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Efficiency and Consolidation in Nepalese Banking: A Bias-Corrected DEA Approach

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Abstract

This study assesses the technical efficiency of Nepalese commercial banks during the consolidation period from FY 2017 to FY 2024, triggered by the NRB's FY 2015/16 capital mandate. Output-oriented VRS technical efficiency scores are estimated using a smoothed bootstrap DEA procedure with 2,000 replications on 199 bank-year observations. A truncated regression with bootstrapped standard errors is subsequently used to identify key determinants of efficiency. The results confirm that conventional DEA substantially overstates efficiency. The average bias-corrected efficiency scores range from 0.722 to 0.873, significantly below the original estimates of 0.796 to 0.914. Most notably, banks that appeared fully efficient under standard DEA were substantially inefficient after the bias correction. Efficiency decomposition suggests that operational factors rather than scale were the primary source of inefficiency. Scale efficiency, however, deteriorated significantly after 2022, suggesting the emergence of post-consolidation diseconomies. Based on bias-corrected scores, public-sector and joint-venture banks performed at broadly comparable levels, with efficiency scores of 0.845 and 0.836, respectively, while domestic private banks remained noticeably behind at 0.766. The second-stage regression results, however, reveal that once bank-industry level and macroeconomic characteristics are taken into account, ownership type does not significantly influence efficiency. Other key second-stage efficiency drivers include bank size, income diversification, and capital adequacy, while market concentration and merger activity have a negative effect on efficiency. These findings indicate that the ongoing consolidation wave in the banking industry has generated short-run efficiency losses and regulators need to prioritize operational integration and scale optimization within the sector.

Keywords: Nepalese banking, M & A, Technical efficiency, Bias-corrected DEA, Truncated regression, Simar-Wilson Bootstrap, Banking consolidation

JEL Classification: G21, G34, C14

Introduction

Evaluating how effectively banks perform their intermediation function is crucial, as it reflects their ability to transform real inputs such as capital,

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labor, and physical assets into the financial outputs that facilitate economic activity. Banks perform this function to reduce information asymmetries and manage systemic risk by screening borrowers, thereby mitigating moral hazard and adverse selection (Hughes & Mester, 2019). In light of these theoretical considerations, understanding and enhancing banking efficiency becomes a priority for policymakers, regulators, and bank executives seeking to identify performance gaps, resource misallocations, and the institutional conditions that contribute to high performance. This priority is particularly important for developing economies like Nepal, where the banking system has experienced a radical structural transformation over the past decade.

During this period, Nepal's banking sector experienced a wave of mergers and acquisitions (M & A) among financial institutions, encouraged by policies introduced by the Nepal Rastra Bank (NRB). The earliest push came with the Merger Bylaws in 2011, which established the initial regulatory framework for consolidation in the industry. The pace of consolidation, however, remained slow, and the NRB subsequently introduced mandatory capital requirements through the Monetary Policy of FY 2015/16, requiring commercial banks to quadruple their minimum paid-up capital within a two-year compliance window ending in FY 2017. This triggered the largest consolidation wave in the history of the Nepalese banking industry. As M & A persisted until FY 2024, the number of commercial banks operating in Nepal declined substantially, from 28 in FY 2017 to 20 by FY 2024. Although these mergers and acquisitions helped significantly reduce the number of banks, their impact on bank performance and operational efficiency has not been fully explored empirically. Against this backdrop, the present study investigates three core inquiries: first, how has the technical efficiency of Nepalese commercial banks evolved over the consolidation era of FY 2017-2024; second, do efficiency levels differ systematically across ownership categories - public sector, joint venture, and domestic private banks; and third, which bank-level, industry-level and macroeconomic factors, including M&A activity, have exerted a systematic influence on efficiency outcomes during this period?

Addressing these questions requires rigorous analysis of technical efficiency, the standard approach in the banking literature for evaluating how efficiently institutions transform inputs into financial outputs. In Nepal, several studies have applied Data Envelopment Analysis (DEA) to estimate bank-level efficiency by comparing performance among peers and identifying the best-practice frontier. However, while DEA is popular for its flexibility and minimal structural assumptions, it raises serious statistical issues when DEA is used for formal inference. As noted by Simar and Wilson (2007), the conventional

DEA efficiency scores have ill-defined statistical inference procedures and are systematically biased. Because the efficiency scores are calculated relative to an estimated frontier, they exhibit an upward bias in finite samples. Furthermore, the estimated DEA scores are serially correlated, which implies that using these scores in the traditional two-stage approach, where DEA efficiency scores are regressed against environmental variables using Tobit or OLS models, is not appropriate, as these models fail to adequately capture the sampling variability of first-stage estimates. These methodological shortcomings of the standard two-stage approach may lead to erroneous conclusions regarding the actual determinants of efficiency.

Motivated by these limitations, this paper estimates bias-corrected technical efficiency scores for Nepalese commercial banks over the period FY 2017-2024 using the smoothed bootstrap procedure of Simar and Wilson (1998, 2000). These scores are then used in a second-stage truncated regression following Algorithm #1 of Simar and Wilson (2007), replacing the theoretically inconsistent Tobit and OLS models conventionally used in the literature.

This study makes three key contributions to the existing literature. Methodologically, it is the first DEA-based study of bank efficiency in Nepal to apply the Simar and Wilson bootstrap procedure, thereby correcting the upward bias inherent in conventional DEA estimates. To the best of our knowledge, and as confirmed by the literature reviewed in Section 2, no previous DEA-based bank efficiency study in Nepal has employed the Simar-Wilson bootstrap procedure to estimate bias-corrected technical efficiency scores. Second, it identifies the key drivers that have had a systematic impact on efficiency during this transformative period. Third, by identifying the specific determinants of efficiency, this study provides regulators and bank executives alike with practical insights regarding future consolidation policies in developing economies.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature on bank efficiency and the applications of the Simar-Wilson techniques. Section 3 describes the data and methodology, including input-output choice and the smoothed bootstrap algorithm. Results and discussion are presented in Section 4 with bias-corrected efficiency scores and second-stage regression results. Section 5 concludes by summarizing the key findings of this study and its policy implications.

