Exploring Bank Efficiency in Indonesia: A Dual Method Approach Using Data Envelopment Analysis and Stochastic Frontier Analysis

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Abstract: This study evaluates the efficiency of 76 commercial banks in Indonesia over the period 2020-2021, using both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The dataset includes key inputs such as interest cost and labor cost, while outputs for DEA are split into interest income and non-interest income, and the total income is used for SFA. DEA is applied with both Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models, with output orientation to maximize interest income and non-interest income. The CCR model assumes constant returns to scale (CRS), while the BCC model assumes variable returns to scale (VRS), allowing for scale differences among banks. For SFA, both the Cobb-Douglas and Translog production functions are used to model the relationship between inputs and outputs, with the former assuming a simpler linear relationship and the latter accounting for non-linearities. The results show high correlation between the efficiency scores obtained from both DEA and SFA, suggesting that both methods produce similar rankings of bank performance. However, SFA's flexibility in capturing inefficiencies through random noise makes it a more robust method for analyzing bank performance in volatile environments. Spearman's rank correlation is employed to assess the relationship between the efficiency rankings from both methods, revealing strong consistency in their assessments.

Keywords: banking performance; Cobb-Douglas; efficiency; data envelopment analysis; stochastic frontier analysis; Translog function.

JEL Classification: G21; C14; C67.

Introduction

In an increasingly competitive global financial landscape, evaluating the efficiency of banks is vital for fostering economic stability and growth. Particularly in emerging markets such as Indonesia, understanding the factors that drive banking efficiency is crucial for policymakers, financial institutions, and investors. Efficient banks not only contribute to better resource allocation but also enhance profitability, improve service delivery, and bolster financial system stability. However, measuring bank efficiency remains a complex task, as it requires a careful analysis of both input and output variables. This study aims to explore the efficiency of banks in Indonesia by applying two predominant techniques: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), utilizing production orientation.

The choice of DEA and SFA is motivated by the distinctive features each method offers in assessing efficiency. DEA, a non-parametric approach, evaluates the relative efficiency of banks by constructing an efficient frontier against which performance is measured. The Banker-Charnes-Cooper (BCC) and Charnes-Cooper-Rhodes (CCR) models in DEA are widely used to assess efficiency from an output orientation, where the goal is to maximize output (e.g., total income) for a given set of inputs (Charnes, Cooper, and Rhodes 1978). In contrast, SFA is a parametric technique that models the relationship between inputs and outputs through a specified production function, such as the Translog or Cobb-Douglas model, and considers stochastic variations in efficiency. SFA's production orientation focuses on minimizing the inputs (e.g., interest cost and labor cost) for a given output, allowing for the identification of inefficiencies arising from both observed and unobserved factors (Aigner, Lovell, and Schmidt 1977).

A key feature of this study is the focus on two critical inputs: interest cost and labor cost. Interest cost, representing the cost of capital, is central to banking operations. It affects the bank's profitability and pricing strategies, as well as its ability to compete in the market (Fare, Grosskopf, and Lovell 1994). The ability to manage interest expenses effectively is critical in determining a bank's operational efficiency and profitability. Similarly, labor cost reflects the efficiency of human resources, which is essential for delivering banking services and generating income. The role of labor in banking efficiency cannot be overstated, as a highly skilled workforce can enhance service quality and operational productivity (Sufian, Kamarudin, and Nassir 2016). By focusing on these two key inputs, this study aims to examine their influence on banking efficiency, with a particular emphasis on total income as the output variable. Total income captures the revenue-generating capacity of banks, providing a comprehensive measure of performance that reflects the effectiveness of banks in utilizing their resources to generate returns.

