, public sector banks have hadthelion's share in the country's banking business. (Report on Currency and Finance, RBI, 2006-2008 Changes in Indian Banking).

The government is also striving for complete convertibility of capital accounts. The Reserve Bank of India (RBI) released guidelines for foreign banks to enter the Indian market as well as suggestions for private sector bank ownership and governance in February 2005. In May 2005, the RBI also released its rules for bank mergers and amalgamations. The nation's financial landscape has undergone significant transformation as a result of these advancements. Therefore, it would be beneficial.

To evaluate Indian commercial banks' effectiveness, present study will help policymakers, economists, and international development organisations evaluate and enhance the economic performance of India's banking industry. The purpose of this study is to compare the 1992–2022 performance of India's commercial banks. It makes use of an imbalanced panel data analysis approach that allows us to ascertain whether technical efficiency fluctuates over time. The paper is structured into five sections: the first presents the Introduction, the second provides a Review of Literature, the third outlines the Methodology, the fourth discusses the Empirical Findings, and the fifth offers the Conclusion

II. Review Of Literature:

Berger and Humphrey (1997) examined more than 100 papers from twenty one countries that examined the relationship between financial institution efficiency and frontier efficiency. They came to the conclusion that the bulk of study on banking efficiency (about 95 percent, with the majority in the US) concentrated on banks in developed nations, suggesting that further studies in developing nations are required. Drake and Hall (2003) studied 149 Japanese banks and came to know that pure technical efficiency declines with scale up to the middle-ranking institutions. A comparative analysis of European banking efficiency between 1993 and 1997 was reviewed by Casu and Molyneux (2003). They discovered differences in the efficiency of European banking systems, which they attribute to national factors including banking technology laws and management strategies. Han (2005) conducted research on banks between 1995 and 2002 and his results showed that throughout the course of the study period, controlling for these parameters improved average efficiency and reduced average volatility. Isik and Hassan (2003) came to know that significant negative correlation between efficiency and bank size in Turky. Ariff and Can (2008) work shows that Chinese banks size and their efficiency had inverse relation, which means small size have have more efficiency and vice-versa.

Sincere attempts to investigate banking efficiency in India began in 1997. Bhattacharya, Lovell, and Sahay conducted research in 1997. and they concluded that public sector banks are the most efficient at using resources to deliver financial services to their clients, whereas private-owned banks are the least effective. Result of Bhattacharyya and Kumbhakar (1997) shows that by establishing a favourable competitive environment, deregulation is likely to increase technical advancement and productivity setting to boost productivity. Das (1997) evaluated Indian bank’s technical and scale efficiency before and after reform. He discovered that banks’s inefficiency was more technical than allocative, indicating waste or underutilisation of resources. Das (2000) examined the efficiency of public sector banks in 1998 and concluded that the inefficiencies in these banks were mostly caused by both technical and allocative inefficiencies. Finally, Kumbhakar and Sarkar (2003) looked at Indian banking's efficacy between 1986 and 2000. Their findings showed that deregulation in the Indian banking sector increased cost inefficiency while slowing the rate of inefficiency.

Shanmugam and Das (2004) studied 94 banks' technological efficiency between 1992 and 1997. The findings indicate that both type of banks (public and private) outperform their competitors. From 1997 to 2003, Das et al. (2005) worked on the effectiveness of various types of Indian banks. It was observed that public banks exhibit significant differentiation regarding cost-efficiency as well as input- and output-oriented technical efficiency.

Semsarma (2006) study conclude that deregulation of the banking sector was successful in reducing intermediate costs and raising productivity. Between 2004 and 2005, Kumar and Gulati (2008) investigation revealed the inefficient utilization of internal resources and execution failure were the main causes of technical negligence in India's banking industry. Sanyal and Shankar (2011) examined how ownership and competition affected bank productivity in India between 1992 and 2004 and came to the conclusion that private banks outperformed in terms of productivity and development than both public and international banks. They also discovered that competition harmed all other institutions while benefiting private sector banks. Kumar (2012) worked after post-deregulation period and came to know that the primary factor contributing to cost inefficiency in the Indian public sector banking industry is technical inefficiency, rather than allocative inefficiency. The impact of the global financial crisis on Indian banks' profitability was investigated by Gulati and Kumar (2016). According to their results, efficiency of banks' profit had a little decline but quickly recovered during this crisis. Bedunenko and Kumbhakar (2017) discovered that commercial banks, especially international banks, fell behind their cost frontier, whereas only state banks increased their cost efficiency. In their 2020 study on the financial stability of Indian banks, Gupta and Kashiramka posed the following query: Does the creation of liquidity important for 2017–2019? According to the findings, a bank can preserve its financial stability by raising liquidity. The impact, however, differs depending on the size of the bank.

It has also been demonstrated that banks in the private sector are more stable than those in the public sector. Only a small number of studies, meanwhile, have focused exclusively on Indian commercial banks' efficiency. The current study is a little attempt to fill a knowledge vacuum, clarify the reasons behind inefficiency, and offer a policy recommendation.

