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Credit risk and bank efficiency in Vietnam: DEA-DDF and Bayesian Tobit approaches

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ABSTRACT

This study investigates credit risk and technical efficiency of listed commercial banks in Vietnam using a two-stage approach. In the first stage, efficiency is measured by Data Envelopment Analysis with a Directional Distance Function (DEA-DDF), where loan loss provisions are treated as undesirable outputs, and lending, interest income, and non-interest income as desirable outputs. The results show that average efficiency improved from 0.861 in 2016 to 0.936 in 2023, with 2020 marking a key turning point when efficiency became more stable, reflecting the positive effects of banking restructuring policies. In the second stage, Bayesian Tobit regression reveals that return on assets has the strongest positive impact on efficiency, while non-interest income, non-performing loans, and the capital adequacy ratio negatively affect efficiency, suggesting challenges related to credit risk, income diversification, and conservative capital strategies. Overall, the findings provide evidence of risk-adjusted efficiency in Vietnamese banks and highlight the critical role of credit risk in shaping banking performance.

1. Introduction

The banking sector is a crucial pillar of the Vietnamese economy. Therefore, assessing banking performance is important, especially in the context of an emerging market where the banking sector reflects a hybrid structure - combining market mechanisms with tight state control (Casu et al., 2004). The rapid development of the Vietnamese banking system, coupled with a series of restructuring efforts to respond to adverse shocks, especially from NPLs and the COVID-19 pandemic, has created a complex and unique research context. High levels of NPLs increase loan loss provisions (LLP), reduce profits, and limit lending capacity, thus weakening overall efficiency (Louzis et al., 2012; Fiordelisi et al., 2011). Therefore, a risk-adjusted efficiency measurement method is necessary and consistent with Basel II standards.

This paper focuses on measuring risk-adjusted bank efficiency, emphasizing the impact of credit risk, especially NPLs, over the period from 2016 to 2023. The paper is conducted into two phases: (i) The first stage uses Data Envelopment Analysis with Directional Distance Function (DEA–DDF) to assess bank efficiency. This method, developed by Chung et al. (1997), is particularly suitable for high-risk banking environments; (ii) The second stage employs Bayesian Tobit regression to examine the influence of bank-specific financial and macroeconomic factors, utilizing Markov Chain Monte Carlo (MCMC) simulation to ensure robust inference, even in the presence of small or unbalanced datasets (Liu et al., 2023). By focusing on 26 listed banks, this paper contributes new insights into the relationship between credit risk and risk-adjusted bank efficiency in Vietnam. This study enhances empirical literature through an integrated methodology of non-parametric and Bayesian techniques.

2. Literature review

2.1. Bank efficiency: DEA-DDF method

Studies on bank efficiency often use Stochastic Frontier Analysis (SFA), Data Envelopment Analysis (DEA), and financial ratios (Rashidi, 2023). Among them, DEA, a non-parametric method introduced by Charnes et al. (1978), evaluates efficiency across multiple inputs and outputs. However, in production processes, companies not only produce desired outputs but also undesirable outputs, which can distort efficiency assessments if not considered.

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Within the banking sector, undesirable outputs such as non-performing loans or loan loss provisions may significantly affect efficiency estimates if not properly accounted for.

To address this issue, Chung et al. (1997) introduced the Directional Distance Function (DDF), which allows for the simultaneous expansion of desirable outputs and reduction of undesirable outputs. Fukuyama and Weber (2017) emphasized the suitability of DDF in risk-intensive environments, as it captures both efficiency and risk exposure more effectively. In contrast, SFA adjusts for statistical noise but is generally more aligned with cost-efficiency measurement rather than risk-adjusted output evaluation (Berger and Humphrey, 1997). Given the rising credit risk in Vietnam, the DDF approach offers a more accurate reflection of technical efficiency under conditions of financial risk.

2.2. Accounting for undesirable output: The role of NPLs and LLPs

Undesirable outputs exert a significant impact on the efficiency models. Huang and Chung (2017) argued that excluding undesirable outputs can lead traditional efficiency models to overestimate bank performance. This is particularly true in contexts where banks face elevated credit risks, such as in emerging markets or during periods of financial crisis.

2.3. Determinants of efficiency: From classical Tobit to Bayesian approaches

Research on bank efficiency has evolved from traditional Tobit regression models to more advanced Bayesian approaches, reflecting a growing demand for more robust and flexible analytical tools. The two-stage DEA with Tobit regression models has emerged as a widely adopted methodology, as it effectively addresses the censored nature of efficiency scores while remaining relatively straightforward to implement and interpret. This approach has proven useful in identifying key determinants of efficiency, including profitability, bank size, and macroeconomic conditions (Istaiteyeh et al., 2024; Maji and Saha, 2024). Despite the rise of Bayesian methods, Tobit models remain popular due to their ease of application, transparency in interpretation, and strong theoretical grounding, which facilitates replication and cross-country comparison in banking efficiency research.

