Evaluating Indian Banks’ Performance Before and After COVID-19: A DEA-Based Study

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1. Introduction

1.1. Problem statement and Research aim

The global economy underwent significant changes and transformations due to the COVID-19 pandemic and India was no exception. Even before pandemic India's GDP was on a decline and this disruption has caused the crisis to further accelerate the downfall by 24.4% leading to recession of the economy (www.mospi.gov.in, n.d.). Since banks are important to maintain economic stability their performance during and shortly after the pandemic was very important in shaping India's economic recovery. Recognizing the economic downturn, the Reserve Bank of India (RBI) introduced several regulatory measures, including loans and moratoriums on loan repayments, relaxation in classifying non-performing assets (NPAs) (Rbi.org.in, 2025). This embarked banks to create new strategies and practices to manage risks, protect its financial stability. By the time of FY 2022, with an 8.7% growth rebound in the Indian economy (IMF, 2022), the banking sector showed its commitment and capacity for resilience and adaptability.

The study aims to assess the performance and understand effective measures taken by 20 major Indian banks in two distinct periods: before the pandemic (FY 2019) and after (FY 2023). We have used Malmquist Productivity Index (MPI) within the Data Envelopment Analysis (DEA) framework. The primary objective is to analyze the degree to which banks have converted their financial inputs (total assets, expenses, and deposits) into outputs like net profit, interest income, and investments over this period (Pathak, n.d.). Through analyzing the efficiency trends, this research helps us understand how banks have adjusted to economic challenges. It also explores how different strategies and management practices contributed to productivity growth while highlighting differences in banking efficiency among various banks. The findings and recommendations are crucial for the underperforming and under efficient banks to incorporate similar strategies of the efficient banks to improve the country's economic stability further and improve the sector's overall ability to cope with future economic disruptions (Barr, Siems and Wells, 2021).

2. Methodology

This section outlines the methodological framework adopted to evaluate the efficiency and productivity of Indian commercial banks during the pre-and post-COVID-19 periods. The research uses Data Envelopment Analysis (DEA) and the Malmquist Productivity Index (MPI) to measure bank performance, utilizing a non-parametric frontier approach. The study follows a quantitative design based on secondary data extracted from the financial statements of 20 Indian commercial banks listed on the National Stock Exchange (NSE). These banks will be considered as the DMUs for the DEA (Charnes et al., 1978; Banker et al., 1984). The evaluation spans two temporal segments: the pre-pandemic period (FY 2018 to FY 2020) and the post-pandemic period (FY 2021 to FY 2023).

No.	Bank Name	No.	Bank Name
1	Axis Bank	11	IDFC First Bank
2	Bandhan Bank	12	IndusInd Bank
3	Bank of Baroda	13	Karur Vysya Bank
4	Bank of Maharashtra	14	Kotak Mahindra Bank
5	Canara Bank	15	Punjab National Bank
6	City Union Bank	16	South Indian Bank
7	Equitas Small Finance Bank	17	State Bank of India
8	HDFC Bank	18	UCO Bank
9	ICICI Bank	19	Union Bank of India
10	IDBI Bank	20	Yes Bank

Table 1: DMUs Selected for Analysis

This approach facilitates both cross-sectional efficiency assessments and longitudinal productivity analyses. The objective is to assess both cross-sectional efficiency at a given time and productivity changes over time.

2.1. Data Collection

We obtained financial data about from the Screener website spanning FY 2018 to FY 2023. Screener functions as a trustworthy platform by gathering financial data from audited reports together with exchange filings of Indian listed companies.

Category	Variable	Description
Inputs	Total Assets	Total financial resources under the bank's control, representing operational scale.
	Operating Expenses	Administrative and operating costs incurred in running the bank.
	Deposits	Funds collected from customers are used as a base for lending and investment.
Outputs	Net Profit	Net earnings after all expenses, reflecting overall financial performance.
	Interest Income	Revenue is generated primarily from loans and interest-bearing assets.
	Investment	Funds allocated to financial instruments, indicating capital utilisation.