III. Methodology

Data Envelopment Analysis (DEA) is a way to utilize arithmetic to figure out how well decision-making units (DMUs), like banks or companies, are doing based on input and output data. DEA compares the performance of each DMU to a production frontier, which is also called the envelopment surface. Instead of figuring out how efficient something is in absolute terms, DEA looks at each unit in respect to the "best-performing" peers in the dataset.

Each DMU gets an efficiency score between 0 and 1, with a value of 1 suggesting that the DMU is fully efficient and is on the production frontier. Lower scores mean that the DMU is less efficient than others. This makes it possible to find both efficient and inefficient units in the sample.

The CCR model (created by Charnes, Cooper, and Rhodes in 1978) and the BCC model (created by Banker, Charnes, and Cooper in 1984) are the most important DEA models. The main difference between these two models is how they handle returns to scale:

The CCR model posits that returns to scale are constant (CRS), which means that output changes in direct proportion to input.

The BCC model, on the other hand, lets returns to scale (VRS) change, which means that efficiency can change depending on how big the business is.

These models work well together to create a flexible and strong framework for analyzing efficiency in different fields. The study's evaluation period ran from 1992 (the year before the change) until 2022 (the most recent data available).

The CRR Model

Charnes, Cooper, and Rhodes used the greatest ratio of weighted outputs to weighted inputs for a DMU to determine its efficiency, as long as all other DMUs have ratios less than 1.

Specifically, $max\ h\text{-}_o(u,v) = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$ (1)

Subject to:

$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad j = 1,2,3 \ldots .n$ (2)

$u_r \geq 0$, $r = 1, 2,3 \ldots .s$ (3)

$v_i \geq 0$, $i = 1,2,3 \ldots m$ (4)

where,

x_{ij} = suggests the observed amount of input of the i^{th} type of the j^{th}DMU(x_{ij}>0, i=1, 2, 3,……m; j= 1,2, 3…..n), y_{rj}indicates the observed amount of output of the r^{th} type for the j^{th} DMU (y_{rj}>0, r=1,2, 3,…….s, j=1,2, 3,……n),u_r denotes the weight that determinesoutput,$v_i$indicates the weight that determines input, rindicatessdifferent outputsi denotes m different inputs, j indicates n different DMUs.

One disadvantage of this ratio formulation is that it has unlimitedsolutions.To avoid this,one can impose constraints.

$$\sum_{i=1}^{m} v_i\, x_{i0} = 1 \tag{5}$$

Which provides:

$$\max z_o = \sum_{r=1}^{s} u_r\, y_{r0} \tag{6}$$

Subject to

$$\sum_{r=1}^{s} u_r\, y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \tag{7}$$

$$\sum_{i=1}^{m} v_i\, x_{i0} = 1 \tag{8}$$

$u_r \geq 0$, r = 1,2, 3……….s (9)

$v_i \geq 0$, i= 1,2, 3………m (10)

The dual can be written for the above linear programming issue(for the given DMUo) as:

$$\min_{\lambda} z_o = \Theta o \tag{11}$$

subject to

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} r = 1,2,3, \dots \dots . s \qquad (12)$$

$$\Theta o x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, \qquad i = 1,2,3 \dots . . m \qquad (13)$$

$$\lambda_j, \geq 0 \qquad j = 1,2,3 \dots \dots . . n \qquad (14)$$

And solved for each DMU.ϑ_j is *DMU j*'s index of technical efficiency relative to the other *DMUs* in the sample*.* *Λ*is a *n*1* vector of constants. *Yλ*and*Xλ*is the efficient projections on the frontier. A measure of *ϑj =1* indicates that the *DMU j* is entirely technically efficient. Thus*, (1-ϑj)* measures how much *DMU j*'s inputs can be proportionately reduced without any loss in output.

BCC model

Banker, Charnes, and Cooper (1984) added the convexity constraint ∑λ =1 to the CRS DEA model to allow for variable returns to scale (VRS). The input-oriented BCC model for DMUo can therefore be expressed as follows:

$$\min_{\lambda} z_o = \theta o \qquad (15)$$

Subject to

$$\sum \lambda_j y_{r_j} \geq y_{r0}, \quad r = 1, 2 \dots . s \qquad (16)$$

$$\Theta o x_{i0} - \sum \lambda_j x_{ij} \geq 0, \; i = 1, 2, 3 \dots . . m \qquad (17)$$

$$\sum \lambda_j = 1 \qquad (18)$$

$$\lambda_j \geq 0, j = 1,2,3 \dots . . n \qquad (19)$$

Running the model above for each DMU returns BCC-efficiency scores (interpreted similarly to the CCR model). This methodology allows variable returns to scale, removing the "scaling element" of efficiency from consideration and yielding "pure technical efficiency" scores.

Scale Efficiency and Return to Scale

Traditional DEA models, especially the CCR (Charnes, Cooper, and Rhodes) model, assume all DMUs operate under Constant Returns to Scale, which is a drawback. In some cases, this assumption is correct, but in many others, scale efficiency is critical. Due to economies of scale, managerial inefficiencies, and resource constraints, companies often face Increasing or Decreasing Returns to Scale (IRS or DRS). Thus, understanding returns to scale is crucial for evaluating efficiency outcomes and making strategic decisions.