Recent studies have increasingly used Bayesian methods, which offer significant improvements over classical methods. Unlike traditional methods that provide only single estimates, Bayesian techniques generate probability ranges for parameters, allowing for a better understanding of uncertainty and more reliable results. This approach allows for better handling of complex data structures and missing information and provides a more detailed analysis of efficiency components and scale effects. Bayesian methods also provide greater flexibility in model design and the ability to handle outlier data points and non-normal patterns common in banking datasets.

However, Tobit models have important limitations that can affect the reliability of the results. The key assumptions of normal distribution and constant variance often fail in bank data, which include very different types of banks operating in different regulatory and competitive environments. This can lead to biased estimates and inaccurate efficiency ratings (Istaiteyeh et al., 2024). Many studies also suffer from data quality issues, including small sample sizes, limited time periods, or the use of pooled data that obscure differences across banks.

These methodological issues present a worrying inconsistency in the research findings. Bank size and capital adequacy ratio exhibit conflicting relationships with efficiency across studies and cases, suggesting either fundamental problems in model design or that these relationships are highly context-dependent (Takahashi and Vasconcelos, 2022). Risk factors such as non-performing loans and credit risk measures also show an unstable relationship with efficiency, possibly due to measurement issues, cause-and-effect issues, or a lack of attention to how banks manage risk (Abdulahi et al., 2023). The shift from the Tobit approach to the Bayesian approach represents a necessary advancement in bank efficiency research, driven by the need for more sophisticated and reliable analytical tools. While classical approaches have the advantage of being computationally easy and interpretable, Bayesian techniques offer flexibility, better handling of uncertainty, and the ability to handle the complex and diverse nature of modern banking data.

2.4. Determinants of efficiency in the Vietnamese banking system

Studies on bank efficiency in Vietnam have increased in recent years. Minh et al. (2013) used DEA and a super-efficient model to evaluate the performance of 32 Vietnamese commercial banks during the period 2001–2005 and identified the determinants of bank performance through Tobit regression. The results showed that bank size and market share positively affected efficiency. Or Vu and Nahm (2013) applied SFA to measure the profit efficiency of Vietnamese banks from 2000 to 2006. They applied Tobit regression to determine the impact of factors on efficiency. The study found that larger banks were more efficient; poor asset quality and over-capitalization hindered efficiency. Furthermore, macroeconomic indicators – such as higher GDP growth and lower inflation – have improved profitability.

Sang (2017) used DEA to estimate technical efficiency scores for 34 Vietnamese commercial banks from 2007 to 2015 and the role of income diversification using a Tobit regression. The results confirmed that greater income diversification contributed positively to bank efficiency. In addition, Stewart et al. (2016) applied bootstrap techniques to improve the reliability of efficiency estimates. However, these methods often ignore unexpected outcomes and do not incorporate credit risk into the efficiency model. To fill this gap, Le (2018) examined the interaction between technical efficiency, capitalization, and risk in Vietnamese banks from 2007 to 2011. Using DEA in the first stage and a three-stage least squares (3SLS) regression model in the second stage, the study found low average technical efficiency and a negative relationship between credit risk and capitalization. Interestingly, improvements in efficiency can paradoxically increase risk exposure—a finding consistent with the "skimping hypothesis". Banks that achieve high efficiency with low risk are also those with higher capital ratios.

Le et al. (2022) used a Transfrontier DEA model to account for technological heterogeneity across banking groups. Next, they used a reduced regression with bootstrapping to identify the main drivers of efficiency and correct for potential bias in the DEA estimates. Their findings show a decreasing trend in bank efficiency over time, significant efficiency differences across ownership types, and nonlinear effects of both nonperforming loans and bank size on efficiency.

Most recently, Thanh et al. (2023) used Bayesian regression techniques to examine the impact of non-interest income on the profitability of 30 commercial banks in Vietnam during the period 2011 - 2020. The results showed that non-interest income, bank size, debt-to-equity ratio, operating expenses, deposit interest rates, and inflation have positive and statistically significant impacts on profitability. In contrast, neither GDP growth rate nor loan loss provisions has a statistically significant impact on the profitability of Vietnamese commercial banks.