Recent studies have further emphasized the importance of efficiency analysis in the Indonesian banking sector, particularly under conditions of economic uncertainty and macroeconomic shocks. Ariefianto *et al.* (2026) investigated how bank intermediation inefficiency in Indonesia responds to macroeconomic disturbances and found that inefficiency levels are highly sensitive to external economic conditions, highlighting the importance of robust efficiency measurement frameworks that can distinguish between managerial inefficiency and stochastic shocks. Their findings reinforce the relevance of SFA in capturing random disturbances affecting banking performance. Similarly, Febrianto, Amin, and Ramadhani (2026) examined the impact of the COVID-19 pandemic on bank cost efficiency in Indonesia using SFA, comparing conventional and Islamic banks. Their study revealed that stochastic frontier models provide valuable insights into cost efficiency dynamics during crisis periods and demonstrated that external shocks significantly influence banking operational performance. These studies confirm that efficiency analysis remains highly relevant in Indonesia's banking industry, particularly when banks face volatile macroeconomic and regulatory environments.

This study builds on prior research that has employed both DEA and SFA to assess banking efficiency in various contexts. For instance, Akbary *et al.* (2025) investigated the role of digital transformation in the efficiency of Indonesian banks, showing that the adoption of digital technologies can significantly improve operational efficiency by reducing transaction costs and enhancing customer service. On the other hand, Raju (2018), who assessed the efficiency of urban co-operative banks in India, also underscore the relevance of using both DEA and SFA in evaluating bank efficiency. Raju's study found that while DEA offered a robust comparative analysis of efficiency across banks, SFA provided deeper insights into the stochastic nature of inefficiency, especially in the context of banks with differing operational environments. Similarly, Silva *et al.* (2016) conducted a comparative study of DEA and SFA applied to Chinese local banks, revealing how each methodology captures efficiency from different perspectives - DEA focusing on comparative performance and SFA providing a detailed understanding of inefficiencies.

Nguyen *et al.* (2025) further explored the cost efficiency of Vietnamese banks, comparing the two methods and concluding that SFA is particularly useful in capturing stochastic inefficiencies that are not visible in DEA. Their study emphasizes the importance of method choice depending on the research context, as each method provides unique insights into the performance of financial institutions. Similarly, Vu *et al.* (2019) examined banking efficiency in Vietnam using both parametric and non-parametric methods, comparing the strengths and weaknesses of each approach. Their study found that while DEA provided valuable insights into the relative efficiency of banks, SFA offered more flexibility in modeling the stochastic nature of inefficiencies, particularly when accounting for unobserved factors like managerial skill or regulatory impacts. Moreover, Akandekumtiim & Moyo (2024) conducted a comparative analysis of parametric and non-parametric efficiency measures in the Ghanaian banking sector, emphasizing the importance of choosing the right methodology based on the research context. They concluded that SFA was better suited for addressing stochastic variations in efficiency, while DEA was advantageous for its simplicity and ability to handle multiple inputs and outputs without making strong parametric assumptions.

The research presented in this study extends these findings by applying both DEA and SFA to the Indonesian banking sector. By integrating output orientation (DEA) and production orientation (SFA), this study offers a comprehensive evaluation of banking efficiency, with a specific focus on the impact of interest costs and labor costs on total income. Abidin *et al.* (2024) previously compared SFA and DEA but only focused on the BCC and Cobb-Douglas models. This study compares four models simultaneously: BCC and CCR in DEA, Cobb-Douglas and Translog in SFA. The combination of the BCC and CCR models in DEA with the Cobb-Douglas and Translog production functions in SFA provides a novel and comprehensive framework for evaluating bank efficiency in Indonesia. This dual approach allows for a more nuanced understanding of efficiency that considers the stochastic nature of inefficiency (captured by SFA) and the comparative performance across banks of varying sizes and scales (captured by DEA). It also bridges the gap between non-parametric and parametric methodologies, offering a more comprehensive analysis of bank efficiency than studies relying solely on one approach. This study is expected to contribute significantly to the understanding of how different methodological approaches can inform banking efficiency in Indonesia, offering new insights for policymakers, bank managers, and researchers.