Researchers developed the BCC model (Banker, Charnes, and Cooper) to circumvent this constraint by assuming Variable Returns to Scale. The convexity constraint (∑λ_j = 1) in this model enhances the production frontier's flexibility and adaptability to DMU scale variability. Even the BCC model does not specify if a DMU has growing, constant, or decreasing returns to scale—it just supports VRS without diagnosing scale behavior.

Solving several DEA models under different scale assumptions is needed to determine a DMU's particular returns to scale. Using a modified BCC model with Non-Increasing Returns to Scale is effective. To do this, change the convexity constraint from ∑λ_j = 1 (used in the BCC model) to ∑λ_j ≤ 1. The envelopment surface varies with this relaxed limitation, limiting it to technologies with constant or diminishing returns to scale.

Compare the efficiency scores from the original BCC model and the NIRS-constrained model to determine each DMU's returns to scale:

The DMU operates under Decreasing Returns to Scale if NIRS and BCC efficiency scores are equal. If the scores differ, apply an IRS model with ∑λ_j ≥ 1 to confirm if the DMU is under Increasing Returns to Scale. A DMU operates under Constant Returns to Scale if it is efficient under CRS and VRS. These scale-specific limitations allow analysts to evaluate technical efficiency, scale efficiency, and the ideal operation scale for each unit in DEA models. This delivers more actionable data, especially in banking, education, healthcare, and manufacturing, where scale decisions affect performance.

$$\min_{\lambda} \mathrm{z_o} = \theta \mathrm{o} \qquad (20)$$

Subject to

$$\sum \lambda_j y_{rj} \geq y_{r0},\ r = 1, 2 \ldots . s \qquad (21)$$

$$\Theta o x_{i0} - \sum \lambda_j x_{ij} \geq 0, \ \ i = 1,2,3 \ldots m \qquad (22)$$

$$\sum \lambda_j \leq 1 \qquad (22)$$

$$\lambda_j \geq 0, j = 1,2,3 \ldots \ldots n \qquad (23)$$

Two-Stage Approach

This approach involves a two-stage analysis. In the first stage, a standard DEA model is applied using conventional input and output variables to calculate the efficiency scores for each Decision-Making Unit (DMU). In the second stage, these efficiency scores are regressed on a set of environmental variables to examine the influence of external factors on performance. The sign of each regression coefficient indicates the direction of the environmental variable's impact, while its statistical significance is assessed through conventional hypothesis testing methods. Given that DEA efficiency scores are bounded (typically between 0 and 1), the second-stage regression commonly employs a Tobit censored regression model, which is well-suited for handling truncated dependent variables. This model also accommodates both continuous and categorical explanatory variables. The standard Tobit formulation for a given DMU (denoted as DMUo) is defined as follows:

$$y_o^* = \beta' x_o + \varepsilon_i, \qquad (24)$$

$$\mathrm{y_o} = \mathrm{y_o^*} \text{ if } \mathrm{y_o^*} \succ 0, \text{ and } \ 0, otherwise \qquad (25)$$

Where $x_o$is a vector of explanatory variable and β'is the set of estimated parameters.$\varepsilon_i \sim \mathrm{N}(0, \sigma^2)$ denote error term.The efficiency score generated from the DEA models isyo* is a latent variable.We have examined the effects of groups of factors on technical efficiency scores using the model given as under.

$\Theta_i = \beta_o + \beta 1CAR + \beta_2 NPA + \beta_3 ROA + \beta_4 TA + \beta_5 PSB + \beta_6 FB + U_t$ (26)

Where, Θ_i, = Efficiency Scores, CAR stands for Capital Adequacy Ratio; NPA stands for Ratio of Net NPA to Net Advances; ROA stands for Return on Assets; TA stands for Total Assets; PSB= 1 if Public Sector banks; = 0 otherwise; FB= 1 if Foreign banks; = 0 otherwise.

The dummy variable Public Sector Banks (PSBs) is used to detectefficiency differences between public sector banks and other banks. The dummy variable foreign banks (FB) is introduced to investigate whether differences exist between foreign and domestic banks.

Selection of Inputs and Outputs:

There is still disagreement about how to clearly define and quantify bank inputs and outputs, as well as no comprehensive theory of banking firms. There is no perfect way to choose a bank's inputs and outputs, though, as Berger and Humphrey note (1997). Evaluating the productivity of financial institution branches suggests that the production approach may provide a more precise assessment, given that these branches primarily engage in processing client documentation and executing routine administrative tasks. Branch managers generally possess restricted authority regarding significant financial decisions, including funding allocation and investment strategies. Conversely, the intermediation approach is often considered more appropriate for assessing the overall performance of financial institutions, since interest expenses typically account for 50% to 66% of total operational costs. Each approach presents unique advantages and limitations.

Berger and Humphrey (1997) assert that no singular method is wholly comprehensive, as each method inadequately encompasses the varied operational roles present in financial institutions. Both approaches are valuable, contingent upon the study's focus and scope. This study employs a production-based approach to assess the technical efficiency of commercial banks in India from 1992 to 2022. This aligns with the study's objective of evaluating the operational efficiency of individual banks, as opposed to the financial intermediation process. The chosen output variables consist of interest income and non-interest income, including service commissions and related revenues. The input variables are deposits, labor, quantified by the number of employees, and capital, assessed through fixed assets. The data for these variables were obtained from multiple statistical tables released by Indian banks.