In summary, most existing studies use DEA or SFA to measure bank efficiency but do not adjust for risk factors - especially undesirable outputs such as NPLs and LLP. Furthermore, in the second stage of analysis, the impact of determinants on bank efficiency is usually assessed using Tobit regression. Although Thanh et al. (2023) used Bayesian regression techniques to examine the impact of non-interest income on profitability, it was not a two-stage DEA approach.

Therefore, this study will fill the research gap by using DEA-DDF and Bayesian Tobit regression to assess the risk-adjusted technical efficiency of banks in Vietnam. By treating LLP as an undesirable output and leveraging Bayesian inference, the proposed framework provides a more robust, risk-sensitive assessment of bank performance. This approach will help to limit the shortcomings of Tobit regression and better account for data quality issues, including small sample size, limited time horizon, or the use of pooled data that obscure differences across banks. In addition, in this study, there are factors that show conflicting relationships with efficiency as stated by Takahashi and Vasconcelos (2022).

3. Methodology

This paper uses a two-stage DEA to evaluate the technical efficiency of listed commercial banks in Vietnam. First, DEA-DDF estimates the risk-adjusted efficiency score, overcoming the limitation of traditional DEA with undesirable output. Second, Bayesian Tobit regression explores bank-specific financial and macroeconomic determinants, effectively handling data censoring and uncertainty. This integrated framework is well-suited to the context of risk-prone and data-constrained banking in Vietnam.

3.1. Stage one: Efficiency measurement using DEA–DDF

The DEA–DDF framework, proposed by Chung et al. (1997), extends the traditional DEA (Charnes et al., 1978) by allowing the simultaneous expansion of desirable outputs and contraction of undesirable ones. This is critical to banking, where undesirable outputs such as LLPs reflect credit risk. The DDF is defined as:

$$\vec{D}(x, y, b; g_y, g_b) = \sup\{\beta: (x, y + \beta g_y, b - \beta g_b) \in T\} \quad (1)$$

where, $x \in R^M$ is the input vector, $y \in R^S$ is the desirable output vector, $b \in R^Q$ is the undesirable output vector, $g = (g_y, -g_b)$ is the directional vector, $\beta \geq 0$ is the inefficiency score, and T is the production possibility set defined under variable returns to scale (VRS). The efficiency score is computed as 1 – β, with values ranging from 0 (fully inefficient) to 1 (fully efficient).

The selection of variables is based on the financial intermediation approach (Berger and Humphrey, 1997) because Vietnamese banks mainly operate as traditional financial intermediaries, with 70-80% of their funding coming from customer deposits.

- With inputs reflecting the core resources banks include: deposits (the main source of funding), personnel and management expenses, interest and similar expenses (the cost of funds), and equity (the capital base for risk-taking and Basel II compliance). Choosing cost-based measures rather than quantity (e.g., number of employees) better reflects the quality of resources and efficiency in Vietnam's diverse banking environment.
- Desirable outputs: loan to customers (core intermediation products), non-interest income (Net income from service activities + net income from foreign exchange trading + Gains/(Losses) from proprietary trading of securities + net gains from investment securities trading + net income from other activities + income from capital contribution and equity investments), interest and similar income (main revenue from intermediation activities).

- Undesirable output: loan loss provisions (LLP) as the undesirable output instead of NPL for three reasons. First, LLP is forward-looking and reflects management's risk assessment capabilities, while NPL is backward-looking and only captures loans already past due over 90 days. Second, LLP has greater standardization as listed Vietnamese banks follow uniform accounting standards (VAS/IFRS) and are audited by international firms, whereas NPL classification can be manipulated through VAMC transactions or delayed recognition during COVID-19 debt restructuring programs. Third, LLP aligns with Vietnam's Basel II implementation since 2018, where the State Bank of Vietnam focuses on provisioning adequacy rather than merely monitoring absolute NPL ratios.

To calculate the DEA DDF efficiency score, the study uses the Google Colab tool with Python programming codes. Implementation on Google Colab: The DEA–DDF model is implemented using Python on Google Colab. The pandas library is used to load and preprocess data from input and output Excel files stored on Google Drive, accessible via the google.colab.drive module. The pulp library is used to construct and solve the DDF as a linear programming problem. Specifically, a custom function, ddf_score, is developed to calculate the efficiency score for each decision-making unit (DMU). Data and Sample: The sample comprises 26 listed Vietnamese commercial banks (Table 1) over the period 2016–2023. The data were collected from the audited annual financial statements of banks listed on the Ho Chi Minh City Stock Exchange (HSX) and the Hanoi Stock Exchange (HNX). The variables were collected as follows: (i) customer deposits: deposits from customers from balance sheet; (ii) personnel and management expenses: cash payment to employees and management” from cash flow statement; (iii) interest expenses: interest and similiar expenses from income statement; (iv) equity: shareholders’ equity from balance sheet; (v) customer loans: loan to customer from balance sheet; (vi) interest income: interest and similar income; (vii) non – interest income: net income from service activities + net income from foreign exchange trading + Gains/(Losses) from proprietary trading of securities + net gains from investment securities trading + net income from other activities + income from capital contribution and equity investments, all items from income statement; (viii) loan loss provisions: provision expenses for credit losses.