Despite the extensive literature on banking efficiency, important gaps remain in the Indonesian context. Previous studies generally applied DEA or SFA separately and rarely examined the consistency of efficiency rankings across different frontier assumptions, particularly within Indonesia's heterogeneous banking industry. Existing comparative studies also relied on limited model combinations, restricting the analysis of scale effects and functional form sensitivity. Furthermore, post-pandemic conditions, digital transformation, and macroeconomic volatility have increased the importance of incorporating both deterministic and stochastic perspectives in efficiency measurement (Ariefianto *et al.* 2026; Febrianto *et al.* 2026). Therefore, this study contributes by simultaneously comparing CCR and BCC models in DEA alongside Cobb-Douglas and Translog specifications in SFA, providing a more comprehensive framework for evaluating scale efficiency, technical efficiency, and stochastic inefficiency in Indonesian banks, as well as offering implications for banking regulation, digital transformation, and risk management practices.

1. Literature Review

1.1 Data Envelopment Analysis in Banking Efficiency

Data Envelopment Analysis (DEA) is a non-parametric method that evaluates the relative efficiency of decision-making units (DMUs), such as banks, by comparing each bank's performance against an efficient frontier constructed from the best-performing units. The Charnes-Cooper-Rhodes (CCR) model assumes constant returns to scale (CRS), while the Banker-Charnes-Cooper (BCC) model assumes variable returns to scale (VRS), which accounts for scale differences among banks (Charnes, Cooper, and Rhodes 1978). DEA is particularly beneficial for cross-sectional comparisons, allowing researchers to evaluate multiple inputs and outputs simultaneously without requiring specific functional forms.

Numerous studies have utilized DEA to assess banking efficiency across different contexts. Sufian, Kamarudin, and Nassir (2016) examined the efficiency of banks in Malaysia, finding that the BCC model effectively captured efficiency differences across banks of varying sizes. Similarly, Silva, Tabak, and Oliveira (2016) applied DEA to assess the efficiency of Chinese local banks, demonstrating its robustness in cross-bank performance comparisons. Akandekumtiim and Moyo (2024) extended this approach by analyzing Ghanaian banks, emphasizing DEA's ability to handle multiple inputs and outputs, making it ideal for cross-sectional efficiency evaluations.

However, DEA has limitations. One major drawback is its inability to account for stochastic noise, which may lead to biased efficiency estimates, especially when considering external shocks or measurement errors. Fare *et al.* (1994) highlighted this limitation, arguing that DEA overlooks random errors, a critical factor in understanding the full scope of inefficiencies. Korneyev et al (2022) also noted that while DEA is effective for benchmarking, it does not address external fluctuations impacting efficiency, which can be crucial in dynamic banking environments. Similarly, Benbachir (2025) pointed out that DEA might not adequately capture the stochastic variations in efficiency, particularly in uncertain market conditions.

1.2 Stochastic Frontier Analysis in Banking Efficiency

Stochastic Frontier Analysis (SFA) is a parametric method that models the relationship between inputs and outputs through a specified production function, accounting for both inefficiency and random noise (Aigner, Lovell, and Schmidt 1977). By incorporating stochastic elements, SFA provides a more nuanced understanding of inefficiencies, particularly in environments where external factors or random disturbances play a significant role. This flexibility makes SFA particularly valuable for banking efficiency analysis in volatile or uncertain market conditions.

SFA has been widely applied in various banking sectors. Nguyen, Thi, and Pham (2025) compared DEA and SFA in the Vietnamese banking sector and concluded that SFA provided a more accurate measure of inefficiency by capturing random fluctuations in the data. Raju (2018) also explored the efficiency of urban co-operative banks in India, finding that SFA was better suited to identify inefficiencies, particularly in banks with diverse operational environments. Silva, Tabak, and Oliveira (2016) further corroborated this conclusion, noting that SFA outperformed DEA in capturing inefficiencies resulting from stochastic disturbances, such as economic shocks or regulatory changes.

Despite its advantages, SFA has limitations, notably its requirement for a specified functional form. Additionally, SFA assumes a particular distribution for the inefficiency term, which can limit its flexibility in modeling inefficiencies across different banking systems (Tim Coelli, Rao, and Battese 1998). As Haque, Tausif, and Ali (2020) noted, these assumptions may not fully capture all forms of inefficiency, especially in diverse banking environments.