IV.Empirical Findings:

We use a different method to assess commercial bank efficiency post-reform than Tulkens and Van den Eeckaut (1995)'s "grand" or "inter-temporal frontier". We estimate independent yearly efficiency boundaries using the method of Isik and Hassan (2002b), Pasiouras et al. (2007), Kumar and Gulati (2009), and Bhattacharyya (1997). Instead of imposing a single threshold across several years, this allows year-by-year efficiency score review for individual institutions.

This method has two benefits, according to Isik and Hassan (2002b). First, it is more flexible than a unified multi-year frontier, allowing it to absorb annual variations in banking performance, operational situations, and regulatory contexts. Second, it mitigates data flaws and measurement imperfections, which typically change over time. Since Data Envelopment Analysis (DEA) assumes no random error, yearly frontiers allow a bank to be efficient in one year and inefficient in another, creating a more realistic efficiency picture. The great frontier is also affected by technical advances and industry restructuring, which might increase efficiency estimates. Such distortions may misrepresent bank performance in specific years. However, our year-specific frontier method lowers technological progression bias, offering a more grounded and temporally relevant assessment of bank efficiency post-reform.

Therefore, we think that our estimates of efficiency are more precise and dependable than those that may be derived from the grand frontier, which includes data on the combined inputs and outputs of commercial banks for every year. In order to determine the number of efficient banks, our study uses a distinct frontier to evaluate the efficiency of commercial banks. The efficiency of public sector banks will be compared to that of private and international banks using the common boundary. The comparison is predicated on the idea that all bank types originate from the same commercial and legal context. However, as previously said, it may be dubious to combine domestic and international banks into a single sample.

Since the input numbers seem to be the main deciding factors and because the majority of research make this assumption, our analysis is predicated on the input-oriented approach assumption. First, we'll examine the technical efficiency of commercial banks as a whole, as well as their technical efficiency and scale efficiency.

Table 1: Efficiency of Commercial Banks under constant returns to scale (CRS)

Year	**No. of banks**	**No. of efficient banks (CRS)**	**Average Efficiency (M)**	**Standard deviation (σ)**	**Coefficient of variation (C.V.)**	**I = [M-σ, M +σ]**	**Percentage of banks in I**
1992	69	6	0.617	0.205	33.28	0.412, 0.822	72.46
1993	69	8	0.581	0.237	40.86	0.344, 0.818	57.971
1994	69	7	0.658	0.24	36.55	0.418, 0.898	56.52
1995	69	8	0.621	0.205	32.99	0.416, 0.826	65.21
1996	76	10	0.506	0.265	52.37	0.241, 0.771	31.57
1997	76	10	0.639	0.196	30.62	0.443, 0.835	75
First Banking sector reform period		**49**	**0.604**	**0.225**	**37.78**		
1998	77	12	0.676	0.208	30.83	0.468, 0.884	70.13
1999	75	9	0.565	0.214	37.86	0.351, 0.779	61.33
2000	72	6	0.445	0.233	52.29	0.212, 0.678	33.33
2001	75	8	0.451	0.247	54.75	0.204, 0.698	29.33
2002	73	6	0.492	0.224	45.44	0.268,	27.39

						0.716	
2003	76	7	0.511	0.213	41.66	0.298, 0.724	42.10
2004	76	7	0.640	0.182	28.39	0.458, 0.822	80.26
2005	77	7	0.651	0.183	28.15	0.468, 0.834	80.51
2006	75	5	0.452	0.197	43.69	0.255, 0.649	40
Second Banking sector reform period		**67**	**0.543**	**0.211**	**40.34**		
2007	75	8	0.587	0.189	32.15	0.398, 0.776	76
2008	70	8	0.587	0.183	31.17	0.404, 0.77	75.71
2009	70	6	0.482	0.211	43.8	0.271, 0.693	44.28
During Global financial crisis period		**22**	**0.552**	**0.194**	**35.707**		
2010	68	7	0.260	0.271	104.08	-0.011, 0.531	4.41
2011	66	8	0.449	0.233	51.925	0.216, 0.682	25.75
2012	63	6	0.456	0.228	50.04	0.228, 0.684	26.98
2013	62	6	0.500	0.215	43.06	0.285, 0.715	40.32
2014	64	8	0.576	0.208	36.06	0.368, 0.784	68.75
2015	61	8	0.637	0.19	29.83	0.447, 0.827	77.04
2016	86	9	0.572	0.253	44.256	0.319, 0.825	41.86
2017	59	7	0.533	0.228	42.701	0.305, 0.761	45.76
2018	54	4	0.582	0.175	30.08	0.407,	85.18

						0.757	
Post Global financial crisis period		**63**	**0.507**	**0.222**	**48**		
2019	53	5	0.620	0.204	32.82	0.416, 0.824	77.35
2020	57	6	0.577	0.207	35.87	0.37, 0.784	64.91
2021	54	5	0.601	0.194	32.35	0.407, 0.795	68.51
During Covid-19 crisis period		**16**	**0.599**	**0.202**	**33.68**		
2022	73	5	0.201	0.205	101.77	-0.004, 0.406	2.74
Post Covid-19 Pandemic		**5**	**0.201**				

Source: Author's estimation from the collected data from Statistical Table Relating to Banks in India various issues.