3.2. Stage two: Determinants of efficiency using Bayesian Tobit regression

In the second stage, Bayesian Tobit regression is applied to analyze the determinants of DDF efficiency scores, which are censored between 0 and 1. Bayesian Tobit outperforms classical Tobit by addressing small sample bias, heteroskedasticity, and parameter uncertainty through posterior inference (Liu et al., 2023). The model is specified as:

$$DDFscore_i = \beta_0 + \beta_1 ROA_i + \beta_2 CAR_i + \beta_3 LLP_i + \beta_4 NII_i + \beta_5 NIM_i + \beta_6 INF_i + \beta_7 GDP_i + \varepsilon_i \quad (2)$$

$$DDFscore_i = \begin{Bmatrix} 0 & if\ DDFscore_i \leq 0 \\ DDFscore_i & if\ 0 < DDFscore_i < 1 \\ 1 & if\ DDFscore_i\ \geq 0 \end{Bmatrix} \quad (3)$$

where, $\varepsilon_i \sim N(0, \sigma^2)$, β_0 is the intercept, and β_1 to β_7 are coefficients.

Explanatory variables: The dependent variable $DDFscore_i$, represents risk-adjusted technical efficiency. Independent variables are selected based on their relevance to bank efficiency in emerging markets and prior literature, as summarized in Table 2.

Bayesian Tobit regression was implemented in Stata (v15) using the bayes: Tobit command, specifying censoring at [0, 1]. The Metropolis-Hastings algorithm ran for 12,500 MCMC iterations, with 2,500 burn-in samples and weakly informative priors: N (0, 100) for coefficients and Inverse Gamma (0.01, 0.01) for variance. Diagnostic tools were applied to assess convergence.

Table 1: Bank list with DMUs code

No.	DMUs code	Bank name
1	ABB	An Binh Commercial Joint Stock Bank
2	ACB	Asia Commercial Joint Stock Bank
3	BAB	Bac A Commercial Joint Stock Bank
4	BID	Joint Stock Commercial Bank for Investment and Development of Vietnam
5	BVB	Bao Viet Joint Stock Commercial Bank
6	CTG	Vietnam Joint Stock Commercial Bank for Industry and Trade
7	EIB	Vietnam Export Import Commercial Joint Stock Bank
8	HDB	Ho Chi Minh City Development Joint Stock Commercial Bank
9	KLB	Kien Long Commercial Joint Stock Bank
10	MBB	Military Commercial Joint Stock Bank
11	MSB	Vietnam Maritime Commercial Joint Stock Bank
12	NAB	Nam A Commercial Joint Stock Bank
13	NCB	National Citizen Bank
14	OCB	Orient Commercial Joint Stock Bank
15	PGB	Petrolimex Group Commercial Joint Stock Bank
16	SGB	Saigon Bank for Industry and Trade
17	SHB	Saigon-Hanoi Commercial Joint Stock Bank
18	SSB	Southeast Asia Commercial Joint Stock Bank
19	STB	Saigon Thuong Tin Commercial Joint Stock Bank
20	TCB	Vietnam Technological and Commercial Joint Stock Bank
21	TPB	Tien Phong Commercial Joint Stock Bank
22	VAB	Viet A Commercial Joint Stock Bank
23	VBB	Vietnam Joint Stock Commercial Bank for Industry and Trade
24	VCB	Joint Stock Commercial Bank for Foreign Trade of Vietnam
25	VIB	Vietnam International Commercial Joint Stock Bank
26	VPB	Vietnam Prosperity Joint Stock Commercial Bank

Table 2: Description of the explanatory variables

Variable	Description	Expected	Reference
ROA	Return on assets, measures profitability	Positive	Stewart et al. (2016)
CAP	Capital adequacy ratio, reflects financial stability	Negative	Le (2018)
BS	Bank size (use logarithm BS)	Positve	Thanh et al. (2023)
NPLs	Non-performance loans, captures credit risk	Negative	Barros et al. (2012) and Sufian and Habibullah (2010)
NII	Non-interest income, represents diversification	Positive/negative	Thanh et al. (2023) and Stewart et al. (2016)
NIM	Net interest margin, measures lending profitability	Positive	Sang (2017)
INF	Inflation, costs increase and uncertainty	Negative	Vu and Nahm (2013)
GDP	GDP growth, boosts loan demand and revenue	Positive	Vu and Nahm (2013)

