A Study on Operational Efficiency of Public Sector Banks in India: Evidence from a Two-Stage DEA–Tobit Framework in the Post-Consolidation Era

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ABSTRACT

Purpose. This study examines the operational efficiency of twelve Indian Public Sector Banks (PSBs) over the financial years 2020–2024—a period encompassing post-consolidation restructuring, the COVID-19 disruption, and accelerated regulatory reforms. It constitutes the first systematic efficiency assessment of the restructured PSB landscape following the landmark 2019–2020 bank mergers that reduced the number of state-owned banks from 27 to 12. Methodology. A two-stage analytical framework is employed. In Stage I, an input-oriented Banker-Charnes-Cooper (BCC) Data Envelopment Analysis (DEA) model under Variable Returns to Scale (VRS) is applied, using three inputs (total deposits, employee expenses, and fixed assets) and two outputs (total advances and investments) to generate bank-level efficiency scores. In Stage II, a Tobit regression model examines the influence of Return on Equity (ROE) and the Net Non-Performing Assets (NPA) ratio on these scores. Key Findings. The sector-wide mean efficiency score of 0.579 reveals a substantial—and largely persistent—gap from the best-practice frontier, implying an average input-reduction potential of approximately 42% without output loss. Efficiency is sharply bifurcated: Punjab & Sind Bank, SBI, and Union Bank consistently approximate frontier performance, while Canara Bank, Bank of Baroda, and Bank of India record deep and structurally entrenched inefficiencies. The Tobit estimates show that neither ROE nor the NPA ratio exerts statistically significant influence on efficiency in the study period, a finding attributed to compressed cross-sectional variation in

NPA levels following RBI-mandated provisioning norms and government recapitalization. Contribution. The study provides the first post-merger, post-COVID empirical efficiency baseline for the restructured Indian public banking sector, demonstrating that consolidation has yielded uneven efficiency gains and that scale and managerial quality—rather than profitability or NPA metrics alone—remain the primary drivers of efficiency heterogeneity.

Keywords: *Data Envelopment Analysis · Bank Efficiency · Tobit Regression · Non-Performing Assets · Public Sector Banks · India · Post-Merger Performance*

1. INTRODUCTION

India's banking sector occupies a position of structural centrality in the national economy that few other institutional domains can match. As a predominantly bank-intermediated financial system, the country relies on its credit institutions to mobilize household savings, allocate capital to productive uses, and sustain the credit requirements of agriculture, industry, and the vast informal economy. Within this architecture, Public Sector Banks (PSBs)—institutions in which the government retains a majority equity stake exceeding 50%—have historically commanded the dominant share of systemic resources, accounting for approximately 59% of total deposits and over 54% of outstanding credit (SBI Research, 2024). Their unparalleled network of branches ensures that financial access extends to geographic and demographic segments that private institutions have historically underserved, positioning PSBs at the intersection of commercial banking and developmental policy.

Yet PSBs' systemic importance has long coexisted uneasily with documented operational inefficiencies. They are routinely outperformed by private and foreign counterparts on profitability, cost efficiency, and total factor productivity—a divergence attributable to legacy staffing structures, high operating costs, excess branch infrastructure, and a risk culture shaped by implicit government guarantees and political considerations (Sahoo, Das, & Das, 2025; Hafsal, Suvvari, & Durai, 2020). The chronic burden of Non-Performing Assets (NPAs) further compounds these structural weaknesses: empirical evidence estimates that NPAs have generated an efficiency loss of approximately 16.2% across the Indian banking sector, with PSBs bearing a disproportionate share—a striking efficiency gap of 25.6% compared to just 4% for private sector banks (Hafsal et al., 2020).

The post-reform trajectory of PSBs has been further shaped by a landmark consolidation drive. Following the integration of State Bank of India's associate banks in 2017, an even more sweeping round of amalgamations between 2019 and 2020 reduced the PSB universe from 27 to just 12 institutions. Whether these structural realignments have translated into genuine operational improvement—or merely reshuffled organizational complexity—remains an empirical question of considerable policy urgency. Compounding this uncertainty, the COVID-19 pandemic injected macroeconomic turbulence that simultaneously disrupted credit demand, elevated NPA risks, and forced accelerated digitalization, further complicating the assessment of reform-era efficiency outcomes.

Research Gap and Contribution

Despite the volume of DEA-based banking efficiency literature, a critical lacuna persists: virtually no published study rigorously evaluates PSB operational efficiency in the post-consolidation period using data spanning the 2019–2020 mergers and the COVID-19 episode. Existing analyses are anchored in pre-merger data and typically omit NPAs as endogenously produced, undesirable outputs—an omission that systematically overstates efficiency for institutions with high NPA burdens (Arya & Singh, 2021; Hafsal et al., 2020). Furthermore, the two-stage DEA–Tobit approach—now established as the methodological benchmark in frontier efficiency research—remains underutilized in the Indian PSB context.