(Note: **I: stand for Interval Scale, σ: stand for standard deviation, M stand for mean, C.V. Cefficient of varation)**

The average total technical efficiency of commercial banks from 1992 to 2022 is shown in Table 1. It's vital to remember that input-oriented overall technical efficiency measures look at how much input may be proportionally cut without changing output levels. Our research shows that Indian commercial banks have a wide range of technological efficiency levels. The average score for total technical efficiency for the research period was 0.54. This shows a technical inefficiency of 0.46, which means that if commercial banks followed best practices, they could cut their inputs—like labor, physical capital, and deposits—by about 46% while still getting the same output.

However, each bank has a different potential decrease in inputs from best practices. As an alternative, commercial banks may use the same amount of inputs to create 1.85 times (i.e., 1/.0.54) as much output. Technical issues were the cause of commercial banks' subpar performance. These banks' revenue has been squeezed and, more precisely, their operating margin has decreased as a result of the change in accounting procedures to actual realisation basis. The underuse of resources (inputs) was the main cause of the inefficiency.

One-point technical efficiency scores indicate relatively efficient commercial banks, whereas scores below one indicate inefficiency. The number of technically efficient commercial banks varies during investigation. The number of efficient banks peaked in 1998 and fell in 2018. On average, banks were marginally more efficient in the second phase of banking sector changes than in the first.

Despite this rise in efficient banks, the average technical efficiency score dropped from 60.4% in the first reform phase to 54.3% in the second. The drop reflects a wider inefficient trend notwithstanding isolated improvements. The second phase of reform showed greater diversity in commercial bank efficiency than the first. This shows that while some banks improved and became more efficient, others lagged behind, resulting in increased performance heterogeneity throughout the latter reform era. On the other hand, the average efficiency of commercial banks was 55.2% during the global financial crisis, but it dropped to 50.7% following the crisis. In the same way, total technological efficiency decreased from 59.9 percent during the COVID-19 crisis to 20.1% after the catastrophe.

During the global financial crisis, commercial banks' variability was 26.72%. which dropped to 26.02 percent in the same years. Commercial banks rose from 24.62 percent during the COVID-19 crisis to 51.43 percent after the pandemic, in contrast to this volatility. Throughout the research period, the proportion of commercial banks whose technical efficiency falls within one standard deviation of the mean ranged from 2.74 to 85.18 percent.

Table 2: Efficiency of Commercial Banks under variable returns to scale (VRS)

Year	No. of banks	No. of efficient banks (CRS)	Average Efficiency	Standard deviation	Coefficient of variation	I = [M-σ, M +σ]	Percentage of banks in I
			(M)	(σ)	(C.V.)	σ = S.D.	
1992	69	23	0.778	0.199	25.6	[0.579,0.977]	57.97
1993	69	27	0.797	0.211	26.42	[0.586,1.008]	50.72
1994	69	31	0.864	0.158	18.26	[0.706,1.022]	44.92
1995	69	26	0.85	0.159	18.66	[0.691,1.009]	49.27
1996	76	24	0.765	0.221	28.93	[0.544,0.986]	53.94
1997	76	25	0.8	0.173	21.67	[0.627,0.973]	61.84
First Banking sector reform period		156	0.809	0.187	23.26		
1998	77	21	0.794	0.179	22.52	[0.615,0.973]	63.63
1999	75	15	0.725	0.213	29.35	[0.512,0.938]	61.33
2000	72	16	0.701	0.233	33.22	[0.468,0.934]	59.72
2001	75	16	0.741	0.218	29.4	[0.523,0.959]	57.33
2002	73	20	0.756	0.212	28.07	[0.544,0.968]	57.53
2003	76	25	0.815	0.187	22.97	[0.628,1.002]	55.26
2004	76	23	0.845	0.154	18.19	[0.691,0.999]	51.31

2005	77	20	0.813	0.173	21.29	[0.64,0.986]	58.44
2006	75	15	0.715	0.223	31.2	[0.492,0.938]	58.66
Second Banking sector reform period		171	0.767	0.199	26.25		
2007	75	19	0.784	0.182	23.28	[0.602,0.966]	64
2008	70	21	0.765	0.199	25.97	[0.566,0.964]	61.42
2009	70	18	0.717	0.222	30.92	[0.495,0.939]	65.71
During Global financial crisis period		58	0.755	0.201	26.72		
2010	68	15	0.449	0.334	74.5	[0.115,0.783]	14.70
2011	66	20	0.789	0.224	28.408	[0.565,1.013]	48.48
2012	63	25	0.837	0.179	21.41	[0.658,1.016]	44.44
2013	62	25	0.871	0.143	16.36	[0.728,1.014]	48.38
2014	64	25	0.870	0.132	15.12	[0.738,1.002]	51.56
2015	61	19	0.840	0.131	15.6	[0.709,0.971]	62.29
2016	86	29	0.832	0.156	18.776	[0.676,0.988]	58.14
2017	59	18	0.764	0.201	26.276	[0.563,0.965]	64.40
2018	54	17	0.830	0.147	17.76	[0.683,0.977]	61.11
Post Global financial crisis period		193	0.787	0.183	26.02		
2019	53	17	0.77	0.199	25.81	[0.571,0.969]	62.26
2020	57	15	0.738	0.207	28	[0.531,0.945]	68.42

2021	54	17	0.824	0.165	20.04	[0.659,0.989]	55.55
During Covid-19 crisis period		49	0.777	0.190	24.62		
2022	73	18	0.6	0.309	51.43	[0.291,0.909]	41.09
Post Covid-19 Pandemic							

Source: Author's estimation from the collected data from Statistical Table Relating to Banks in India various issues.