3.3. Rationale for methodological integration

DEA–DDF is selected over traditional DEA to address the limitation of ignoring undesirable outputs like LLPs, a critical issue in Vietnam's banking sector. Bayesian Tobit is chosen over Tobit for its ability to handle small samples, heteroskedasticity, and negative outputs (Liu et al., 2023), which are prevalent in Vietnam's banking data. The use of Google Colab for the first stage leverages its free computational resources and integration with Google Drive, while Stata is utilized in the second stage for its robust Bayesian estimation capabilities, particularly the bayes: Tobit command, which provides reliable inference for censored data.

4. Results and discussion

4.1. Technical efficiency results from DEA – DDF

The DDF efficiency score in the study sample shows a mean score of 0.886 and a median of nearly 0.996, indicating that most Vietnamese banks operate at a relatively good level of efficiency. The distribution has a strong left skew (-1.96), reflecting that nearly half of the sample (49.8%) achieved perfect efficiency, while only 13.5% of banks had low efficiency below 0.7. The coefficient variation of 21.05% shows significant differences between banks but is still at an acceptable level for comparative efficiency research. As summarized in Table 3, these descriptive statistics highlight the general efficiency pattern and variation across banks.

The findings indicate a steady improvement in efficiency over time, increasing from an average score of 0.861 in 2016 to 0.936 in 2023. The year 2020 represents a key turning point, as the standard deviation fell to 0.143, the lowest in the period, showing greater consistency in banks' efficiency. After 2020, efficiency scores not only continued to rise but also showed less variation. This trend suggests that banking restructuring and digital transformation policies had a positive and stabilizing effect on the sector.

Table 3: DDF efficiency scores

Category	Value	Statistical significance
	Sample characteristics	
Observations (N)	207	26 banks × 8 years (2016-2023)
Data completeness	100%	No missing values or outliers
	Central tendency	
Mean	0.8861	High overall efficiency
Median	0.9957	Near-perfect efficiency
Mode	1.0000	Perfect efficiency most common
	Dispersion	
Standard deviation	0.1865	Moderate variability
Coefficient of variation	21.05%	Reasonable heterogeneity
Range	0.7840	[0.2160, 1.0000]
Interquartile range	0.1567	[0.8433, 1.0000]
	Distribution shape	
Skewness	-1.96	Left-skewed ($p < 0.001$)
Kurtosis	3.22	Leptokurtic distribution
Jarque-Bera test	67.34	Non-normal ($p < 0.001$)
	Efficiency classification	
Perfect efficiency (≥ 0.999)	103 (49.8%)	Nearly half of sample
High efficiency (0.900-0.999)	40 (19.3%)	Strong performance group
Medium efficiency (0.700-0.899)	36 (17.4%)	Moderate performance
Low efficiency (< 0.700)	28 (13.5%)	Underperforming group

To confirm the reliability of the DDF efficiency scores, this study used Bootstrap DEA analysis (Simar and Wilson, 2007). The results confirmed the high reliability of the DDF efficiency scores, with an overall reliability score of 75.3/100 at a reliable level. The coefficient of variation of only 3.83% demonstrates that the efficiency scores have excellent stability during the bootstrap process, while the near-zero bias (-0.0009) confirms that the estimation method is not systematically biased. The 95% confidence interval has an average width of 0.0991, equivalent to a margin of error of ±0.05 points, indicating reasonable precision and suitability for the research purpose. Table 4 summarizes the Bootstrap DEA results, confirming the consistency and stability of DDF efficiency estimates. Analysis by efficiency group shows clear differences in stability: the highly efficient group (≥

0.90) shows a very low CV (1.58%), the medium efficient group (0.70-0.89) has a good CV (3.61%), while the low efficient group (< 0.70) maintains an acceptable CV (9.50%). This reflects the logical pattern that banks operating near the efficient frontier tend to be more stable than less efficient banks. Statistical tests strongly support the validity of the method, with the bias test giving a p-value = 0.756 (no significant bias) and the normal distribution test giving a p-value = 0.142 (satisfying the distribution assumption).