The present study addresses these gaps by applying an input-oriented BCC-DEA model under VRS to a balanced panel of twelve PSBs over 2020–2024, followed by a Tobit regression to identify efficiency determinants. In doing so, it makes three substantive contributions: (i) it provides the first post-merger, post-COVID efficiency baseline for the restructured PSB universe; (ii) it rigorously tests the influence of both profitability and credit-risk metrics on operational efficiency; and (iii) it generates actionable bank-level diagnostics relevant to regulatory and managerial decision-making. The remainder of the paper is organized as follows: Section 2 reviews the theoretical and empirical literature; Section 3 details the methodology; Sections 4 and 5 present findings and discussion, respectively; Sections 6–8 provide conclusions, implications, and limitations.

2. LITERATURE REVIEW

2.1 Theoretical Foundations of Banking Efficiency

The measurement of productive efficiency traces its formal intellectual lineage to Farrell (1957), whose decomposition of efficiency into technical and allocative components provided the conceptual scaffold on which subsequent frontier methodologies were erected. Technical efficiency—a firm's capacity to maximize output from a given input bundle, or equivalently, to minimize inputs for a given output level—remains the central construct in banking efficiency analysis. Banker, Charnes, and Cooper (1984) operationalized this concept through the BCC extension of Charnes, Cooper, and Rhodes' (1978) seminal DEA formulation, relaxing the assumption of Constant Returns to Scale (CRS) to accommodate the wide size heterogeneity that characterizes real banking systems.

The conceptualization of banking production has been equally consequential. The intermediation approach, which treats deposits and borrowed funds as inputs transformed—via labor and physical capital—into earning assets such as loans and investments, has achieved clear consensus in the empirical literature over the production approach (which counts both deposits and loans as outputs). Its theoretical grounding in Sealey and Lindley's (1977) intermediation model and its empirical alignment with observed bank balance sheets make it the natural choice for PSB efficiency analysis, a position adopted in the present study (Mittal & Singh, 2024; Sahoo et al., 2025).

2.2 Global Evidence: DEA in Banking Research

The foundational surveys of Berger and Humphrey (1997) and Fethi and Pasiouras (2010) document a literature that has grown to encompass well over a thousand studies spanning multiple continents and methodological traditions. The consistent message from cross-country analyses of advanced economies is that technical inefficiency in banking is substantial—typically ranging between 20% and 30% of best-practice performance—and is systematically related to ownership structure, market competition, and the regulatory environment. State-owned banks have consistently underperformed private counterparts in technical efficiency across the United States, European Union, and major Asian markets, a finding driven by differences in managerial incentive structures, corporate governance quality, and the extent to which commercial imperatives are subordinated to public policy objectives (Kumar & Charles, 2012).

Evidence on bank mergers and consolidations—directly relevant to the Indian context—is notably mixed. While scale economies theory predicts efficiency gains from consolidation, empirical studies frequently document short-run efficiency deterioration as integration costs, organizational disruption, and cultural incompatibilities offset scale benefits. Milenkovic et al. (2022) find that post-merger efficiency improvements typically materialize with a lag of two to four years, and that gains are conditional on the quality of pre-merger due diligence and the strategic coherence of the absorbing institution. The divergence between theoretical predictions and empirical outcomes underscores that consolidation is a necessary but not sufficient condition for efficiency improvement—a lesson with direct implications for the assessment of India's recent PSB amalgamations.

2.3 Indian Banking Efficiency: Convergence and Divergence

In the Indian context, the post-1991 liberalization period generated a rich empirical literature whose findings have evolved substantially over time. Early studies—including Bhattacharyya et al. (1997) and Saha and Ravisankar (2000)—offered cautiously optimistic assessments, finding that PSBs improved their efficiency over the reform decade and in some cases outperformed newly entered private competitors who had yet to consolidate their market presence. These findings were broadly consistent with the hypothesis that competitive exposure disciplines incumbent institutions. Mahesh and Rajeev (2009) extended this evidence base, concluding that deregulation had a positive effect on PSB efficiency, supporting the intended disciplining mechanism of the liberalization agenda (Kumar & Charles, 2012).

However, as private banks matured and widened their technological and operational advantages, the narrative shifted markedly. Bhatia and Mahendru (2015) and Sahoo et al. (2025) document a consistent and widening efficiency gap between PSBs and their private counterparts, with PSBs encumbered by excess staffing, legacy infrastructure, and a risk culture shaped by government capital backstops. Hafsal et al. (2020) provide particularly compelling evidence using a two-stage network DEA framework that explicitly incorporates NPAs as undesirable outputs: their analysis reveals that NPAs generate an average efficiency loss of 25.6% for PSBs—nearly six times the 4% loss estimated for private banks—a disparity that conventional DEA models, which ignore undesirable outputs, systematically conceal.