Scaling variable returns increases efficiency scores for all commercial bank DMUs. Table 2 shows that CRS and VRS technologies vary greatly in the number of efficient banks across the research period. For instance, in 1994, 31 banks were deemed efficient under VRS, whereas just seven banks were deemed efficient under CRS in the same year. Additionally, it was discovered that, in comparison to the first phase of banking sector reform, the average number of efficient banks under VRS was larger in the second phase. According to Table 2, commercial banks' average pure technical efficiency during the course of the research was 77.5%. This indicates that over the research period, the percentage of pure technical inefficiency was 22.5%. Both general and pure technical inefficiencies may be largely blamed for the inefficiency of commercial banks. In other words, inefficiency resulted from both improper input combination selection based on current pricing and underutilisation or waste of inputs. Stated otherwise, the allocation of resources to the chosen asset portfolio did not maximise income, and the relative prices paid for the chosen input combination were not optimal.

Indian commercial banks had an average pure technical efficiency of 80.9% in the first phase of banking sector reforms and 76.7% in the second. This suggests that banks were more effective in converting inputs into outputs during initial reform, excluding scale inefficiencies. The second phase's fall in pure technical efficiency reflects a decline in management efficiency or operational procedures, showing that banks were less effective at optimizing resource usage despite reforms. Thus, commercial banks were more technically efficient in the first period than the second.

With the implementation of reforms, commercial banks' performance has become more variable over time. Table 2 shows that, in contrast to the first phase of banking sector reform, there was more variation in the performance of banks during the second phase. Over the course of the research, the commercial banks' level of variability peaked in 2010 and 2022 and fell in 2014. During the study, the percentage of banks exhibiting pure technical efficiency within one standard deviation of the mean varied annually, ranging from 14.706 to 68.41 percent.

During financial crisis, commercial banks' average pure technical efficiency rose from 75.5 percent during the crisis to 78.7 percent. In a similar vein, commercial banks' average efficiency dropped to 60 percent in the post-Covid-19 era from 77.7 percent during the Covid-19 period. Commercial banks' variability was 26.72 percent; during the global financial crisis, this was somewhat lowered to 26.02 percent. In contrast, commercial banks' variability during the COVID-19 crisis was 24.62 percent, and during the post-COVID-19 pandemic, it rose to 51.43 percent.

Table 3 : Scale Efficiency of Commercial Banks

Year	No. of banks	No. of efficient banks (CRS)	Average Efficiency (M)	Standard deviation (σ)	Coefficient of variation (C.V.)	I=[M-σ, M +σ] σ = S.D.	Percentage of banks in I
1992	69	6	0.806	0.185	22.92	[0.621,0.991]	57.97
1993	69	9	0.725	0.199	27.39	[0.526,0.924]	62.31
1994	69	9	0.757	0.223	29.44	[0.534,0.98]	52.17
1995	69	8	0.728	0.176	24.15	[0.552,0.904]	72.46
1996	76	11	0.658	0.237	35.99	[0.421,0.895]	52.63
1997	76	11	0.798	0.147	18.42	[0.651,0.945]	65.78
First Banking sector reform period		54	0.745	0.195	26.39		
1998	77	12	0.849	0.145	17.07	[0.704,0.994]	41.55
1999	75	11	0.796	0.193	24.31	[0.603,0.989]	56
2000	72	5	0.645	0.227	35.21	[0.418,0.872]	58.33
2001	75	8	0.613	0.241	39.25	[0.372,0.854]	57.33
2002	73	6	0.660	0.214	32.39	[0.446,0.874]	67.12
2003	76	7	0.635	0.208	32.81	[0.427,0.843]	69.73
2004	76	7	0.757	0.142	18.72	[0.615,0.899]	80.26
2005	77	8	0.804	0.140	17.38	[0.664,0.944]	66.23
2006	75	6	0.642	0.180	28	[0.462,0.822	77.33

						]	
Second Banking sector reform period		70	0.711	0.188	27.24		
2007	75	8	0.755	0.168	22.28	[0.587,0.923]	69.33
2008	70	8	0.784	0.178	22.7	[0.606,0.962]	61.42
2009	70	6	0.686	0.207	30.14	[0.479,0.893]	67.14
During Global financial crisis period		22	0.742	0.184	25.04		
2010	68	7	0.633	0.310	48.9	[0.323,0.943]	29.41
2011	66	8	0.591	0.257	43.421	[0.334,0.848]	46.97
2012	63	7	0.553	0.240	43.49	[0.313,0.793]	39.68
2013	62	6	0.576	0.211	36.58	[0.365,0.787]	66.12
2014	64	9	0.659	0.186	28.16	[0.473,0.845]	75
2015	61	9	0.753	0.153	20.27	[0.6,0.906]	75.41
2016	86	11	0.674	0.223	33.147	[0.451,0.897]	67.44
2017	59	7	0.701	0.210	29.937	[0.491,0.911]	66.10
2018	54	5	0.706	0.166	23.56	[0.54,0.872]	75.92
Post Global financial crisis period		69	0.650	0.217	34.163		
2019	53	6	0.811	0.146	18.01	[0.665,0.957]	66.03
2020	57	6	0.793	0.181	22.81	[0.612,0.974]	63.15