Table 4: Bootstrap DEA results summary

Measure	Value
Sample and method	
Observations (N)	207 (26 banks × 8 years)
Bootstrap replications	1,000
Efficiency statistics	
Mean DDF score	0.8861
Standard deviation	0.1861
Perfect efficiency rate	49.8% (103 DMUs)
Bootstrap reliability	
Coefficient of variation	3.83%
Bootstrap bias	-0.0009
95% CI average width	0.0991
Group analysis	
High efficiency (≥ 0.90) CV	1.58%
Medium efficiency (0.70-0.89) CV	3.61%
Low efficiency (< 0.70) CV	9.50%
Statistical validation	
Bias test (p-value)	0.756
Temporal trend	p < 0.001
Overall assessment	
Reliability score	75.3/100

DDF model with undesirable output (LLP); Bootstrap CI at 95% level

4.2. Determinant of efficiency using Bayesian Tobit regression

To examine the determinants of DDF efficiency, this study employs a second-stage Bayesian Tobit regression, using the technical efficiency scores from the first-stage DEA-DDF as the dependent variable. The model incorporates both bank-specific financial indicators and macroeconomic variables and is estimated on a panel of 207 observations, of which 186 are uncensored and 22 are right-censored. Posterior estimates were derived using Bayesian simulation methods, with results reported based on 95% credible intervals (CI). The estimation converged successfully, and the credible intervals provide reliable inference about the statistical significance of the predictors. Table 5 reports the Bayesian Tobit regression results, presenting the posterior mean, standard deviation, and 95% credible intervals for each predictor.

Accordingly, Return on Assets (ROA) has a strong positive impact, indicating that banks with higher profitability are also more efficient, and higher profitability facilitates more efficient use of resources and improves banks' ability to manage inputs and outputs. This finding is consistent with previous studies (Stewart et al., 2016) and supports the hypothesis that higher profitability improves technical efficiency by allowing banks to allocate resources more efficiently.

Table 5: Bayesian Tobit regression results

Variable	Mean	SD	95% CI	Significance
LnBS	-0.035	0.014	[-0.062, -0.008]	Significant (-)
ROA	10.222	2.651	[5.192, 15.152]	Significant (+)
CAP	-1.552	0.530	[-2.517, -0.530]	Significant (-)
NII	-6.121	2.715	[-11.272, -1.028]	Significant (-)
NIM	0.590	0.411	[-0.187, 1.370]	Not significant
NPLs	-31.375	6.605	[-44.636, -19.757]	Significant (-)
INF	0.391	2.597	[-4.185, 5.642]	Not significant
GDP	-0.062	0.717	[-1.441, 1.257]	Not significant
Constant	2.310	0.274	[1.822, 2.838]	
Sigma (error SD)	0.176	0.009	[0.159, 0.193]	

BS is negatively correlated with efficiency, suggesting that larger banks may have risk-related inefficiencies or operating costs. This is contrary to the empirical results of Thanh et al. (2023), but consistent with Berger and Mester (1997), who argued that efficiency is not necessarily proportional to size – sometimes large banks bear the burden of governance, risk control, and operating costs.

NPLs exhibit one of the strongest negative effects on efficiency. Higher NPL ratios are associated with significantly lower DDF scores, a 1-unit increase in NPLs reduces the DDF score by 31.37 units, emphasizing the important role of credit risk on bank efficiency. This finding is consistent with the hypothesis that higher credit risk negatively affects efficiency due to bad assets (Barros et al., 2012; Sufian and Habibullah, 2010; Le, 2018). This underscores the importance of credit risk management in improving bank efficiency in Vietnam.

Non-Interest Income – NII also demonstrates a significantly negative impact. A 1-unit increase in NII reduces the DDF score by 6.12 units, supporting the hypothesis that diversification through non-interest income may reduce efficiency in Vietnam due to operational complexity, underdeveloped fee-based services (Stewart et al., 2016), and diversification through non-interest income increases bank risk (Le, 2018). This suggests that Vietnamese banks may face challenges in managing non-traditional revenue streams effectively. This has, in fact, happened in many banks when they expanded their operations into investment banking, life insurance, and faced financial instability. This result is contrary to the study of Sang (2017), when income diversification has a positive impact on bank efficiency.

Although NIM is positively related to efficiency, the 95% CI includes zero, indicating the relationship is not statistically significant. This suggests that variations in interest income relative to earning assets do not have a robust or consistent effect on technical efficiency.

Capital adequacy ratio (CAP) exhibits a statistically significant negative association with DDF. The Bayesian Tobit regression estimates indicate that a one-unit increase in CAP corresponds to a 1.552-point decrease in DDF efficiency, with a 95% CI of [-2.517, -0.530], excluding zero. This inverse relationship suggests that banks maintaining higher capital buffers may experience reduced operational efficiency, possibly due to the opportunity cost of holding excess capital or the conservative management strategies adopted by well-capitalized banks. This result is similar to Le (2018). Macroeconomic variables, including Inflation (INF) and GDP growth, do not show a significant relationship with technical efficiency. This suggests that bank-specific factors, rather than macroeconomic factors, play a more important role.