2.4 Methodological Evolution and Two-Stage DEA

The methodological sophistication of banking efficiency research has advanced considerably beyond the original single-stage DEA framework. The adoption of the Malmquist Productivity Index (MPI) enabled dynamic analysis, decomposing total factor productivity growth into efficiency-change and technology-change components. Indian studies deploying the MPI have generally found that productivity growth is driven more by technological diffusion—particularly the spread of information technology and digital banking—than by improvements in pure managerial efficiency, suggesting that PSBs have benefited from economy-wide technological advances without commensurate internal operational improvement (Mittal & Singh, 2024; Kumar & Charles, 2012).

The most consequential methodological development, however, has been the adoption of the two-stage DEA–Tobit approach. In this framework, Stage I generates bank-level efficiency scores via DEA, and Stage II employs Tobit regression to identify the exogenous determinants of these scores—a specification required because DEA scores are censored between 0 and 1 and violate the assumptions of Ordinary Least Squares regression (Tobin, 1958). This approach has become the standard in the international banking efficiency literature and provides the methodological template adopted in the present study (Sahoo et al., 2025; Hafsal et al., 2020). Notably, the treatment of NPAs as undesirable outputs within the DEA framework—now well established in the advanced methodological literature—remains the exception rather than the rule in Indian banking studies, creating a methodological gap that the present analysis partially addresses through the Tobit specification.

2.5 Research Gaps

Three gaps emerge from this review as directly relevant to the present study. First, the transformative consolidation wave of 2019–2020 has not been subjected to rigorous efficiency analysis with post-merger data—an absence that precludes empirical validation of the reform rationale. Second, the interactive effects of the COVID-19 pandemic on PSB efficiency—through disrupted credit flows, regulatory forbearance, and forced digitalization—remain empirically uncharacterized. Third, the two-stage DEA–Tobit methodology, while internationally established, has been unevenly applied in the Indian PSB context, with few studies employing the full framework over a post-consolidation sample. The present study addresses all three gaps simultaneously.

3. RESEARCH METHODOLOGY

3.1 Research Design and Data

The study employs a quantitative, longitudinal panel design, tracking twelve Indian Public Sector Banks over five financial years (2020–2024), generating 60 bank-year observations. The sample encompasses all PSBs operating as independent entities following the 2019–2020 consolidation—making it the most structurally complete and contemporaneous sample available for the post-merger period. Secondary data are sourced from the Reserve Bank of India's statistical publications, the PROWESS database maintained by the Centre for Monitoring Indian Economy (CMIE), and individual bank annual reports, consistent with established practice in the Indian banking efficiency literature (Hafsal et al., 2020; Kumar & Charles, 2012). The intermediation approach is adopted in defining the bank production function, classifying deposits, employee expenses, and fixed assets as inputs and total advances and investments as outputs.

3.2 Stage I: DEA Model Specification

Data Envelopment Analysis (Charnes, Cooper, & Rhodes, 1978) is a non-parametric, linear programming technique that evaluates the relative efficiency of Decision-Making Units (DMUs) by constructing an empirical best-practice frontier from observed input-output data, without imposing a pre-specified functional form on the production relationship. This property eliminates the risk of production function misspecification that afflicts parametric alternatives such as Stochastic Frontier Analysis (Banker, Charnes, & Cooper, 1984).

The study employs the BCC model under Variable Returns to Scale (VRS), chosen in preference to the original CCR (CRS) model for two substantive reasons. First, the twelve sampled PSBs exhibit wide heterogeneity in asset size—State Bank of India operates at a scale many multiples larger than Punjab & Sind Bank—rendering the CRS assumption theoretically inappropriate. Imposing CRS conflates pure technical inefficiency with scale inefficiency, yielding biased scores for institutions operating away from their optimal scale (Banker, Charnes, & Cooper, 1984). Second, an input-oriented model is adopted, addressing the question of how much inputs could be proportionally reduced while maintaining observed output levels—an orientation chosen because PSBs' output levels are partly constrained by regulatory mandates (priority sector lending requirements, government-directed credit programs), making input rationalization the more policy-relevant efficiency dimension.

Formally, let n = 12 DMUs (banks), where DMU j employs m = 3 inputs to produce s = 2 outputs. For each DMU o under evaluation, the input-oriented BCC-DEA model solves:

Minimize θ

Subject to: $\Sigma_j \lambda_j x_{ij} \leq \theta x_{io} \quad \forall i = 1, \ldots, m$

$$\Sigma_j \lambda_j y_{rj} \geq y_{ro} \qquad \forall r = 1, \ldots, s$$

$$\Sigma_j \lambda_j = 1 \text{ (VRS constraint)}; \;\; \lambda_j \geq 0 \;\; \forall j$$

where $\theta \in (0, 1]$ is the efficiency score to be minimized, λ_j are non-negative peer weights, x_{ij} and y_{rj} are the input and output quantities of DMU j, and the convexity constraint $\Sigma_j \lambda_j = 1$ defines the VRS frontier. The program is solved independently for each bank-year observation, yielding a panel of annual efficiency scores. A score of $\theta = 1.000$ places the bank on the frontier; the shortfall $(1 - \theta)$ quantifies the proportion by which inputs could be reduced without reducing outputs.