Table 2: DEA Model Variables Used for Efficiency Evaluation

The correlation matrix reveals key financial relationships in the banking sector. Total Assets strongly correlate with Interest Income (0.9883) and Investment (0.9880), indicating that larger banks generate more interest and invest more. Operating Expenses moderately correlate with Investment (0.9705) and Interest Income (0.9587), suggesting higher expenses align with greater investments and earnings. Total Deposits highly correlate with Interest Income (0.9911) and Investment (0.9812), reflecting their role in funding investments. Net Profit, however, shows weaker correlations, especially with Operating Expenses (0.7383) and Interest Income (0.7530), implying profitability depends on broader factors like market conditions and strategy (Table 2, Appendix A).

2.2. Model Selection: Input-Oriented DEA

We utilize the input-oriented BCC (Charnes, Cooper and Rhodes, 1978) DEA model, which assumes Variable Returns to Scale (VRS). VRS allows the model to account for the fact that changes in inputs do not always result in proportional changes in outputs—an important consideration in the banking sector where institutions operate at different scales and may experience increasing or decreasing returns. This flexibility is crucial because not all banks are of similar size or capacity, and assuming Constant Returns to Scale (CRS) could misrepresent the actual efficiency of smaller or larger banks. The BCC model enables us to isolate managerial inefficiency from scale inefficiency, providing a more realistic and nuanced assessment of performance in the heterogeneous banking industry (Banker et al., 1984).

For each Decision-Making Unit (DMU), the model solves:

$$\min_{\theta, \lambda} \theta$$

Subject to:

Input Constraints (with efficiency factor θ)

$$\sum_{j=1}^{n} \lambda_j X_{ij} \leq \theta X_{ij}, \qquad \forall \text{i}$$

Output Constraints

$$\sum_{j=1}^{n} \lambda_j Y_{rj} \leq \theta Y_{rj}, \qquad \forall \text{r}$$

Convexity Constraint (for VRS)

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

Non-negativity Constraint

$$\lambda_j \geq 0, \quad \forall \text{j}$$

X_{ij} represents the **input** matrix (Total Assets, Operating Expenses, Total Deposits). Y_{rj} represents the **output** matrix (Net Profit, Interest Income, Investment). λ_j represents the weights assigned to the DMUs. θ represents the efficiency score (values between 0 and 1). the **convexity constraint** is a condition applied in the Variable Returns to Scale (VRS) model to ensure that the production possibility set (PPS) is convex. The model is **input-oriented**, meaning it seeks to minimize inputs while maintaining the same level of outputs. This problem is solved for each DMU to determine its efficiency score. If θ = 1, the DMU is efficient; otherwise, it is inefficient.

2.3. Malmquist Productivity Index (MPI)

To track changes in productivity over time, the Malmquist Productivity Index (MPI) was employed (Färe et al., 1994). To assess changes in productivity over time, we apply the Malmquist Productivity Index (MPI), which decomposes productivity into two components,

Efficiency Change (EC): Reflects improvements in operational efficiency (catching up to the frontier).

Technological Change (TC): Reflects shifts in the production frontier (innovation or system-wide improvement).

MPI Formula:

$$MPI = \sqrt{\frac{D_t^t(x_{t+1}, y_{t+1})}{D_t^t(x_t, y_t)} \cdot \frac{D_{t+1}^{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}^{t+1}(x_t, y_t)}}$$

Where $D_t^t(x, y)$ is the distance function at time t.

Decomposition:

$$MPI = EC \times TC$$

If MPI > 1: Productivity improved

If MPI < 1: Productivity declined

The calculations were implemented using the deaR package in R. The R script includes data preprocessing. The negative values in Net Profit column are expected for some DMUs. One approach to handling negative data in DEA models is to use translation-invariant methods, which transform all negative values into positive ones by adding a sufficiently large scalar to the affected variables (Zhu, 2003). MPI computations are done using the make_malmquist() and malmquist_index() functions.

Assumptions and Limitations:

DEA relies on a deterministic frontier structure without statistical noise treatment which makes it easily affected by data outlier distortions and measurement errors (Cooper et al., 2011). The computed efficiency scores depend on the best organizational performers within the sample and will shift if different groups of DMUs are evaluated (Emrouznejad & Yang, 2018). The results should not be directly applied to other banks outside the evaluation scope. The model contains an assumption of homogeneity across decision-making units (DMUs) although actual banking institutions differ in operational settings and dimensions of size and risk management approach which could distort the evaluation accuracy (Liu et al., 2013). External factors such as macroeconomic conditions along with regulatory changes cannot be included in DEA because they could significantly affect bank performance (Paradi & Zhu, 2013).