In summary, the results from this stage analysis substantiate the findings from the DEA–DDF model and offer concrete policy implications. Targeted strategies to reduce LLPs—through better credit screening, monitoring, and resolution—can directly enhance technical efficiency. Moreover, optimizing income composition and maintaining profitability through core operations remain essential for sustaining high performance levels among Vietnamese commercial banks.

4.3. Robustness checks

To validate the robustness of the findings, a second Bayesian Tobit regression model was estimated to use the original DDF efficiency scores from Stage 1, without adjusting for undesirable outputs. The estimation results remain consistent with the main model, reaffirming the significance of key determinants such as ROA, CAP, NII, and adjusted NPL. Specifically, ROA continues to exhibit a significantly positive relationship with bank efficiency, while CAP, NII, and NPL maintain their negative associations, consistent with theoretical expectations. The signs and magnitudes of the coefficients are stable across both model specifications. Table 6 presents the robustness check results, confirming that the estimated coefficients remain consistent and reliable under alternative model settings. Moreover, the credible intervals (CI 95%) for significant variables do not include zero, further confirming the reliability of the results. The posterior diagnostics from the MCMC process indicate good convergence and estimation quality. These findings collectively reinforce the robustness of the main conclusions and suggest that the results are not sensitive to model specifications.

4.4. Discussion

Bayesian Tobit regression analysis has shown the extent to which factors affect the risk-adjusted technical efficiency of 26 listed Vietnamese commercial banks during the period 2016–2023. The results highlight the important role of profitability (ROA), credit risk exposure (NPLs), capital adequacy ratio (CAP), bank size (BS), and non-interest income (NII) in shaping bank efficiency, while other factors such as net interest margin (NIM) and macroeconomic variables (INF and GDP) are not statistically significant.

Table 6: Robustness check results

Model specification	LnBS	ROA	CAP	NII	NPLs	NIM	INF	GDP
Baseline model	−0.035**	10.222**	−1.552**	−6.121**	−31.375**	ns	ns	ns
Without macro variables	−0.038**	10.311**	−1.501**	−6.059**	−30.981**	ns	–	–
Weak prior specification	−0.033**	9.871**	−1.489**	−6.207**	−32.201**	ns	ns	ns
Excluding top 5% outliers	−0.036**	10.188**	−1.537**	−6.088**	−30.774**	ns	ns	ns

**: indicates 95% credible interval does not include zero; ns: not significant; –: variable excluded from model

ROA has a positive and statistically significant impact on technical efficiency, and this shows the important role of profitability in improving technical efficiency. In the context of Vietnam, where the banking sector is undergoing a strong restructuring process, this result suggests that banks with higher ROA are better equipped to optimize resource allocation and achieve higher efficiency, especially in a competitive and rapidly evolving market. The significant negative impact of NPLs on efficiency suggests higher credit risk and impacts on technical efficiency. For Vietnamese banks, this result highlights the importance of effective credit risk management, especially in the context of the historical challenges of NPLs in the sector. The negative impact of NPLs may also reflect the lingering impact of economic uncertainties during the study period, such as the NPL resolution period, the banking system restructuring period, and the COVID-19 pandemic, which may have exacerbated credit risk for some banks. Similarly, the significant negative impact of NII suggests that diversification through non-interest income reduces efficiency in Vietnamese banks. In Vietnam, this result may reflect challenges in managing non-interest income sources, including limited expertise in fee-based products and the immaturity of the market for these services. This finding contrasts with studies in developed markets where diversification through non-interest income often improves efficiency, highlighting the context-specific nature of this relationship.

Meanwhile, the CAP shows a statistically significant negative correlation with DDF DEA. This inverse relationship suggests that banks maintaining higher capital buffers may suffer from reduced operational efficiency, possibly due to the opportunity cost of holding excess capital or due to the conservative management strategies adopted by well-capitalized banks and as required by the State Bank of Vietnam. For bank size (BS), it is negatively correlated with efficiency, suggesting that larger banks may experience inefficiencies or risk-related operating costs, possibly due to the burden of governance, risk control, and operational costs that larger banks bear.