Literature Review

Efficiency is defined as the "comparison of observed inputs (or resources) and outputs (or products) with what is optimal" (Aparicio et al., 2020, p.4). More specifically, technical efficiency is the ratio of observed to minimum input for a given output, or the ratio of observed to maximum output for a given input (Aparicio et al., 2020). This measure benchmarks units against a best-practice frontier reflecting optimal resource utilization under existing technology, independent of price considerations. To measure this, frontier efficiency methods have emerged as the dominant analytical framework, as they overcome the limitations of traditional financial ratios, which fail to account for the multi-input and multi-output nature of banking. These methods accommodate complex production processes and can incorporate undesirable outputs, such as non-performing loans (Kumar & Gulati, 2008).

The efficiency literature broadly classifies frontier approaches into parametric and non-parametric approaches. Parametric techniques such as Stochastic Frontier Analysis (SFA) require specifying a functional form and making explicit assumptions about the distributions of inefficiency and random error. In contrast, non-parametric methods (most notably DEA), require minimal structural assumptions to build a piecewise linear frontier and are flexible enough to incorporate multiple inputs and outputs in their specification. A systematic review by Akdeniz et al. (2023) of 305 bank efficiency studies conducted from 1989-2019 confirms the dominance of frontier methods, with 89% of studies using them to estimate technical efficiency. Among them, non-parametric approaches (61%) were preferred to parametric approaches (28%), with DEA alone accounting for 60% of all non-parametric applications.

The methodological shift

Despite its popularity, the traditional two-stage DEA approach, which first estimates efficiency scores and then regresses them on contextual variables using standard methods such as Tobit or OLS, has faced significant criticism. In their influential work, Simar and Wilson (2007) point out two primary shortcomings of the traditional two-stage DEA framework. First, the traditional first- and second-stage estimation lacks a coherent data-generating process that links the first-stage efficiency estimation to the second-stage contextual variables, thus providing no theoretical justification for the relationship between the two stages. Second, the conventional DEA wrongly assumes that the estimated DEA scores are independent. As DEA scores are estimated relative to a sample-specific frontier, they are serially correlated because altering one efficient unit can change the efficiency scores of many others in the sample. This inherent dependence in DEA scores violates core statistical principles, thereby yielding invalid standard errors and confidence intervals (Simar & Wilson, 2007; Badunenko & Tauchmann, 2019). Also, due to finite-sample bias, the conventional DEA scores are artificially inflated, resulting in an unnatural clustering of units at the frontier (full efficiency).

To address this problem of finite-sample bias, Simar and Wilson (1998, 2000) proposed a smoothed bootstrap method. This technique approximates the sampling distribution of the DEA efficiency estimator, thereby enabling estimation of the finite sample bias and the subsequent construction of the bias-corrected efficiency scores. For the second stage, Simar and Wilson (2007) recommend a truncated regression as more appropriate than OLS or Tobit regression for analyzing efficiency determinants, because the efficiency scores are no longer clustered at the frontier or at full efficiency after bias correction. In this study, we employ Simar and Wilson (Algorithm #1) in the second stage for identifying the main drivers of efficiency. Though the "Double Bootstrap" (Algorithm #2) is often considered as the benchmark for full statistical inference in DEA efficiency literature, Algorithm #1 with the theoretically appropriate truncated regression framework also provides a meaningful improvement over the conventional practice of using OLS or Tobit regression in the second stage. A growing body of bank efficiency-based research has used the Simar and Wilson (2007) bootstrap method, with studies consistently showing its advantages over the conventional two-stage approach in estimating technical efficiency and analyzing its determinants (Delis & Papanikolaou, 2009; Ahmad et al., 2015; See & He, 2015; Bahrini, 2017; Jimenez-Hernandez et al., 2019).

Drivers of efficiency

The literature on DEA and SFA-based applied efficiency studies has examined a wide range of bank-industry-level and macroeconomic determinants of bank efficiency. The findings are largely mixed and vary significantly by region and analytical framework under consideration.

Bank size

Efficiency and bank size exhibit an ambiguous relationship in the literature. Small banks are expected to be more efficient as they can maintain closer relationships with customers and thus have superior credit information (Berger et al., 2017). Others argue that large banks have the advantage of economies of scale (Moutsianas & Kosmidou, 2016). This ambiguity is reflected in the empirical literature, where some studies have found a negative relationship between efficiency and bank size (Kumar & Gulati, 2008), while others have found gains for larger banks due to economies of scale (Wang et al., 2014). However, these scale advantages may eventually be offset by diseconomies of complexity as banks continue to grow (Delis & Papanikolaou, 2009).

Capitalization

A well-capitalized bank is generally associated with better technical efficiency, as a higher capital adequacy ratio acts as a cushion to absorb shocks more effectively (Das and Ghosh, 2006), though some studies also report insignificant effects (Goswami et al., 2019).

Ownership

With respect to ownership, public banks are often associated with lower efficiency than private or joint-venture foreign banks due to their broader growth and development mandates (See & He, 2015). On the other hand, foreign banks have access to superior technology and human capital transferred from their parent institutions (Bonin et al., 2005; Claessens et al., 2001), which gives them an efficiency advantage over domestic and state-owned banks.

Competition and asset quality

Market structure has a complex relationship with bank efficiency. A concentrated market might reduce competitive pressure, resulting in lower efficiency levels (Jimenez-Hernandez et al., 2019). In contrast, higher competition can discipline banks and cause them to work more efficiently. Competition can also compress margins and lead to higher risk-taking, resulting in larger NPLs and deteriorating bank performance (Mateev et al., 2022). Weakening asset quality increases banks' spending on monitoring and managing problem loans, leading to lower efficiency and performance (Das & Ghosh, 2006).