The Malmquist Productivity Index (MPI) enables productivity change measurement, yet its accuracy relies heavily on precise input data as well as on offsetting strong data points (Färe et al., 1994). To perform MPI calculations correctly you need precise distance functions that must not be estimated imprecisely since such errors could wrongly identify productivity patterns. The translation-invariant methods applied to negative value transformation (such as Net Profit) can result in bias that degrades the reliability of productivity measurement results (Zhu, 2003).

3. Output Interpretations

3.1. VRS Efficiency

The analysis of efficiency scores (2020,2023) shows overall bank efficiency improvements, with most banks maintaining or enhancing their performance. Axis Bank, Bank of Baroda, IDBI Bank, and Union Bank of India showed notable efficiency gains, while Bank of Maharashtra and Karur Vysya Bank experienced declines. Several banks, including HDFC, SBI, Yes Bank, and ICICI, maintained full efficiency (1.000) throughout the period. The overall trend suggests stable or improved operational performance across the banking sector, with some banks needing adjustments to enhance resource utilization.

No.	Bank	Pre-Pandemic	Post-Pandemic
1	Axis bank Limited	0.947	1
2	Bandhan Bank	1	1
3	Bank of Baroda	0.975	1
4	Bank of Maharashtra	1	0.940
5	Canara Bank	1	1
6	City Union Bank	1	1
7	Equitas Small Finance Bank	1	1
8	HDFC Bank	1	1
9	ICICI Bank	1	1
10	IDBI Bank	0.867	0.978
11	IDFC First Bank	1	1
12	IndusInd Bank	1	1
13	Karur Vysya Bank	0.965	0.910
14	Kotak Mahindra Bank	1	1
15	Punjab National Bank	1	1
16	South Indian Bank	1	1
17	State Bank of India	1	1
18	UCO Bank	1	1
19	Union Bank of India	0.970	1
20	Yes Bank	1	1

Table 5: Efficiency (VRS)

3.2. Productivity Performance

Tables 5 to 7 present bank performance for TFP change and its components—technical and efficiency change. A Malmquist TFP index value below one indicates a decline, while values above 1 reflect improvements. Subtracting 1 from the reported values gives the average annual change. These measures assess performance relative to best practices.

The Malmquist Index (MI) tracks productivity shifts by combining technical and efficiency changes. Karur Vysya (+12.95%), Axis (+11.54%), ICICI (+7.57%), South Indian (+8.22%), and UCO (+2.88%) saw notable improvements, reflecting technological and efficiency gains.

Union Bank (-5.96%), Bank of Maharashtra (-8.36%), and Kotak Mahindra (-13.68%) faced moderate declines. City Union (-38.69%), IDBI (-41.00%), Yes Bank (-40.10%), and SBI (-28.95%) experienced significant drops, signalling efficiency losses. While some banks improved, others require strategic action to counter declining trends (Table 6).

No.	Bank	MI	No.	Bank	MI
1	Axis bank Limited	1.1154	11	IDFC First Bank	0.7987
2	Bandhan Bank	0.9948	12	IndusInd Bank	0.7972
3	Bank of Baroda	0.9940	13	Karur Vysya Bank	1.1295
4	Bank of Maharashtra	0.9164	14	Kotak Mahindra Bank	0.8632
5	Canara Bank	0.9911	15	Punjab National Bank	0.8638
6	City Union Bank	0.6131	16	South Indian Bank	1.0822
7	Equitas Small Finance Bank	0.8495	17	State Bank of India	0.7105
8	HDFC Bank	0.9917	18	UCO Bank	1.0288
9	ICICI Bank	1.0757	19	Union Bank of India	0.9404
10	IDBI Bank	0.5900	20	Yes Bank	0.5990

Table 6: Relative Malmquist Index Change

Efficiency Change (EC) measures a bank's ability to convert inputs into outputs efficiently. Axis (+28.65%), Karur Vysya (+25.42%), ICICI (+24.33%), and South Indian (+17.18%) saw the highest gains, reflecting strong operational improvements. Moderate progress was observed in Bandhan (+6.36%), Union Bank (+7.54%), and HDFC (+3.82%). Conversely, Kotak Mahindra (-13.83%), Equitas (-14.84%), and IndusInd (-6.03%) faced declines, indicating operational challenges. SBI (-3.30%) and Yes Bank (-4.02%) showed slight drops. While many banks improved efficiency, some must address inefficiencies to enhance performance (Table 7).