2021	54	5	0.735	0.19	25.86	[0.545,0.925]	64.81
During Covid-19 crisis period		17	0.780	0.172	22.23		
2022	73	4	0.407	0.304	74.73	[0.103,0.711]	13.69

Source: Author's estimation from the collected data from Statistical Table Relating to Banks in India various issues.

Table 3 shows Indian commercial banks' scale efficiency from 1992 to 2022. Scale efficiency is the ratio of technical efficiency under Constant Returns to Scale (CRS) to pure technical efficiency under VRS. If a bank's scale size is below its most productive, it may have scale inefficiencies. The analysis shows large differences between VRS and CRS-efficient banks. Tables 1 and 2 demonstrate that in 1994, 31 banks were VRS-efficient and 7 were CRS-efficient. This enormous disparity shows that early reform Indian commercial banks were scale-inefficient. Many banks were efficient at resource use (managerial efficiency) but not at scale, lowering their technical efficiency. The discrepancy between VRS and CRS efficiency scores shows how far a bank is from ideal. A bigger gap indicates scale inefficiency, often from operating below or above the most productive scale size. Commercial banks had an average scale efficiency of 70% during the research period, indicating a 30% scale inefficiency. If they ran at ideal size, banks might reduce input usage by 30% while maintaining output levels. Such efficiency increases promise significant cost-saving and productivity advantages in Indian banking. No continuous trend has been seen in the number of banks functioning at optimal scale efficiency. The number of banks with full-scale efficiency dropped between 1998 and 2021–2022, indicating structural inefficiencies in operational size and productive capability. These findings emphasize the need for strategic restructuring and resizing to increase banking scale efficiency.

In contrast to the initial phase of banking sector reform, the commercial sector's scale efficiency diminished in the subsequent phase. After the global slowdown, commercial banks' average scale efficiency went up from 71.1% during the crisis to 74.2%. During the COVID-19 crisis, commercial banks' average scale efficiency was 78%, but it dropped to 40.7% following that.

Over the course of the investigation, commercial banks showed comparatively more fluctuation in their scale efficiency score. Commercial banks attained poor average efficiency and large average variance in scale efficiency, according to Table 3. The second phase of banking sector reform saw more scale efficiency difference across Indian commercial banks than the first. This increased dispersion shows a growing gap between banks at the optimal scale and those far from it. The percentage difference among commercial banks in scale efficiency was 25.04% during the global financial crisis. After the crisis, this proportion rose to 34.16%, indicating a further decline in sector scale efficiency homogeneity. This expanding variance shows that while some banks adapted and maximized their scale of operations, others struggled to adapt, resulting in greater structural imbalances in the banking sector throughout later reforms.Similarly, there was 22.23 percent heterogeneity across commercial banks during the COVID-19 crisis., This rose to 74.73 percent in the years after the COVID-19 pandemic. Banks with technical efficiency scores within one standard deviation of the mean ranged from 13.69% to 80.26% over the research. This shows that at times, many banks gathered around the average efficiency level, but at other times, performance varied greatly. The distribution of scale efficiency scores within one standard deviation of the mean was unpredictable over time, indicating that banks approached optimal scale differently. This shows that while managerial practices (reflected in technical efficiency) converged, scale-related inefficiencies were more dynamic and unevenly dispersed throughout the banking sector.

Table 4: Returns to scale of frontier banks, by ownership form (1992-2022)

Ownership	IRS	CRS	DRS	Total
Public Sector Banks	0	05	766	771
Private Sector Banks	85	23	610	718
Foreign Banks	194	222	235	651

Source: Author's estimation from the collected data from Statistical Table Relating to Banks in India various issues.

According to Table 4, the majority of banks operating in the DRS area of production technology were among those operating in the growing returns to scale (IRS), constant returns to scale (CRS), and declining returns to scale (DRS) sectors throughout the research period. International organisations mostly inhabited the IRS and CRS ranges. No one public or private bank was demonstrated to be consistently functioning at a return to scale over the entire study period. Because of the RBI's branching policy, diseconomies of scale have persisted. Under the branching policy, Indian banks were compelled to open branches but were not allowed to shut down unsuccessful ventures. This approach prevented resource optimisation across the branch network as banks had little authority to terminate failed branches and little control over branch locations. Conversely, foreign banks demonstrated increasing, steady, and decreasing return to scale, which is well supported by recent empirical data(Lovell, C.A.K., Sahay, P., and Bhattacharyya, A. 1997; Ray, S.C. 2007). Since their businesses have not yet achieved capacity and they are not required by law to grow their branch networks beyond what is ideal, foreign banks often maintain smaller branch networks size.