The insignificant impact of NIM, INF, and GDP on efficiency is also noteworthy. The insignificant impact of NIM suggests that interest income does not play a major role in driving efficiency, possibly due to competitive pressures on interest margins in Vietnam. The macroeconomic variables, INF and GDP, also did not show any strong impact, which could be due to economic disruptions during the study period, such as the COVID-19 pandemic, which caused significant fluctuations in these indicators

5. Conclusion and recommendation

This study identifies and measures the factors affecting the technical efficiency of risk adjustment for 26 listed Vietnamese commercial banks in the period 2016–2023, using a Bayesian Tobit regression model. The results reveal that profitability (ROA) has a significant positive effect on efficiency, while credit risk (LLP) and non-interest income (NII) have significant negative effects. Other factors, including capital adequacy (CAP), net interest margin (NIM), inflation (INF), and GDP growth (GDP), do not exhibit robust effects on efficiency. These findings are robust to various sensitivity checks, including alternative priors, exclusion of macroeconomic variables, and comparison with a classical Tobit model, as well as diagnostic checks confirming the reliability of the MCMC sampling process.

The research results help to propose important implications for policy makers and bank managers in the Vietnamese banking sector. For policymakers, fostering a conducive environment for bank profitability remains paramount. This could entail sustaining stable monetary frameworks, alleviating excessive regulatory pressures, and promoting financial innovation to enhance banks' capacity to generate returns. Given the detrimental effect of credit risk (LLP), there is a pressing need to bolster credit risk management systems. Policymakers are encouraged to introduce stringent loan classification protocols, intensify monitoring of non-performing loans, and facilitate debt restructuring mechanisms to mitigate credit risk and elevate efficiency. Moreover, the adverse impact of non-interest income (NII) underscores the necessity for a measured approach to diversification. Investments in infrastructure and capacity-building—such as enhancing customer financial literacy and equipping bank personnel with skills to manage fee-based services—should be prioritized to ensure sustainable expansion into non-traditional income streams.

For bank managers, the results underscore the importance of prioritizing profitability (ROA) to enhance technical efficiency. This can be achieved through strategies such as optimizing operational cost structures, improving the quality of loan portfolios, and adopting technological solutions to streamline processes. The negative influence of LLP calls for strengthened credit risk management practices, including rigorous credit evaluation procedures and diversification of loan exposures to reduce vulnerabilities to high-risk sectors. Similarly, the unfavorable effect of NII advises a cautious pursuit of non-interest income diversification, necessitating investments in staff training and technological capabilities to develop competitive fee-based offerings, while preserving a strategic focus on core interest-based activities where comparative advantages lie. Finally, the negligible effect of CAP suggests that excessively high capital buffers may not translate into efficiency gains, enabling managers to strike a balance between regulatory compliance and strategic priorities such as lending expansion and innovation.

6. Limitations and future research

This study has several limitations including: (i) the focus on 26 listed commercial banks limits generalizability, as it excludes unlisted, foreign, and joint venture banks; (ii) the analysis includes the COVID-19 pandemic, where structural disruptions and government interventions may have temporarily affected both risk behavior and performance – effects that conventional models may not fully account for; (iii) the lack of controls for institutional heterogeneity, such as ownership structure, governance quality, and strategic orientation, also limits the explanatory scope of the model.

To address these shortcomings, future studies should expand the sample to include unlisted and foreign banks and extend the time frame beyond the immediate post-pandemic recovery period to better isolate the structural drivers of performance. Methodologically, more advanced frameworks such as the DEA Network can be used to analyze performance across distinct banking functions such as capital mobilization, intermediation, and risk management. Finally, comparative studies across ASEAN countries using standardized efficiency models can provide valuable regional insights and highlight institutional factors that influence cross-country differences in banking efficiency.

List of abbreviations

3SLS	Three-stage least squares
Basel II	Second Basel Accord
BS	Bank size
CAP	Capital adequacy ratio
CI	Credible interval
CV	Coefficient of variation
DDF	Directional distance function
DEA	Data envelopment analysis
DEA–DDF	Data envelopment analysis with directional distance function
DMU	Decision-making unit
DMUs	Decision-making units
GDP	Gross domestic product

HNX	Hanoi Stock Exchange
HSX	Ho Chi Minh City Stock Exchange
IFRS	International Financial Reporting Standards
INF	Inflation
LLP	Loan loss provisions
MCMC	Markov Chain Monte Carlo
NII	Non-interest income
NIM	Net interest margin
NPL	Non-performing loans
NPLs	Non-performing loans
ROA	Return on assets
SD	Standard deviation
SFA	Stochastic frontier analysis
VAMC	Vietnam Asset Management Company
VAS	Vietnamese accounting standards
VRS	Variable returns to scale

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Compliance with ethical standards

Conflict of interest

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