1	Axis bank Limited	1.2865	11	IDFC First Bank	1.0056
2	Bandhan Bank	1.0636	12	IndusInd Bank	0.9397
3	Bank of Baroda	1.0494	13	Karur Vysya Bank	1.2542
4	Bank of Maharashtra	0.9992	14	Kotak Mahindra Bank	0.8617
5	Canara Bank	1.0000	15	Punjab National Bank	0.9863
6	City Union Bank	1.0000	16	South Indian Bank	1.1718
7	Equitas Small Finance Bank	0.8516	17	State Bank of India	0.9670
8	HDFC Bank	1.0382	18	UCO Bank	1.0000
9	ICICI Bank	1.2433	19	Union Bank of India	1.0754
10	IDBI Bank	1.0000	20	Yes Bank	0.9598

Table 7: Changes in Relative Efficiency

The technical change (TC) values indicate varying degrees technological progress and regress among Indian banks. Technical Change (TC) measures the technology shift over time, with values above 1 indicating progress and values below 1 indicating regression. In the given data, Karur Vysya Bank (+2.88%), Bank of Maharashtra (+0.18%), and Canara Bank (-0.25%) show the highest technological advancements. Mid-range performers like Axis Bank (-0.89%), HDFC Bank (-6.47%), and ICICI Bank (-5.28%) indicate moderate regression. On the other hand, Punjab National Bank (-38.69%), IndusInd Bank (-41.00%), and Equitas Small Finance Bank (-37.59%) have faced significant declines, suggesting challenges in adopting new technologies or inefficiencies in operations. The variations in percentage changes highlight that while some banks are improving their technological capabilities, others need to enhance their strategies to keep up with industry advancements (Table 8).

No.	Bank	TC	No.	Bank	TC
1	Axis bank Limited	0.8670	11	IDFC First Bank	0.7943
2	Bandhan Bank	0.9353	12	IndusInd Bank	0.8483
3	Bank of Baroda	0.9472	13	Karur Vysya Bank	0.9006
4	Bank of Maharashtra	0.9171	14	Kotak Mahindra Bank	1.0018
5	Canara Bank	0.9911	15	Punjab National Bank	0.8759
6	City Union Bank	0.6131	16	South Indian Bank	0.9236
7	Equitas Small Finance Bank	0.9975	17	State Bank of India	0.7347
8	HDFC Bank	0.9552	18	UCO Bank	1.0288
9	ICICI Bank	0.8652	19	Union Bank of India	0.8745
10	IDBI Bank	0.5900	20	Yes Bank	0.6241

Table 8. Relative Technical Change

4. Challenges

While overall bank efficiency improved between 2020 and 2023, several structural challenges remain. Technological regression is evident in several large banks, including State Bank of India (TC = 0.7347), HDFC Bank (TC = 0.9552), and ICICI Bank (TC = 0.8652). This suggests that while scale economies may drive their efficiency, innovation and technological advancement have not kept pace which is a known risk when firms rely more on established routines than innovation (Färe et al., 1994).

Meanwhile, operational efficiency declined for banks such as Kotak Mahindra Bank (EC = 0.8617) and Equitas Small Finance Bank (EC = 0.8516), suggesting inefficiencies in resource allocation or delayed post-pandemic recovery (Zhu, 2014). The disparity in productivity performance is also noteworthy. While Karur Vysya Bank (MI = 1.1295) and Axis Bank (MI = 1.1154) improved, IDBI Bank (MI = 0.5900) and Yes Bank (MI = 0.5990) saw significant productivity declines, revealing inconsistent managerial responses to external shocks — a finding consistent with prior studies on bank heterogeneity in crisis periods (Avkiran, 2011).

5. Managerial Recommendations

Banks with declining technological change scores, such as State Bank of India and Equitas Small Finance Bank, should invest strategically in digital infrastructure to support productivity growth. Transitioning to cloud-based core banking platforms would improve scalability, flexibility and cost-efficiency. Additionally, AI-based systems for credit risk modelling and fraud detection can strengthen internal controls and automate complex decision-making processes. To improve customer engagement, banks should develop mobile-first platforms supported by intelligent personal finance assistants. These investments are critical to pushing the production frontier forward and are aligned with prior research linking digital transformation to banking productivity (Chen, Skully and Brown, 2005).