1.3 Comparing DEA and SFA in Banking Efficiency Research

The comparative use of DEA and SFA in banking efficiency research has attracted significant attention, with studies recognizing that both methods offer complementary insights into bank performance. Vu, Nguyen, and Dinh (2019) compared the two methods in assessing banking efficiency in Vietnam. They found that while DEA provided valuable insights into relative efficiency, SFA offered a deeper understanding of inefficiencies by accounting for stochastic factors. This view is echoed by Akandekumtiim & Moyo (2024) , who found that SFA was more effective at capturing inefficiencies caused by external fluctuations, while DEA excelled in providing comparative efficiency measures across banks.

Coelli *et al.* (2005) argued that DEA is particularly effective for benchmarking efficiency, especially in cases with multiple inputs and outputs, whereas SFA is better suited for capturing inefficiencies arising from random noise or external shocks. (Benbachir 2025) and Shaik, (2022) both observed that SFA's ability to incorporate random errors made it more suited for modeling efficiency in dynamic and unpredictable environments, while DEA provided a robust comparative analysis of bank performance.

Further, Alrafadi *et al.* (2016) demonstrated the value of combining DEA with other econometric techniques to improve the robustness and accuracy of efficiency assessments. This combined approach allows for a more comprehensive analysis of efficiency, particularly in environments where multiple factors influence bank performance.

1.4 Correlation Between Efficiency Measured by DEA and SFA

This study posits the hypothesis that there is a significant correlation between the efficiency scores derived from DEA (using both the BCC and CCR models) and SFA (using Cobb-Douglas and Translog production functions). Nguyen *et al.* (2025) and Akandekumtiim & Moyo (2024) have shown that while both methods tend to yield similar overall efficiency rankings, SFA provides a more detailed measure of inefficiency by accounting for stochastic variations. This study seeks to test whether the correlation between efficiency measures from DEA and SFA holds in the context of Indonesian banks, particularly focusing on the impact of key inputs such as interest costs, labor costs, and total income.

2. Method

The sample consists of 76 commercial banks operating in Indonesia during 2020–2021, including state-owned banks, regional development banks (BPD), private domestic banks, foreign-owned banks, and digital banks supervised by the Financial Services Authority (OJK). Banks were selected based on three criteria: (1) availability of complete annual financial statements for both years, (2) consistency in reporting interest income, non-interest income, interest cost, and labor cost variables, and (3) absence of missing observations that could bias frontier estimation. The period 2020–2021 was selected because it represents the immediate post-COVID-19 disruption phase, during which Indonesian banks experienced significant operational adjustments, digital transformation acceleration, and macroeconomic uncertainty. This period provides an important context for evaluating whether banking efficiency remained stable under crisis-related shocks.The data was sourced from publicly available financial reports published by the banks, with particular focus on annual reports and financial statements obtained from the Financial Services Authority of Indonesia (OJK) and global financial databases like the World Bank. A balanced panel dataset is employed, which includes a mix of both large and small banks operating in Indonesia, ensuring a broad representation of the banking sector. The primary variables for input and output selection are as follows:

1. Inputs for both DEA and SFA
    a. Interest Cost: Representing the cost of capital, interest cost is a key input that affects a bank's operational cost structure and profitability. It reflects the price of borrowing or obtaining funds for lending operations.
    b. Labor Cost: Representing human resource expenses, labor cost is central to the bank's operational efficiency in providing services. It accounts for the wages and benefits paid to employees who directly contribute to banking operations.

2. Output
   a. SFA Output: Total Income, which combines both interest income and non-interest income. Total income is a comprehensive measure of bank performance, capturing both revenue streams.
   b. DEA Outputs: The analysis for DEA splits the output into two components:
      - Interest Income: Represents income derived from lending activities and investments.
      - Non-Interest Income: Represents income from fees, commissions, and other non-lending activities.

These variables are selected based on their relevance to the Indonesian banking sector and their critical role in determining the operational efficiency and profitability of banks.