3.3 Variable Selection

Input and output variables are selected in accordance with the intermediation approach (Sealey & Lindley, 1977) and consistent with the preponderance of Indian banking DEA studies. Three inputs are employed: (i) Total Deposits—the primary funding source and core input in the financial intermediation process; (ii) Employee Expenses—total staff costs including salaries and allowances, capturing the human capital dimension of operating costs and reflecting the significant workforce burden that has historically constrained PSB efficiency; and (iii) Fixed Assets—net book value of premises and equipment, representing the physical capital infrastructure deployed in banking operations. Two outputs are employed: (i) Total Advances—gross credit extended to borrowers, constituting the core income-generating asset of any intermediary; and (ii) Investments—portfolio holdings in government securities and approved instruments, a significant and regulated component of PSB asset portfolios reflecting both statutory liquidity requirements and active treasury management. The 3-input, 2-output specification satisfies the standard rule that the DMU count should exceed three times the sum of inputs and outputs (Cooper, Seiford, & Tone, 2007), ensuring adequate discriminatory power.

3.4 Stage II: Tobit Regression

Since DEA efficiency scores are bounded between 0 and 1, Ordinary Least Squares (OLS) regression is inappropriate due to the censored nature of the dependent variable—OLS estimates would be inconsistent and biased (Tobin, 1958). Accordingly, a two-limit Tobit model estimated by Maximum Likelihood Estimation (MLE) is employed in Stage II:

$$\theta_{it}^* = \beta_0 + \beta_1(ROE_{it}) + \beta_2(NPA_{it}) + \varepsilon_{it}\ ; \quad \varepsilon_{it} \sim N(0, \sigma^2)$$

where θ_{it}^* is the latent efficiency score of bank i in year t, observed as $\theta_{it} = \theta_{it}^*$ when $0 < \theta_{it}^* \leq 1$ and censored at 1 when $\theta_{it}^* > 1$. Return on Equity (ROE) serves as a profitability determinant; a positive coefficient is theorized on the grounds that better-managed, more profitable banks more efficiently deploy resources. The Net Non-Performing Assets ratio (NPA) proxies credit risk and asset quality deterioration; a negative coefficient is hypothesized, since higher NPA ratios divert managerial attention, erode capital adequacy, and constrain productive credit creation. Model validity is assessed through the Jarque-Bera and Shapiro-Wilk tests for residual normality and the Breusch-Pagan test for heteroscedasticity.

4. RESULTS AND ANALYSIS

4.1 Aggregate Efficiency: Sector-Wide Underperformance

Table 1 summarizes the descriptive statistics of the DEA efficiency scores computed across 60 bank-year observations. The sector-wide mean efficiency score of 0.579 constitutes the headline finding of Stage I: on average, Indian public sector banks operate at barely 57.9% of best-practice performance, implying an average input-reduction potential of approximately 42% without any sacrifice in output levels. This represents a significant and systemic departure from the efficiency frontier, one that has persisted through post-merger restructuring and the COVID-19 period.

Table 1. DEA Summary Statistics – Indian Public Sector Banks (2020–2024)

Parameter	Value
Number of Observations	60
Number of Banks	12
Study Period	2020 – 2024
Mean Efficiency Score	0.579
Maximum Efficiency Score	1.000
Minimum Efficiency Score	0.220 (Canara Bank, 2024)
Standard Deviation	0.268

Note. VRS input-oriented BCC-DEA model. Efficiency scores bounded between 0 (fully inefficient) and 1 (fully efficient). All 12 PSBs operating as independent entities post-consolidation included.

The distribution of scores reveals considerable dispersion: the range of 0.780 percentage points (from 0.220 to 1.000) and the concentration of observations in the lower quartile of the [0,1] interval underscore that efficiency underperformance is not a marginal phenomenon but a structural condition for the majority of sampled institutions. This finding is broadly consistent with Hafsal et al. (2020) and Sahoo et al. (2025), who similarly document mean efficiency scores well below the frontier for Indian PSBs, though the present study's post-consolidation data reveal that recent structural reforms have not meaningfully shifted the sector-level average.

4.2 Bank-Level Efficiency: A Bifurcated Landscape

Table 2 presents year-wise efficiency scores for each institution, ordered by mean efficiency, while Table 3 classifies banks into efficiency tiers. The data reveal a sharply bifurcated landscape defined by a small cluster of frontier performers and a large cohort of persistently underperforming institutions.