Banks facing declining efficiency, including Kotak Mahindra Bank and Yes Bank, should restructure internal operations through tools like process mining to identify service bottlenecks. Inefficient or low-performing branches could be consolidated or digitised, with a renewed focus on reskilling employees in areas such as digital compliance and analytics. Banks underperforming across both efficiency and technology, like IDBI Bank, should consider digital-first service delivery models, including paperless account onboarding and AI-supported loan origination. Regulatory innovation frameworks like the RBI sandbox can offer a controlled environment for piloting such changes. Peer-learning platforms coordinated by the Indian Banks' Association can also facilitate knowledge transfer from high-performing banks such as Karur Vysya Bank. These strategies reflect global evidence that both managerial capability and technological innovation are essential for long-term banking sector resilience (Altunbas, Evans and Molyneux, 2001).

6. Conclusion

This study analysed the efficiency and productivity of 20 major Indian banks before and after the COVID-19 pandemic using DEA and the Malmquist Index. The findings reveal a mixed performance: while some banks (e.g., Axis, Karur Vysya, ICICI) improved efficiency through better resource management, others (e.g., Kotak Mahindra, IDBI, Yes Bank) struggled with technological regression and declining productivity. The RBI's regulatory measures provided stability, but persistent inefficiencies highlight the need for banks to adopt advanced technologies (e.g., AI, digital banking) and optimize operations. The study underscores that balancing operational efficiency with technological progress is critical for long-term stability.

By addressing these gaps, Indian banks can better withstand future economic shocks and support sustainable growth.

7. References

Altunbas, Y., Evans, L. and Molyneux, P. (2001). Bank ownership and efficiency. Journal of Money, Credit and Banking, 33(4), pp.926–954. https://doi.org/10.2307/2673890

Avkiran, N.K. (2011). Association of DEA super-efficiency estimates with financial ratios: Investigating the case for Chinese banks. *Omega*, 39(3), pp.323–334. https://doi.org/10.1016/j.omega.2010.07.002 [Accessed 28 Mar. 2025].

Banker, R.D., Charnes, A. and Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), pp.1078–1092. https://doi.org/10.1287/mnsc.30.9.1078.

Barros, C.P., Managi, S. and Matousek, R. (2012). The technical efficiency of the Japanese banks: Non-radial directional performance measurement with undesirable outputs. *Omega*, 40(1), pp.1–8. https://doi.org/10.1016/j.omega.2011.03.002. [Accessed 28 Mar. 2025]

Barr, R., Siems, T. and Wells, N. (2021). *Are Banks Near the DEA Efficient Frontier Better-Off?* [online] Available at: https://s2.smu.edu/~barr/pubs/2021-CSBSbanking.pdf [Accessed 2 Apr. 2025].

Barkah Kristianto and Riko Hendrawan (2019). *Indonesian Listed Bank Efficiency in 2008 – 2017 using Data Envelopment Analysis (DEA)*. https://doi.org/10.5220/0008427500550064.

Charnes, A., Cooper, W.W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. European Journal of Operational Research, 2(6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8 [Accessed 22 Mar. 2025]

Chen, X., Skully, M. and Brown, K. (2005). Banking efficiency in China: Application of DEA to pre- and post-deregulation eras: 1993–2000. *China Economic Review*, 16(3), pp.229–245. https://doi.org/10.1016/j.chieco.2005.02.003

Cooper, W.W., Seiford, L.M., & Zhu, J. (2011). *Handbook on Data Envelopment Analysis* (2nd ed.). Springer.

DataViz | Ministry of Statistics and Program Implementation | Government Of India (no date). *www.mospi.gov.in*. Available at: https://www.mospi.gov.in/dataviz [Accessed 26 Mar. 2025].

Färe, R., Grosskopf, S., Norris, M. and Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, 84(1), pp.66–83.

IMF. (2022). India: 2022 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for India. [online] Available at: https://www.imf.org/en/Publications/CR/Issues/2022/12/21/India-2022-Article-IV-Consultation-Press-Release-Staff-Report-and-Statement-by-the-527283?utm_source=chatgpt.com [Accessed 26 Mar. 2025].