Macroeconomic factors

Evidence is largely inconclusive regarding the relationship between efficiency and macroeconomic factors like GDP growth and inflation. Nasim et al. (2024) found both GDP growth and inflation were negatively related with efficiency when analyzing a global panel of major banks, though the effects differ between developed and developing economies. On the other hand, Blankson et al. (2022) found a positive relationship between inflation and bank efficiency but a negative relationship between GDP growth and efficiency, highlighting the contextual nature of these relationships.

Nepalese evidence

The Nepalese banking efficiency literature remains nascent and fragmented, comprising a mix of frontier and ratio-based methods. Despite the methodological differences, some common patterns do emerge. Bank ownership structure has been found to play an important role, with private and joint venture banks generally performing better than state-owned banks. The earliest work by Gajurel (2010) documents a clear superiority of private banks over public banks in technical, scale, and cost efficiency, while finding managerial efficiency to be broadly comparable across ownership categories. Pathak (2019) found private banks outperformed public banks in an input-oriented constant returns to scale model. This is consistent with Hakuduwal (2018), who similarly reported higher efficiency for foreign joint-venture banks, though the study's mixed sample of commercial and development banks warrants caution in drawing direct comparisons.

With respect to bank size, frontier-based methods largely point to no significant relationship. Jha et al. (2013) and Pathak (2019) found the association between bank size and technical efficiency to be statistically insignificant. Similarly, Thagunna and Poudel (2013) reported no significant relationship between size and efficiency, though their use of a single-year regression with no control variables limits the reliability of their results. On the cost efficiency front, Gajurel (2010) and Panta and Bedari (2015) both indicate a negative relationship, with smaller banks exhibiting higher cost efficiency. Turning to accounting ratio-based studies, while K.C. et al. (2025) and Shrestha et al. (2022) found no significant relationship on limited samples, Shrestha (2025) reported a positive and significant relationship using a more comprehensive dataset. However, results from accounting-based approaches need to be interpreted with caution, as these studies employ efficiency proxies that lack definitional consistency and differ fundamentally from frontier-based measures. Beyond static efficiency, a small body of research has also examined productivity growth over time. Neupane (2013) and Shah et al. (2022) attribute technological progress, rather than pure efficiency gains, as the primary driver of productivity growth in Nepal's banking sector.

Limited empirical work has emerged regarding the recent consolidation wave in the industry. NRB (2022a) found that mergers yielded no immediate technical efficiency gains among the 22 consolidated banks, though this conclusion rests on year-on-year rank comparisons without a robust counterfactual, which limits its ability to isolate the merger effect from broader sectoral trends. By contrast, Adhikari et al. (2026) adopted a more rigorous methodology using a difference-in-differences approach and SFA, and found that regulatory-induced mergers between 2015 and 2017 reduced cost efficiency, whereas voluntary mergers post-2017 had the opposite effect, showing a positive and significant impact on efficiency.

Now, despite this expanding body of work, significant methodological and empirical gaps persist in the Nepalese banking literature. First, the literature frequently employs standard DEA models in the first stage, as seen in Thagunna and Poudel (2012), Neupane (2013), and NRB (2022a), and subsequently runs either Tobit or OLS regressions in the second stage, an approach that Simar and Wilson (2007) demonstrated to be inappropriate. Second, the existing body of work suffers from limitations in sample composition. Several studies either exclude public banks (Thagunna & Poudel, 2012; Neupane, 2013; NRB, 2022) or include them only partially (Neupane, 2013; NRB, 2022), or combine commercial and development banks into a single sample (Hakuduwal, 2018), which severely limits their representativeness. Finally, as evidenced in the preceding review, recent efficiency studies have largely focused on cost efficiency or accounting-ratio-based approaches and have mostly ignored the unique consolidation phase of FY 2017–2024, triggered by the 2015/16 NRB capital mandate. This phase remains largely unexamined through the lens of frontier-based methods of measuring technical efficiency. This study directly addresses the above gaps by presenting the first statistically rigorous, bootstrap-bias-corrected assessment of technical efficiency among Nepalese commercial banks during a period of sector consolidation.

Data and Method

Various conceptual approaches exist in the banking literature to understand the nature of bank behavior and its production process. These approaches, in turn, guide the selection of input and output variables for efficiency analysis. Kumar and Gulati (2014) have summarized several such approaches in the literature, namely the production approach, the intermediation approach, and related variants including the asset approach, the user cost approach, and the value-added approach. This study adopts the widely popular intermediation approach, which sees banks as financial intermediaries that channel funds between depositors and creditors

The analysis employs three inputs, i.e., total staff, fixed assets, and deposits, and two outputs, i.e., net interest income and non-interest income, to measure the technical efficiency of commercial banks in Nepal. This specification satisfies the common DEA dimensionality guidelines, which recommend that the number of decision-making units should be at least three times the total number of inputs and outputs (Cooper et al., 2007)[2]. The inclusion of non-interest income as an output captures shifts in the Nepalese banking sector, reflecting the increasing role of non-traditional banking activities such as fee-based services. The dataset comprises commercial banks covering the period FY 2017-2024, with the

2 Cooper et al. (2007) recommends a minimum sample size of $n \geq \max(m \times s, 3(m + s))$ for DEA. With $m = 3$ inputs and $s = 2$ outputs, this threshold is 15 DMUs. The present sample of 20-27 banks across the study period comfortably exceeds this requirement.

descriptive statistics for both the efficiency frontier variables and the regression determinants summarized in Table 1. The corresponding correlation matrix for the DEA inputs and outputs is presented in Appendix Table B1. Data are collected from multiple issues of the NRB's Bank Supervision Report, published annually. The number of banks in our sample ranges from 20 to 27 across years, representing 97.60% to 100% of total banking industry assets in each year, ensuring comprehensive coverage and thereby significantly reducing the potential for selection bias. To ensure comparability over time, all figures given in monetary units are deflated using the Consumer Price Index with 2014/15 as the base year (2014/15 = 100).