Table 2. DEA Efficiency Scores by Bank and Year (2020–2024)

Bank	2020	2021	2022	2023	2024	Mean
State Bank of India (SBI)	0.807	0.972	**1.000**	**1.000**	**1.000**	**0.956**
Punjab & Sind Bank	**1.000**	0.975	**1.000**	**1.000**	0.886	**0.972**
Union Bank of India	**1.000**	**1.000**	**1.000**	0.856	0.951	**0.961**
Bank of Maharashtra	0.799	0.656	0.681	0.705	0.512	**0.671**
Indian Bank	**1.000**	0.325	0.293	**1.000**	0.299	**0.583**

UCO Bank	0.766	0.610	0.519	0.502	0.434	**0.566**
Indian Overseas Bank	0.600	0.542	0.504	0.498	0.465	**0.522**
Central Bank of India	0.493	0.475	0.449	0.421	0.404	**0.448**
Punjab National Bank	0.298	0.415	0.394	0.429	0.538	**0.415**
Bank of India	0.296	0.318	0.334	0.290	0.350	**0.318**
Bank of Baroda	0.238	0.229	0.246	0.392	0.366	**0.294**
Canara Bank	0.299	0.232	0.230	0.243	0.220	**0.245**

Note. Values of 1.000 (shaded green) indicate full efficiency. Bold mean scores indicate institutions classified as high-efficiency. Scores rounded to three decimal places. Source: RBI statistical publications; CMIE PROWESS; annual bank reports.

Table 3. Efficiency Tier Classification by Mean Score

Bank	Mean Score	Tier
Punjab & Sind Bank	0.972	High Efficiency (≥ 0.900)
Union Bank of India	0.961	High Efficiency (≥ 0.900)
State Bank of India	0.956	High Efficiency (≥ 0.900)
Bank of Maharashtra	0.671	Moderate-High (0.600–0.899)
Indian Bank	0.583	Moderate (0.400–0.599)
UCO Bank	0.566	Moderate (0.400–0.599)
Indian Overseas Bank	0.522	Moderate (0.400–0.599)
Central Bank	0.448	Moderate (0.400–0.599)
Punjab National Bank	0.415	Moderate (0.400–0.599)
Bank of India	0.318	Low Efficiency (< 0.400)
Bank of Baroda	0.294	Low Efficiency (< 0.400)
Canara Bank	0.245	Low Efficiency (< 0.400)

Note. Tier thresholds: High ≥ 0.900, Moderate-High 0.600–0.899, Moderate 0.400–0.599, Low < 0.400.

Three institutions—Punjab & Sind Bank (mean: 0.972), Union Bank of India (0.961), and State Bank of India (0.956)—consistently approximate or achieve frontier performance, qualifying as sector benchmarks. Their efficiency trajectories, however, diverge instructively. SBI's progressive improvement from 0.807 in 2020 to a sustained 1.000 across 2022–2024 reflects the consolidation of synergies from its 2017 associate bank integrations and its substantial investment in digital infrastructure—outcomes consistent with the post-merger efficiency convergence literature (Milenkovic et al., 2022). Punjab & Sind Bank's near-frontier performance throughout the period, by contrast, is partly attributable to its compact and strategically focused balance sheet: a smaller, more homogeneous portfolio facilitates tighter input-output management than the sprawling operations of larger peers. Union Bank's sustained performance, following its 2020 absorption of Andhra Bank and Corporation Bank, provides tentative but encouraging evidence that at least one mega-merger has delivered near-immediate efficiency integration—an outcome that warrants further longitudinal analysis.

At the opposite pole, Canara Bank (mean: 0.245), Bank of Baroda (0.294), and Bank of India (0.318) occupy the low-efficiency tier, operating at between one-quarter and one-third of best-practice performance. Canara Bank's sequential decline—from 0.299 in 2020 to 0.220 in 2024—is particularly striking: it suggests not merely static inefficiency but an actively deteriorating input-output ratio, consistent with the bank absorbing the scale burden of its Syndicate Bank merger without achieving commensurate resource rationalization. Bank of Baroda's persistently depressed scores (range: 0.229–0.392) similarly reflect the protracted integration costs of absorbing Vijaya Bank and Dena Bank in 2019—a finding aligned with global evidence that large, complex mergers impose efficiency costs that take multiple years to reverse (Sahoo et al., 2025).

4.3 Temporal Dynamics: COVID-19 and Post-Merger Trajectories

An examination of year-wise mean efficiency trajectories reveals two distinct temporal forces. The first is a COVID-19-related compression in 2021–2022: a cluster of mid-efficiency banks—including Bank of Maharashtra (0.799 in 2020 declining to 0.512 by 2024), UCO Bank (0.766 to 0.434), and Indian Overseas Bank (0.600 to 0.465)—experienced measurable efficiency deterioration over the study period, reflecting the combined effects of pandemic-related credit stress, elevated NPA formation, and disrupted branch operations. That none of these banks had fully recovered to pre-pandemic efficiency levels by 2024 suggests that the operational recalibration required to absorb the pandemic's structural impact remains incomplete.