Paradi, J.C., Yang, Z., & Zhu, H. (2011). Assessing bank and bank branch performance: Modelling considerations and approaches. *Omega*, 39(3), 323–334.

Pathak, H. (n.d.). *Malmquist Productivity Index Approach in Assessing Performance of Commercial Banks: Evidence from Nepal*. [online] Available at: https://www.nrb.org.np/contents/uploads/2020/07/4-Malmquest-Productivity.pdf [Accessed 2 Apr. 2025].

Rbi.org.in. (2025). *Reserve Bank of India*. [online] Available at: https://www.rbi.org.in/commonman/english/Scripts/PressReleases.aspx?Id=3267 [Accessed 26 Mar. 2025].

Zhu, J. (2003) Quantitative models for performance evaluation and benchmarking : data envelopment analysis with spreadsheets and DEA Excel Solver. Boston: Kluwer Academic.

Appendix

Appendix A

	Mean	Median	Maximum	Minimum	SD
Inputs					
Total Assets	8531586	3433510	59544150	192960	11776869
Operating Expenses	311799	178355	2043030	13040	425715
Total Deposits	6389604	2523255	44685360	107880	8956282
Outputs					
Net Profit	67186	20370	577500	-164330	140303
Interest Income	308367	153505	1899810	11500	394071
Investment	2325460	930840	19131080	23430	3593258

Table 1. Descriptive Statistics of Inputs and Outputs of the Indian Banks

Total Assets	1					
Operating Expenses	0.9626	1				
Total Deposits	0.9956	0.9454	1			
Net Profit	0.8234	0.7382	0.7972	1		
Interest Income	0.9882	0.9586	0.9910	0.7530	1	
Investment	0.9880	0.9705	0.9811	0.7980	0.9711	1