Table 1: Descriptive Statistics of First Stage and Second Stage Variables (2017-2024)

Variable	Observations	Mean	Std. dev.	Min	Max
First Stage Variables					
Staff	199	1553.784	816.165	478	4385
Fixed Assets	199	1947.753	2509.714	89.628	19292.4
Deposits	199	104910.4	52228.75	27158.58	293259.4
Net Interest Income	199	3926.716	1937.934	1067.378	11259.1
Non-Interest Income	199	1072.817	451.419	262.902	2604.106
Second Stage Variables					
Bias-Corrected Efficiency	199	0.795	0.108	0.472	0.958
Bank Size	199	11.680	0.469	10.514	12.800
Risk (%)	199	1.806	1.275	0.010	4.950
Diversification (%)	199	1.173	0.376	0.404	2.761
CAR (%)	199	14.038	2.165	10.390	23.680
Profitability (%)	199	1.385	0.572	0.001	3.706
Competition	199	441.836	59.042	400.298	562.446
Inflation (%)	199	5.105	1.489	2.777	7.670
Economic Growth (%)	199	4.741	3.459	-2.370	8.977

Note: All values are in million NPR except Staff, which is reported in absolute numbers. Std. dev.= standard deviation; Min = Minimum Value; Max = maximum value; Bank Size = natural logarithm of total assets; Risk = non-performing loans to total loans ratio; Diversification = non-interest income to total assets ratio; CAR = capital adequacy ratio; Profitability = return on assets ratio; Competition = Herfindahl-Hirschman index; Inflation = consumer price index; Economic Growth = GDP growth rate.

With the input-output specification established, the next consideration concerns model orientation and returns to scale. Following Coelli et al. (2005), the choice of model orientation should reflect the variables that bank managers can influence most directly. In the Nepalese context, NRB regulations mandate branch network expansion by requiring a presence in all local government bodies and permitting a Kathmandu Valley branch only after three branches have been opened elsewhere (NRB, 2022b). These mandates, alongside minimum capital requirements, constrain banks' ability to freely reduce inputs such as fixed assets and staff. An output-oriented model, which measures efficiency as the proportional expansion of outputs given fixed inputs, is therefore the more appropriate choice. The variable returns to scale (VRS) specification is preferred to constant returns to scale (CRS) because the banking sector exhibits considerable heterogeneity in bank size, a choice empirically supported by the persistent divergence between overall technical efficiency (OTE) and pure technical efficiency (PTE) scores reported in Section 4, confirming that Nepalese commercial banks systematically operate away from their most productive scale size.

Formally, for each bank $k = 1,\ldots,K,$ use a vector of inputs $x_k \in \mathbb{R}_+^m$ to produce a vector of outputs $y_k \in \mathbb{R}_+^s$. The input vector consists of fixed assets, labor, and deposits, while the output vector is comprised of net interest income and non-interest income. For a given bank k, the output-oriented VRS DEA model is formulated as the following linear programming problem:

$$\max_{\phi,\lambda} \phi$$

subject to

$$\sum_{j=1}^{K} \lambda_j y_j \geq \phi y_k$$

$$\sum_{j=1}^{K} \lambda_j x_j \leq x_k$$

$$\sum_{j=1}^{K} \lambda_j = 1, \quad \lambda_j \geq 0$$

where ϕ represents the proportional expansion in outputs that bank k can achieve given its input bundle. The technical efficiency score is defined as $TE_k = 1/\phi_k$, where 1 indicates full technical efficiency and values less than 1 indicate degrees of inefficiency. The model is estimated separately for each year to allow for time-varying production technology.

To overcome the finite sample bias of the standard DEA efficiency model, this study applies the smoothed bootstrap procedure of Simar and Wilson (1998, 2000). Unlike naïve bootstrap methods, which resample data directly and can produce infeasible pseudo-samples, the smoothed bootstrap method preserves the structure of the estimated technology while accounting for sampling uncertainty

(Bogetoft & Otto, 2011). A detailed description of the smoothed bootstrap DEA is provided in Appendix A. Beyond bias correction, the procedure also partially mitigates the sensitivity of DEA scores to outliers, as bias-corrected scores are derived through repeated resampling rather than a single frontier construction, there by reducing the influence of any single extreme observation. To further address the potential influence of extreme values on second-stage regression results, all continuous bank-specific variables were examined at the 1st and 99th percentiles. Macro-level and industry-level variables, which vary only by year, were not subjected to this procedure. The screening revealed only a very small number of observations outside these thresholds, and all were economically plausible. Accordingly, no winsorization or trimming was applied to preserve the original distribution of the data.

In the first stage, bias-corrected efficiency scores are estimated for each bank annually over the period FY 2017-2024 using the dea.boot() function from the Benchmarking package (Bogetoft & Otto, 2025) in R, which implements the smoothed bootstrap algorithm of Simar and Wilson (1998). All estimations are conducted under the VRS assumption with output orientation. In the second stage, these bias-corrected scores are regressed on environmental variables following Algorithm #1 of Simar and Wilson (2007), using a truncated regression model suited for the distribution of bias-adjusted efficiency scores. As recommended by Badunenko and Tauchmann (2019), both the first and second stages employ 2,000 bootstrap replications for robust inference within the Simar-Wilson framework. Taken together, this framework addresses the key limitations of the conventional two-stage DEA procedure, namely finite-sample bias and misspecification of the second-stage estimator, thereby providing a more rigorous efficiency analysis of the Nepalese banking sector.

Results and Discussion

Table 2 reports the first-stage bias-corrected technical efficiency scores alongside the standard DEA scores, both under the VRS assumption. As theorized by Simar and Wilson (2007), conventional DEA scores exhibit a systematic upward bias, as evidenced by the sample averages: the mean bias-corrected pure technical efficiency (PTE-VRS) score of 0.795 is significantly lower than the conventional DEA mean of 0.856. This confirms that standard DEA underestimates inefficiency in finite samples, a finding corroborated by the Wilcoxon signed-rank test, which is statistically significant ($z = 12.14$, $p < 0.001$), thereby validating the use of a bootstrap correction to accurately measure efficiency in the Nepalese banking sector.