The second temporal dynamic concerns post-merger adjustment. Punjab National Bank's gradual improvement—from 0.298 in 2020 to 0.538 in 2024—traces a positive but shallow efficiency convergence trajectory in the four years following its absorption of Oriental Bank of Commerce and United Bank of India. The pattern is consistent with the two-to-four-year integration lag documented by Milenkovic et al. (2022), but the absolute level of 0.538 in 2024 remains well below the sector average, suggesting that PNB's integration process, while directionally positive, is far from complete. This finding has direct implications for post-merger monitoring frameworks: regulators and management should not interpret initial integration as evidence of sustained efficiency improvement.

4.4 Tobit Regression: Determinants of Efficiency

Table 4 presents the Tobit regression results. The intercept ($\beta_0 = 0.636$, $z = 6.008$, $p < 0.001$) is strongly significant and interpretable as the predicted baseline efficiency level when both ROE and NPA equal zero—capturing the average operational efficiency attributable to factors not modeled in the parsimonious two-variable specification.

Table 4. Tobit Regression Results – Determinants of PSB Efficiency (2020–2024)

Variable	Coefficient	Std. Error	z-statistic	p-value	Inference
Constant (β_0)	0.636	0.106	6.008	< 0.001	**Significant *****
Return on Equity (ROE)	−0.332	0.393	−0.845	0.398	Not Significant
Net NPA Ratio	−0.004	0.010	−0.396	0.692	Not Significant

*Note. Dependent variable: DEA efficiency score (censored between 0 and 1). Estimation: Maximum Likelihood (MLE). *** p < 0.001. ROE = Return on Equity; NPA = Net Non-Performing Assets ratio.*

Return on Equity carries a negative coefficient ($\beta_1 = -0.332$) that is statistically insignificant ($z = -0.845$, $p = 0.398$). This result challenges the intuitive expectation that more profitable banks would operate more efficiently and warrants careful interpretation. Within the intermediation framework, DEA efficiency captures the transformation of funding and operational inputs into credit and investment outputs—a fundamentally different dimension of performance from equity returns. A bank can generate high ROE through financial leverage, elevated interest margins, or non-interest income sources (fee-based services, trading gains) without improving its physical input-output efficiency. Moreover, in the PSB context, ROE is substantially distorted by government recapitalization injections and mandatory priority sector lending obligations that decouple accounting profitability from operational performance (Mittal & Singh, 2024). The finding is consistent with Aysan and Ceyhan's (2008) analysis of Turkish state banks, where ROE similarly lacked explanatory power in efficiency regressions, and reflects a broader lesson that financial profitability and operational efficiency measure distinct, though related, dimensions of institutional performance.

The Net NPA ratio likewise carries a negative coefficient ($\beta_2 = -0.004$) that fails to achieve statistical significance ($z = -0.396$, $p = 0.692$), a result that may initially appear to contradict the well-documented efficiency drag of NPAs documented by Hafsal et al. (2020). However, the non-significance is more plausibly explained by the compressed cross-sectional variation in NPA ratios across the sample during the study period. Following the RBI's 2015–2016 Asset Quality Review (AQR) and the subsequent wave of governmentmandated provisioning norms and recapitalization tranches, PSBs' NPA ratios converged toward a narrower distribution by 2020–2024, reducing the statistical leverage available to detect NPA's efficiency effect. This finding is consistent with Istaiteyeh et al. (2024), who report similarly non-significant NPA effects in a Jordanian banking DEA–Tobit study, and underscores the importance of sample selection and time-period context in interpreting second-stage results.

4.5 Model Diagnostics

Table 5. Diagnostic Tests for Tobit Regression Model Assumptions

Diagnostic Test	p-value	Threshold	Interpretation
Jarque-Bera (Normality)	0.0505	> 0.05	Approximately normal (borderline)
Shapiro-Wilk (Normality)	< 0.001	—	Minor deviation; limited practical impact
Breusch-Pagan (Homoscedasticity)	0.6229	> 0.05	No heteroscedasticity

Note. Null hypothesis for Jarque-Bera and Shapiro-Wilk: residuals are normally distributed. Null hypothesis for Breusch-Pagan: residuals are homoscedastic. p > 0.05 = assumption not violated.

The Jarque-Bera test ($p = 0.0505$) provides borderline support for residual normality, while the Shapiro-Wilk test's significant result reflects the well-documented hypersensitivity of this test to minor distributional deviations in samples of moderate panel size—a concern whose practical impact on MLE inference is limited (Long, 1997). The Breusch-Pagan test ($p = 0.6229$) confirms the absence of heteroscedasticity, validating a core assumption of the Tobit specification. Collectively, the diagnostics confirm that the model is adequately specified and that the reported coefficients and inference statistics are reliable.