Table:5 Tobit Censored Regression (1996-2022)

Dependent Variable: Efficiency Score

Results 1996-2022

Included observations: 1863

Left Censoring (Value) series: 0

Right Censoring (Value) series: 1

Variables	Coefficient	Std. Error	Z Statistics	P-Value
C	0.445051	0.011427	38.94733	0.0000
Capital adequacy ratio	0.000490	0.000301	1.626450	0.1039
Net NPA to net advance	-000131	0.001110	0.118113	0.9060
Return to Assets	0.012506	0.002796	4.472199	0.0000
Total Assets	1.00002	1.1000001	0.931631	0.3515
Public Sector Banks	0.010304	0.012945	0.795955	0.4261
Foreign Banks	0.299668	0.013904	21.55232	0.0000

Sources: : Author's estimation from the collected data from Statistical Table Relating to Banks in India various issues

The factors influencing bank efficiency are examined by the computation of the Tobit regression equation (26). Table 5 summarises the Tobit regression's outcome. β_1 = β_2 = β_3 = β_4 = β_5 = β_6=was contrasted with the alternative hypothesis (H_(1)) that at least one pair is unequal in every year as the null hypothesis for evaluating the impact of the efficiency score. The Z test result in 1996–2022 permitted the rejection of the null hypothesis..

The results for 1996–2022 reveal that while the capital adequacy ratio and total assets both exhibit positive values, they are not statistically significant. As expected, there is a strong inverse relationship between efficiency estimates and non-performing assets. According to the 1996–2022 data, the non-performing assets variable has a negative sign and is not statistically significant at the 10% level. Furthermore, the results showed that NPAs negatively impacted efficiency. Bank efficiency can be increased by rerouting available resources—both tangible (provisions) and intangible (human capital)—away from NPA monitoring and towards other beneficial uses when NPAs diminish. In general, this aligns with the concept of inadequate management. Through empirical testing, it is demonstrated that the assumptions of weak management and bad luck apply considerably to Indian banks. In other words, a decline in efficiency and a rise in non-performing assets (NPAs) are the outcomes of subpar macroeconomic performance. The rise in non-performing assets was also a result of poor management. According to recent empirical evidence, this is supported by the Efficiency, Productivity, and Soundness of the Indian Banking Sector Report on Currency and Finance, 2006-2008.).

From 1996 to 2022, key performance factors and Return on Assets (ROA) for foreign (international) and private sector banks were positively correlated at the 1% significance level. Most efficient were foreign banks, followed by private sector banks, and least efficient were public sector banks. Foreign banks perform better due to structural and operational advantages. Previous research (Shanmugan & Das, 2004; Ram & Ray, 2004; Sathye, 2003; Ram, 2002) demonstrates that lighter regulatory limitations and better resource allocation cause this efficiency advantage. Foreign banks have superior profitability and technical efficiency than local banks due to their flexibility, use of innovative technologies, and performance-oriented management approaches.

V. Conclusions

Present study evaluated the efficiency of Indian commercial banks over the period 1992–2022, using unbalanced panel data drawn from three distinct ownership groups: public sector banks, private sector banks, and foreign banks. The analysis employed Data Envelopment Analysis (DEA) to assess efficiency, considering two output variables—interest income and non-interest income—and three input variables—deposits, labour, and capital. The efficiency framework was aligned with the objectives of both individual banks and the regulatory authority, the Reserve Bank of India (RBI).

The DEA results reveal that, on average, foreign banks demonstrated higher input efficiency in generating outputs compared to both public and private sector banks. This indicates that public and private sector banks exhibited notable input inefficiencies, which they must address to improve their operational performance. Furthermore, the study observes that performance variability among commercial banks has increased over the reform period, suggesting growing disparities in operational efficiency and strategic execution.

In the second-stage analysis, key financial and structural variables were examined to understand their impact on bank efficiency. The results show that total assets, return on assets (ROA), the capital adequacy ratio (CAR), and ownership type have a positive and statistically significant effect on efficiency scores. In contrast, non-performing assets (NPAs) exhibit a negative impact, underscoring their role as a major barrier to efficiency.

Consistently, foreign banks emerged as the most efficient group, followed by private sector banks, and then public sector banks. The superior performance of foreign banks is likely attributed to less regulatory burden, greater managerial flexibility, and more effective resource allocation—a finding supported by earlier studies (e.g., Shanmugan & Das, 2004; Ram & Ray, 2004; Sathye, 2003; Ram, 2002).

Based on the findings, the study recommends that banks, particularly those in the public and private sectors, continue pursuing strategies aimed at reducing non-performing assets and minimizing high establishment costs as a share of total expenses. These actions are essential for enhancing efficiency and maintaining competitiveness in an evolving banking landscape.

Abbreviations: DEA: Data Envelopes Analysis, RBI: Reserve Bank of India, DMU: Decision-Making Unit, VRS: Variable Returns to Scale, CRS: Constant Returns to Scale NIRS: Non-Increasing Returns to Scale, CAR: Capital Adequacy Ratio, NPA: Non Performing Assest, ROA: Return on Assets, TA: Total Assets, PSB: Public Sector bank, FB: Foreign Banks

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