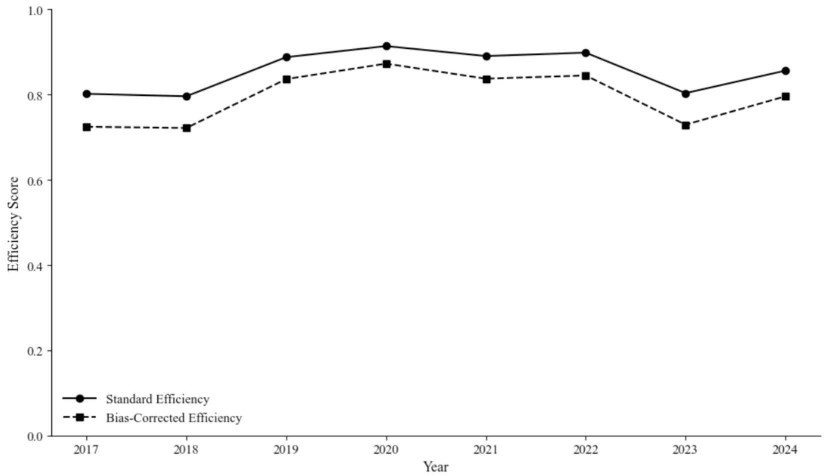
Table 2: Average Annual Technical Efficiency (FY2017 - FY2024)

Year	Original Efficiency	Bias Corrected Efficiency
2017	0.802	0.725
2018	0.796	0.722
2019	0.888	0.837
2020	0.914	0.873
2021	0.891	0.838
2022	0.899	0.845
2023	0.804	0.730
2024	0.856	0.796
Mean	0.856	0.795

Note: Technical efficiency scores range from 0 to 1, with 1 indicating full technical efficiency and scores below 1 indicating degrees of inefficiency.

Temporal trend analysis in Figure 1 reveals that average annual technical efficiency remained elevated between 2019 and 2022, consistently staying above 0.830 and peaking at 0.873 in 2020. These years also saw small standard deviations (ranging from 0.075 to 0.087) around the mean, suggesting a higher degree of performance homogeneity than in other years (range: 0.102 to 0.156). In the latter part of our sample period, efficiency fell sharply to 0.730 in 2023, then recovered to 0.796 in 2024. This decline was also accompanied by higher dispersion as reflected in the coefficient of variation, which rose from 0.10 in 2020 to 0.14 in 2024. This suggests that as the industry recovered from the 2023 dip, the sector became more heterogeneous in efficiency. This downturn and increased dispersion coincided with the reduction in the number of commercial banks from 26 in FY2022 to 20 in FY2023 and likely reflect both structural and macroeconomic pressures contributing to this decline. The intense merger wave towards the end of the sample period likely came with substantial integration costs and a fall in efficiency that temporarily offset the potential scale gains. The banking sector was likely also under pressure from the broader macroeconomic environment characterized by rising NPLs, subdued credit growth, and heightened regulatory oversight (International Monetary Fund, 2024).

Figure 1: Comparative Annual Trend of Technical Efficiency Scores



To understand the structural drivers of efficiency, the model was also estimated under the constant returns-to-scale assumption (OTE). Together with the pure technical efficiency estimated earlier under the variable returns-to-scale assumption, we can break down OTE into PTE and scale efficiency (SE). Formally, this relationship is expressed as:

$$OTE_{crs} = PTE_{vrs} \times SE$$

Table 3: Decomposition of Technical Efficiency (FY2017 - FY2024)

Year	OTE	PTE	SE
2017	0.682	0.725	0.942
2018	0.684	0.722	0.948
2019	0.791	0.837	0.946
2020	0.843	0.873	0.966
2021	0.778	0.838	0.929
2022	0.698	0.845	0.826
2023	0.650	0.730	0.891
2024	0.676	0.796	0.849
Sample Mean	0.725	0.795	0.912

Note: OTE = Overall Technical Efficiency; PTE = Pure Technical Efficiency; SE = Scale Efficiency. All scores are bias-corrected and range from 0 to 1

The decomposition sheds light on whether a bank's inefficiency is mainly due to managerial practices or divergence from the most productive scale of operation. Table 3 shows that the average OTE inefficiency of 27.5% in the banking industry is primarily driven by PTE inefficiency (20.4%) rather than

SE inefficiency (8.8%). This means that the main source of inefficiency in the Nepalese commercial banking industry is operational rather than an inappropriate scale of operations. But interestingly, scale efficiency, which remained stable and near the frontier until 2021 (peaking at 0.966 in 2020), fell sharply to 0.826 in 2022, a reduction of 14 percentage points. This fall is statistically significant, as confirmed by a two-sample Wilcoxon rank-sum test ($z = 5.402$, $p < 0.001$) comparing bank-level SE scores between FY2020 and FY2022. This indicates that as the consolidation wave progressed in the banking industry, some banks may have exceeded their optimal size and are now experiencing decreasing returns to scale, suggesting that these larger banks are struggling with their increased size.

Turning to bank-level average efficiency scores (see Appendix Table B2), the bootstrap bias correction reveals the true efficiencies of the four banks (Civil Bank, Nabil Bank, Nepal Bangladesh Bank, and Standard Chartered Bank) that appeared perfectly efficient under the standard DEA with scores of 1.0. After applying bias correction, their true efficiencies range from 0.869 to 0.885, and this alone justifies adopting the Simar-Wilson bootstrap approach, as it demonstrates that the perfect efficiency under conventional DEA is not a true reflection of performance but a statistical artifact of finite samples.

The top banks by bias-corrected efficiency scores are Agriculture Development Bank Limited (ADBL) and Nepal Bangladesh Bank. Interestingly, while Nepal Bangladesh Bank was one of the banks with a full efficiency score under the standard DEA model, ADBL was never on the frontier. Nepal Credit and Commerce Bank and Prabhu Bank were the least efficient, with scores of 0.676 and 0.683, respectively. In total, the bootstrap procedure systematically revises efficiency scores technically downward for each bank in the sample and can reorder rankings, thereby providing a more realistic and reliable assessment of relative performance.