5. DISCUSSION

The empirical findings of this study reveal an Indian public banking sector that, despite landmark structural reform, remains operationally bifurcated and substantially removed from best-practice efficiency. The mean efficiency of 0.579—implying a 42% excess input utilization relative to the frontier—is not merely a statistical artefact but a structural diagnosis: it reflects the accumulated weight of legacy infrastructure, excess staffing, and governance arrangements that prioritize systemic mandates over operational optimization. Crucially, the finding that this mean has not meaningfully improved over the post-consolidation period (2020–2024) challenges the reform narrative that merger-driven consolidation would yield near-term efficiency dividends.

The efficiency bifurcation documented in the data demands structural explanation. The frontier tier—SBI, Union Bank, and Punjab & Sind Bank—shares characteristics that are analytically instructive. SBI's trajectory, from 0.807 in 2020 to a consistent 1.000 in 2022–2024, is consistent with the hypothesis that the consolidation of associate banks in 2017 required a multi-year integration cycle, the benefits of which materialized within the present study window. The bank's scale, combined with its disproportionate investment in digital infrastructure and centralized risk management, enabled it to absorb integration costs while simultaneously improving its input-output ratio. Punjab & Sind Bank's near-frontier performance throughout illustrates a different pathway: not scale-driven efficiency, but focus-driven efficiency—a compact balance sheet and geographically concentrated operations that minimize coordination costs and facilitate granular input control.

The chronic underperformance of Canara Bank, Bank of Baroda, and Bank of India reveals a third pathway: merger-induced complexity without merger-realized synergy. Bank of Baroda's sustained depression of efficiency scores following its 2019 triple-bank merger reflects what the merger literature terms 'organizational entropy'—the proliferation of overlapping systems, redundant branches, and incompatible operational cultures that large, rapid mergers create. That Bank of Baroda's efficiency scores remained in the 0.229–0.392 range five years post-merger suggests that the anticipated scale economies remain largely unrealized—a finding that has direct implications for the government's ongoing evaluation of whether further PSB consolidation is warranted.

The temporal dynamics add a further dimension. The COVID-19 pandemic imposed an efficiency shock on PSBs that operated through multiple channels: compressed credit demand reduced output levels while staffing and deposit costs remained sticky in the short run; loan moratoriums and regulatory forbearance measures created temporary NPA suppression that may have delayed the disciplining effect of credit stress on operational behavior; and the forced acceleration of digital banking—while potentially efficiency-enhancing in the long run—imposed near-term technology transition costs. The persistence of below-pre-pandemic efficiency levels for several institutions as of 2024 suggests that the pandemic's operational disruption has had more durable effects than typically acknowledged in post-COVID banking assessments.

The Tobit results illuminate a deeper paradox in PSB governance. The statistical non-significance of both ROE and NPA ratio in explaining efficiency variation challenges the conventional policy assumption that improving profitability and reducing NPAs will mechanically translate into operational efficiency gains. The explanatory mechanisms are distinct: efficiency, as measured by DEA, is fundamentally about input-output transformation ratios—how many rupees of credit and investment are generated per unit of deposits, employee cost, and fixed assets. Profitability, by contrast, is a function of interest margins, fee income, provisioning levels, and leverage—dimensions that can be managed largely independently of the physical production process. The NPA non-significance, while seemingly counterintuitive, reflects the genuine compression of cross-sectional NPA variation following RBI's AQR and provisioning mandates: when all banks converge toward a similar NPA range, this variable loses its statistical ability to explain efficiency differences within the sample. This finding does not invalidate the causal mechanism documented by Hafsal et al. (2020)—that NPAs suppress efficiency—but rather indicates that the mechanism operates primarily at cross-sectoral levels of variation (between PSBs and private banks) rather than within the homogenized NPA distribution of the post-AQR PSB universe.

A synthesis of the DEA and Tobit findings points toward three systemic impediments to PSB efficiency that transcend the variables formally included in the model. First, structural over-staffing: PSBs collectively maintain employee headcounts calibrated to the pre-digital branch banking era, and the transition to digital service delivery has not been matched by commensurate workforce rationalization—creating persistent excess in the employee expense input. Second, branch-level productivity differentials: the variance in branch productivity across the PSB network is substantial, and consolidation has not systematically addressed the sub-scale, redundant branches that inflate fixed asset inputs without contributing proportionate output. Third, governance architecture: PSB boards and management teams operate under a dual accountability framework—to shareholders for returns and to the government for policy objectives—that creates strategic ambiguity and incentive misalignment at the operational level. These structural factors, rather than observable financial ratios, are the proximate determinants of the persistent efficiency gap documented in this study.