Table 2. Correlation matrix

Appendix B

R Code for The Analysis

https://github.com/Manas-prog/Optimization/blob/main/Optimization_DEA.R

Data Used for Analysis

https://github.com/Manas-prog/Optimization/blob/main/Bank%20Data_Final.xlsx

Appendix C

Visualizations

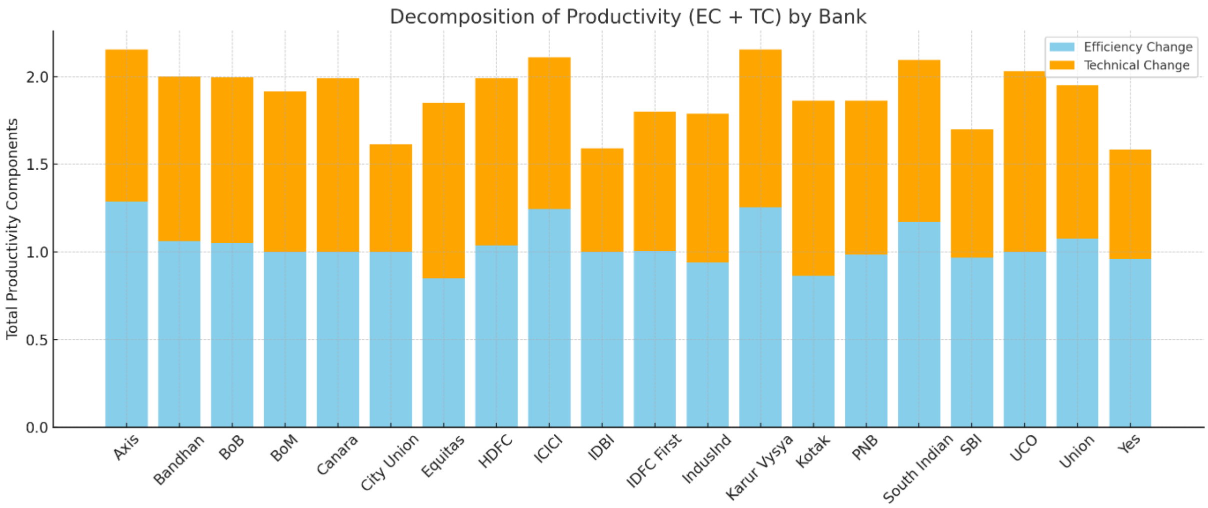

Figure A1: Decomposition of Productivity EC vs. TC

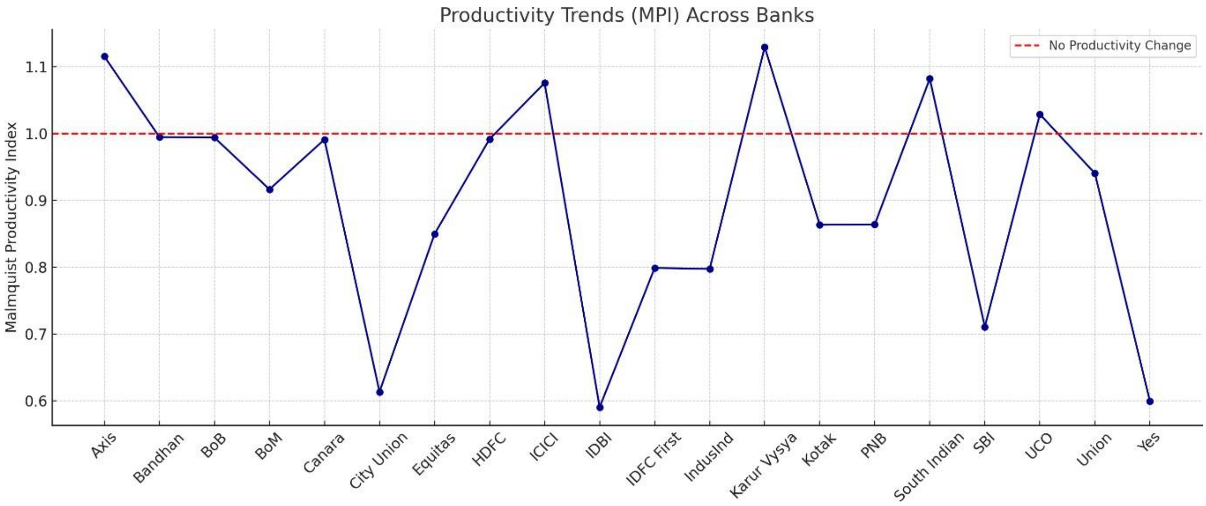

Figure A2: Productivity Trends (Malmquist Productivity Index) Across Banks

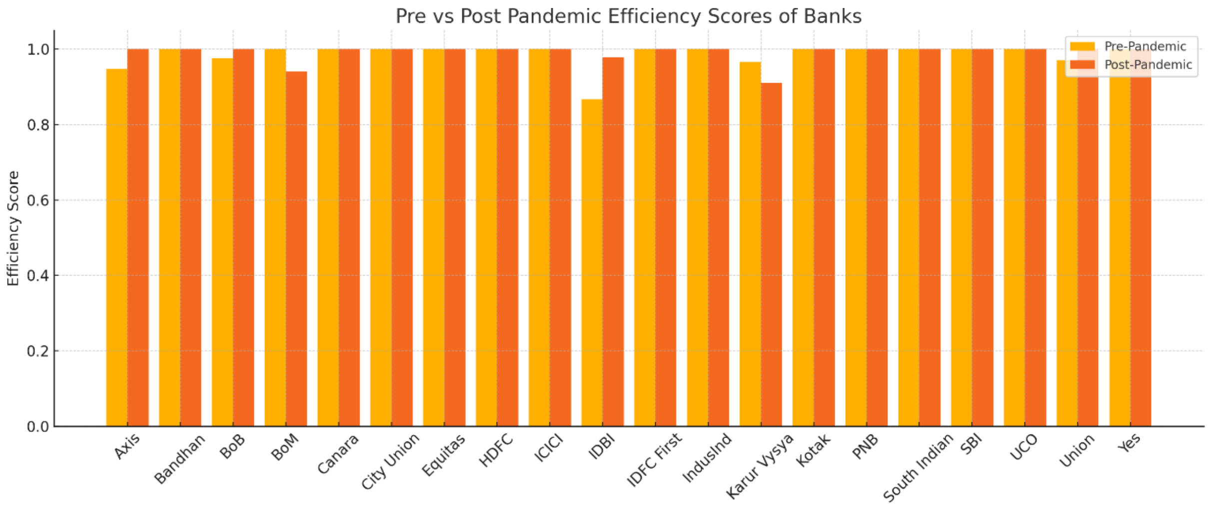

Figure A3: Pre vs Post Pandemic Efficiency Scores of Indian Banks