Differences in efficiency across ownership types

Decomposition by ownership structure (Table 4) reveals that public sector banks achieved the highest average bias-corrected efficiency score (0.845), followed closely by joint venture banks (0.836), while domestic private banks scored considerably lower (0.766). A Kruskal-Wallis test confirmed significant overall differences across ownership groups ($\chi^2(2) = 11.623$, $p = 0.003$). Pairwise Wilcoxon rank-sum tests further clarified the structure of these differences: the gap between public and joint venture banks proved statistically insignificant ($z = -0.693$, $p = 0.488$), indicating broadly comparable efficiency levels, whereas both groups significantly outperformed domestic private banks (public: z = -2.508, p = 0.012; joint venture: z = 2.786, p = 0.005). Domestic private banks thus constitute a statistically distinct, lower-performing group, while public and joint-venture banks share a broadly similar efficiency profile.

Table 4: Technical Efficiency by Ownership Structure (2017-2024)

Ownership	Original Efficiency	Bias-Corrected Efficiency
Domestic Private	0.819	0.766
Joint Venture	0.916	0.836
Public	0.923	0.845

Note: Domestic Private includes privately owned domestic banks; Joint Venture includes private banks with foreign partnerships; Public includes state-owned banks.

The relatively stronger performance of public sector banks in this study contradicts prior Nepalese banking studies as discussed in section 2, which generally found state-owned banks to be less efficient (Gajurel, 2010; Hakuduwal, 2018; Pathak, 2019). However, direct comparisons are not straightforward, as there are methodological differences relative to the previous literature. Gajurel (2010) and Hakuduwal (2018) both found public banks to be less efficient, but they used alternative frontier methods in their analyses, which restrict direct comparisons with our study. Hakuduwal (2018) not only employed an alternative frontier method but also included a mix of commercial and development banks, which limit direct comparisons. Beyond these methodological and sampling differences, the unique consolidation context of our sample period (FY 2017-2024) may also offer a more substantive explanation for the unexpectedly strong performance of public banks. During this period, public banks[3] remained largely untouched by merger and acquisition activity. On the other hand, domestic private banks were the most actively involved in consolidation, with joint venture banks participating to a lesser extent. As merger and acquisition processes invariably entail integration challenges and transitory efficiency losses (Amel et al., 2004), and given that many Nepalese banks acquired poorly performing institutions (NRB, 2022), these M&A activities likely resulted in substantial efficiency impacts on the banks involved. Despite some degree of merger exposure, joint-venture banks navigated these disruptions more effectively, perhaps because of stronger institutional arrangements and human capital inherited from their foreign parent companies. ADBL recorded the highest individual bias-corrected

3 Rastriya Banijya Bank's acquisition of NIDC Development Bank (May 2, 2018) was the sole M&A involving a public sector bank during the sample period. All other M&A activities involved domestic private and joint venture banks.

score (0.885), consistent with its strong performance in previous studies (Jha et al., 2013; Pathak, 2019).

Second stage regression results

Table 5 reports the second-stage truncated regression results using Algorithm #1 of Simar-Wilson, with 2,000 bootstrap replications, based on 199 bank-year observations. Variance Inflation Factor tests confirmed that multicollinearity was not a concern, as all values remained well below the 5 thresholds (Appendix Table B3). The dependent variable is the bias-corrected technical efficiency score under VRS. To control for institutional heterogeneity, bank ownership was included through two dummy variables (Public and Private), with Joint-Venture banks as the reference category. Additionally, an M&A dummy (assigned 1 for banks undergoing merger or acquisition in a given year, 0 otherwise) was also included to isolate the short-term impact of structural consolidation on technical efficiency. The overall model was statistically robust (Wald $\chi^2 = 95.54$, $p < 0.01$).

Table 5: Determinants of Technical Efficiency - Truncated Regression Results

Variable	SW Coeff.	SW Bootstrap Std. Err.
Bank size	0.139***	0.024
Diversification	0.124***	0.034
Risk	0.009	0.007
Profitability	0.031*	0.018
CAR	0.017***	0.005
Competition	-0.001***	0.000
Inflation	0.009	0.006
Economic Growth	-0.011***	0.003
M&A	-0.049**	0.022
Public	-0.011	0.033
Private	-0.017	0.019
Constant	-0.850	0.299
Observations	199	
Wald chi²	95.54***	

Note: SW = Simar Wilson ; *** means p-value < 0.01, ** means p-value < 0.05, *means p-value < 0.10, Bank Size = Natural logarithm of total assets; Diversification = Non-interest income to total assets ratio; Risk = Non-performing loans to total loans ratio; Profitability = Return on assets ratio; CAR = Capital adequacy ratio; Competition = Herfindahl-Hirschman Index; Inflation = Consumer Price Index; Economic Growth = GDP growth rate; M&A = Merger and acquisition dummy; Public = Public ownership dummy; Private = Private ownership dummy (Base category: Joint Venture)

The regression results revealed several statistically significant efficiency drivers. Bank size exerted a positive and highly significant effect (β = 0.139), implying that a 1% increase in total assets is associated with a 0.139-percentage-point improvement in technical efficiency (13.9 percentage point). This is consistent with the modern view of economies of scale in banking, which suggests that larger banks are better positioned to take advantage of technological advancements, achieve greater risk diversification, and spread high fixed overhead costs across a greater volume of output (Hughes and Mester 2013). This provides partial support to NRB's consolidation mandate at the individual bank level by indicating that larger banks make better use of resources. The benefits of size, however, are not guaranteed to be cost-free, as M&A activity may entail short-term efficiency sacrifices during integration, a point discussed in the M&A analysis below. Income diversification also had a significant positive coefficient (β = 0.124), indicating that a 1-percentage-point increase in the non-interest income ratio is associated with a 0.124 increase in the efficiency score (12.4 percentage points). This is consistent with Sanya and Wolfe (2011), who show that banks in developing nations achieve better performance and stability from a broader mix of activities. While the literature in developed economies suggests an "over-diversification discount", in emerging financial markets like Nepal, spreading banks' operations into non-interest areas such as remittances and fee-charging services seems to provide a buffer against systemic shocks.