6. CONCLUSION

This study provides the first systematic efficiency assessment of India's restructured public banking sector in the post-consolidation, post-COVID era. Applying a two-stage DEA–Tobit framework to a balanced panel of twelve PSBs over 2020–2024, the analysis yields three principal conclusions. First, the Indian public banking sector operates at a mean efficiency of 0.579—well below best-practice—and this structural gap has proved remarkably resistant to the consolidation reforms and regulatory interventions of the study period, suggesting that the root causes of PSB inefficiency lie deeper than organizational structure alone. Second, efficiency is sharply bifurcated: a small cluster of frontier banks (SBI, Union Bank, Punjab & Sind Bank) demonstrates that PSB frontier performance is achievable, but the majority of the sector—including several post-merger anchor banks—remains significantly and persistently inefficient. Third, conventional financial metrics (ROE, NPA ratio) do not significantly explain within-PSB efficiency variation in this period, a finding that reflects both the institutional context of Indian public banking and the methodological insight that operational efficiency and financial profitability are distinct, imperfectly correlated dimensions of institutional performance.

These conclusions carry implications that extend beyond academic interest. The persistence of a 42% average input excess implies that the Indian taxpayer's continued recapitalization of PSBs is subsidizing operational inefficiency as much as it is restoring capital adequacy. Any sustainable reform strategy must therefore address the structural drivers of input excess—workforce calibration, branch rationalization, and governance incentive alignment—rather than focusing exclusively on NPA resolution and capital infusion. The divergent efficiency trajectories of post-merger banks further suggest that the current consolidation architecture has delivered uneven outcomes: the integration design, management capacity, and technology infrastructure of the absorbing institution matter enormously, and policymakers should resist the assumption that consolidation per se produces efficiency.

7. POLICY AND MANAGERIAL IMPLICATIONS

7.1 Regulatory and Policy Implications

For the Reserve Bank of India and the Ministry of Finance, this study yields several actionable messages. The persistent mean efficiency of 0.579 should be treated as a policy target rather than an accepted baseline: RBI's supervisory framework should incorporate DEA-based efficiency benchmarks alongside existing CAMEL ratings, enabling regulators to distinguish between institutions whose capital requirements reflect genuine credit shocks and those whose capital consumption reflects operational inefficiency. Post-merger performance monitoring mechanisms should be formalized, with explicit efficiency improvement milestones set at one, three, and five years post-amalgamation. The stark contrast between Bank of Baroda's continued low efficiency (2024 mean: 0.294) and SBI's frontier performance (1.000) suggests that the consolidation rationale applied uniformly across heterogeneous institutional contexts produces heterogeneous outcomes—a lesson that should inform the design of any future PSB restructuring.

Priority sector lending mandates, while serving vital developmental objectives, impose operational constraints on PSBs that have no private-sector counterpart, creating a structural efficiency disadvantage that is not addressable through bank management alone. Policymakers should consider compensatory frameworks—such as targeted direct benefit transfers or cross-subsidization mechanisms—that achieve priority sector objectives without embedding inefficiency into the PSB operational model.

7.2 Managerial Implications

For bank management, the DEA peer benchmarking exercise embedded in the BCC model provides institution-specific, actionable efficiency targets that go beyond what financial ratio analysis can offer. Canara Bank, with a 2024 score of 0.220, has an empirically identified potential to achieve equivalent outputs while reducing its input bundle by approximately 78%—a diagnosis that should drive concrete programs of workforce restructuring, branch rationalization, and deposit management optimization. Frontier banks—particularly Punjab & Sind Bank, whose near-frontier performance is achieved at a fraction of SBI's scale—represent particularly instructive benchmarks for mid-sized institutions, demonstrating that operational discipline and portfolio focus can compensate for the scale advantages available to larger peers.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study operates within several methodological constraints that qualify its findings and define an agenda for future research. The sample, while structurally complete for the post-consolidation PSB universe, excludes private sector and foreign banks—a constraint that prevents direct efficiency comparison across ownership types and limits the generalizability of the Tobit findings to the PSB institutional context. The two-variable Tobit specification, driven by data availability, captures only a fraction of the exogenous factors potentially relevant to PSB efficiency; future studies should incorporate macroeconomic controls (GDP growth, inflation, interest rate cycles), governance metrics (board composition, government shareholding patterns), and technology proxies (digital transaction volumes, IT expenditure ratios) to develop a richer explanatory model.

The BCC-DEA model, while appropriate for cross-sectional efficiency scoring, does not explicitly incorporate NPAs as an undesirable output within the Stage I optimization—an extension that would yield efficiency estimates more directly comparable to the Hafsal et al. (2020) framework and more faithfully reflective of the true operating performance of institutions with heterogeneous asset quality. Future research deploying directional distance function or slack-based DEA models that explicitly penalize undesirable outputs would constitute a meaningful methodological advancement. Additionally, extending the panel to cover the full post-consolidation period—including the 2025–2030 horizon as integration matures—would provide a more complete assessment of whether the consolidation reform has ultimately delivered its intended efficiency benefits. Finally, the application of dynamic DEA and Malmquist Productivity Index analysis would enable decomposition of efficiency change into technological and managerial components, providing deeper insight into whether observed improvements reflect genuine operational upgrading or merely diffusion of economy-wide technological progress.

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