Capital adequacy ratio (β = 0.017) is also positively and significantly correlated with efficiency. A 1-percentage-point increase in the capital adequacy ratio leads to a 1.7-percentage-point increase in technical efficiency. Profitability (β = 0.031) was significant only at the 10% level, meaning that a 1 percentage-point increase in the ROA ratio would raise efficiency by 0.031, or 3.1 percentage points, indicating that its influence is small once other controls are included. Risk, as proxied by the NPL ratio, was not statistically significant, an unexpected finding, but it is in line with the overall benign credit environment prevailing during FY2017-2024. The average NPL ratio of banks was 1.80%, with a standard deviation of 1.27% and a maximum of 4.95% during the sample period, all below the 5% "red line" limit set by the European Banking Authority (2018) for elevated credit risk. Given the consistently strong credit quality during the sample period, NPL levels were unlikely to have played a significant role in shaping the technical efficiency of bank operations. In line with the quiet life hypothesis (Hicks, 1935), market concentration, measured by the Herfindahl-Hirschman Index, had a negative and significant effect (β = -0.001). This means that as market concentration increases, competitive pressure on bank management decreases, leading to organizational slack and efficiency losses.

Similarly, GDP growth was negative (β = -0.011), such that a 1-percentage point increase in GDP growth was associated with a 1.1-percentage point decline in technical efficiency. This is consistent with Nasim et al. (2024), who show that GDP growth is negatively associated with technical efficiency across 109 major banks in developed and developing nations, due to poorer resource deployment during periods of growth, even as profitability rises. However, inflation was not statistically significant, indicating that it had no systematic effect on technical efficiency over this period.

A key finding of this study is the significant negative and significant coefficient on the M & A dummy (β = -0.049). This means that in the year a bank undertook a merger or acquisition, its technical efficiency declined by approximately 4.9 percentage points, which is equivalent to a 6.2% decrease relative to the sample mean of 0.795. This directly validates the post-merger integration difficulties arising from organizational disruption, cultural frictions, and system consolidation costs (Amel et al., 2004), and thus supports NRB (2022a), which noted that M&A-induced asset and credit expansion in Nepal failed to produce immediate efficiency gains. The result also provides a structural explanation for why domestic private banks, the most active M & A participants, recorded lower average efficiency than public and joint venture banks.

Robustness check

The baseline estimates of the Simar and Wilson algorithm #1 were evaluated for their robustness using a fractional logit model (Appendix Table B4). This specification was chosen over the commonly used Tobit model because bias corrected efficiency scores no longer included values at the exact boundaries of 0 and 1, making the censored regression theoretically inappropriate. The results of the fractional logit model were broadly consistent with the baseline across all key determinants. With the exception of profitability, all other key determinants such as bank size, income diversification, capital adequacy, market concentration, GDP growth, and M&A activity maintained their expected signs and remained statistically significant. Profitability, as measured by ROA, lost statistical significance under the fractional logit model, so its effect is sensitive to modeling assumptions and should be interpreted with caution. Ownership dummies remained insignificant under the fractional logit model, reinforcing the conclusion that, once structural and macroeconomic controls are accounted for, ownership structure does not independently drive efficiency. The consistency of results between the two specifications strengthens confidence in the substantive conclusions drawn from this study.

Conclusion

Existing Nepalese bank efficiency studies rely on the traditional two-stage framework, which has been criticized by Simar and Wilson (2007). This study provides a rigorous, bootstrap-bias-corrected assessment of technical efficiency for Nepalese banks during the consolidation wave from FY2017 to FY2024. These bias-corrected efficiency scores are then examined alongside bank and industry-level and macroeconomic drivers to identify the main determinants of technical efficiency. The analysis yields four primary conclusions. First, as expected, conventional DEA substantially overstates efficiency, with average bias-corrected scores revising efficiency downward from 0.856 to 0.795. Second, the major source of inefficiency is managerial in nature rather than scale, though scale inefficiency rose markedly following the most intense phase of M&A activity in the latter part of our sample period. Third, in terms of ownership groups, public banks (0.845) and joint venture banks (0.836) are on equal footing while domestic private banks (0.766) form a distinct, lower-performing group. The second-stage regression, however, shows that ownership is not an independent determinant of performance, as the efficiency differentials observed in the first stage no longer persist once bank-industry-level and macroeconomic controls are accounted for. Lastly, bank size, income diversification, and capital adequacy are positively associated with efficiency, whereas M&A involvement, GDP growth, and greater market concentration are negatively associated with efficiency scores.

Policy Implications

The results have important policy and managerial implications. The negative and significant merger-and-acquisition dummy coefficient points to post-merger integration frictions, implying that rapid consolidation in the banking industry has caused short-run efficiency losses as consolidated banks adapt their systems, personnel, and corporate cultures. Therefore, regulators and bank management should view consolidation not merely as a one-off balance sheet adjustment but as a protracted process of operational transformation. Additionally, as evidenced by the decreasing returns to scale observed in the latter part of our sample period, the industry appears to have moved to such a phase, so further mergers should be approached with caution. These findings also hold for other South Asian countries facing similar structural pressures. For example, Bangladesh is trying to reduce its total number of banks operating in the financial sector and is looking at consolidation as a means to achieve this. However, these results serve as a caution that such regulatory-induced consolidation requires careful sequencing and robust post-merger integration support to avoid short-term efficiency losses.

Limitations and Future Research

Regardless of the robustness of these findings, this study has some limitations that offer avenues for future research. First, banks are assumed to be single-stage production units that transform inputs into outputs within a 'black box'. A network DEA model could dissect the banking process into sub-processes, enabling more granular identification of sources of inefficiency. Furthermore, while this study includes non-performing loans as one of the second-stage determinants, modeling them directly into the frontier estimation as undesirable outputs could yield a more integrated and risk-adjusted efficiency measure. There is also a possibility of endogeneity between the dependent variable (technical efficiency) and explanatory variables (such as size, profitability, capitalization). Thus, the estimated coefficients represent associations rather than causal effects. This could be addressed in future research through the application of dynamic panel methods, instrumental variables, or other identification strategies. Finally, it should be noted that the results pertain specifically to technical efficiency and should not be generalized to profit or cost efficiency domains, both of which remain major topics requiring further investigation.

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Appendix A: Smoothed Bootstrap DEA

The smoothed bootstrap procedure of Simar and Wilson (1988, 2000), adopted in this study and outlined by Bogetoft and Otto (2011), is explained below. A 'naïve' bootstrap assumes that all differences in efficiency scores are purely random and thus resamples them directly from the efficiency scores, but this is theoretically inconsistent as it ignores the frontier-dependent nature of these scores. Alternatively, resampling from the original input-output observations is equally problematic, as although it produces bootstrap technology sets that are always subsets of the original estimated technology set, it can generate logically infeasible efficiency scores when resampling fails to include the original frontier firms. The smoothed bootstrap procedure overcomes both of these shortcomings.

The procedure begins by computing the original DEA efficiency scores under variable returns to scale for all firms in the sample. A smoothed bootstrap is then implemented by sampling with replacement from these scores and adding random noise drawn from a normal distribution, where a bandwidth parameter controls the degree of smoothing. This helps to avoid the discrete spikes in the empirical distribution associated with a naive bootstrap. To keep all values within bounds, a reflection method is applied so that no bootstrapped score exceeds the upper bound of 1.0. Because adding noise artificially inflates dispersion, a variance-adjustment step then rescales the smoothed values to restore asymptotically correct sampling variance.

The original input vectors are then rescaled radially based on the adjusted bootstrap efficiency scores, retaining each firm's input mix while adjusting the efficiency scale. Using this pseudo-sample, DEA is re-estimated to obtain a set of bootstrap efficiency scores. The process is repeated 2,000 times, yielding an empirical distribution of efficiency estimates for each firm. From this distribution, a bias is calculated by subtracting the mean of the bootstrapped efficiencies from the original DEA efficiency estimate, thus generating a bias-corrected efficiency estimate for each firm.

Appendix B

Table B1: Correlation Matrix of DEA Input and Output Variables

	Staff	Fixed Assets	Deposits	Net Interest Income	Non-Interest Income
Staff	1				
Fixed Assets	0.471*	1			
Deposits	0.807*	0.499*	1		
Net Interest Income	0.789*	0.448*	0.912*	1	
Non-Interest Income	0.501*	0.153*	0.656*	0.650*	1

Note: * denotes significance at the 5% level.

Table B2*:* Bank-Level Average Technical Efficiency Scores (2017-2024)

Bank	Original Efficiency	Bias Corrected Efficiency
Agriculture Development Bank Limited	0.982	0.885
Bank of Kathmandu Limited	0.843	0.799
Century Commercial Bank Limited	0.808	0.757
Citizen Bank International Limited	0.743	0.710
Civil Bank Limited	1	0.869
Everest Bank Limited	0.871	0.805
Global IME Bank Limited	0.885	0.817
Himalayan Bank Limited	0.929	0.862
Kumari Bank Limited	0.781	0.730
Laxmi Bank Limited	0.754	0.707
Machhapuchchhre Bank Limited	0.820	0.765
Mega Bank Limited	0.855	0.802
NIC Asia Bank Limited	0.832	0.759
NMB Bank Limited	0.846	0.795
Nabil Bank Limited	1	0.881
Nepal Bangladesh Bank Limited	1	0.885
Nepal Bank Limited	0.882	0.831
Nepal Credit and Commerce Bank Limited	0.713	0.676
Nepal Investment Bank Limited	0.949	0.871
Nepal SBI Bank Limited	0.831	0.779
Prabhu Bank Limited	0.720	0.683
Prime Commercial Bank Limited	0.876	0.818
Rastriya Banijya Bank	0.910	0.822
Sanima Bank Limited	0.842	0.790
Siddhartha Bank Limited	0.820	0.773

Standard Chartered Bank Nepal Limited	1	0.878
Sunrise Bank Limited	0.862	0.815
Sample Mean	0.865	0.799
Sample Standard Deviation	0.085	0.062

Note: Efficiency scores range from 0 to 1, where 1 indicates full technical efficiency.

Table B3: Variance Influence factor for explanatory variables

Variables	VIF
Competition	2.22
Bank size	2.21
Public	2.14
Profitability	2.04
Diversification	2.01
Risk	1.87
Private	1.63
CAR	1.60
Inflation	1.41
GDP Growth	1.36
M&A	1.10
Mean VIF	1.78

Table B4: Robustness Check - Fractional Logit Regression Results

Variable	SW Coeff.	SW Std. Err.	Frac Logit	Frac Logit Std. Err.
Bank size	0.139***	0.024	0.108***	0.019
Diversification	0.124***	0.034	0.090***	0.020
Risk	0.009	0.007	0.007	0.008
Profitability	0.031*	0.018	0.025	0.017
CAR	0.017***	0.005	0.013***	0.004
Competition	-0.001***	0.000	-0.001***	0.000
Inflation	0.009	0.006	0.005	0.004
GDP Growth	-0.011***	0.003	-0.009***	0.002
M&A	-0.049**	0.022	-0.032*	0.018
Public	-0.011	0.033	0.002	0.027
Private	-0.017	0.019	-0.013	0.014
Constant	-0.850	0.299		
Observations	199	199	199	
Wald chi²	95.54***		155.02***	

Notes: SW = Simar Wilson, *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Simar-Wilson estimates based on Algorithm 1 with 2,000 bootstrap replications.