Prior to estimation, all variables were transformed into logarithmic form to reduce heteroscedasticity and improve comparability across banks of different sizes. Outlier observations were examined using boxplot inspection and z-score evaluation. Extreme observations beyond ±3 standard deviations were winsorized to minimize distortion in frontier estimation while preserving the structure of the dataset. To ensure robustness, efficiency estimates were compared across multiple frontier assumptions, including CRS versus VRS in DEA and Cobb-Douglas versus Translog in SFA. Spearman's rank correlation was subsequently employed to evaluate the consistency of efficiency rankings across models.

2.1. DEA Model Specification

DEA is a powerful nonparametric method used to assess the relative efficiency of Decision-Making Units (DMUs) through linear programming models (Emrouznejad and Cabanda 2013). It enables efficiency analysis within the same cohort by allowing direct peer-to-peer and peer-to-group comparisons across multiple inputs and outputs, supported by a diverse range of model specifications (Manzoni and Islam 2009). The study applies both the Charnes-Cooper-Rhodes (CCR) model and the Banker-Charnes-Cooper (BCC) model, focusing on output orientation, meaning the goal is to maximize outputs (interest income and non-interest income) for given levels of inputs (interest cost and labor cost). The CCR model assumes constant returns to scale (CRS), implying that any proportional increase in inputs will lead to a proportional increase in outputs. Whereas, the BCC model assumes variable returns to scale (VRS), allowing for efficiency variations based on the scale of bank operations, which is especially useful for comparing banks of different sizes.

The efficiency scores for each bank are calculated by solving the following linear programming problem:

$$Eff = \max_{U_i, V_j} \frac{\sum_{i=1}^{m} U_i Y_{is}}{\sum_{j=1}^{n} V_j X_{js}} \tag{1}$$

Subject to:

$$\frac{\sum_{i=1}^{m} U_i Y_{is}}{\sum_{j=1}^{n} V_j X_{js}} \leq 1; \forall s$$

$$U_i, V_j \geq 0; \forall i, \forall j$$

where Y_{is} represents output, X_{js} represents input, and U_i and V_j are weights for the input and output variables, respectively.

An output-oriented approach was selected because Indonesian banks generally possess greater managerial flexibility in expanding revenue generation than in reducing operational inputs in the short run. During the post-pandemic period, banks were primarily focused on maintaining and increasing income through lending expansion, digital services, and fee-based activities rather than aggressively minimizing labor or funding costs. Therefore, output orientation is considered more appropriate for reflecting the strategic behavior of Indonesian commercial banks. DEA estimation was conducted using the Benchmarking package in Rstudio.

2.2 Stochastic Frontier Analysis

Stochastic Frontier Analysis (SFA) is a parametric method that integrates production theory with error components, separating inefficiency from random noise (Aigner, Lovell, and Schmidt 1977). In this study, SFA employs both the Cobb-Douglas and Translog production functions to capture the efficiency of banks. The SFA output is defined as total income, which includes both interest income and non-interest income.

The Cobb-Douglas production function for SFA is specified as:

$$\ln Y_{it} = \alpha_0 + \sum_{j=1}^{J} \beta_j \ln X_{jit} + V_{it} - U_{it} \tag{2}$$

where Y_{it} is the total income of unit *i* at time *t*, X_{jit} represents the *j*-th input (interest cost, labor cost), β_j are the parameters to be estimated, V_{it} denotes the random noise, and U_{it} captures technical inefficiency.

For the Translog production function, the model includes quadratic and interaction terms to capture non-linear relationships:

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j \ln X_{jit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{J} \beta_{jk} \ln X_{jit} \ln X_{kit} + V_{it} - U_{it} \quad (3)$$

where β_{jk} represents the interaction effects between inputs *j* and *k*. Technical efficiency (TE) for each unit is defined as:

$$TE_{it} = \frac{\exp\left(X'_{jit}\beta_j + V_{it} - U_{it}\right)}{\exp\left(X'_{ijt}\beta_j + V_{it}\right)} = \exp(-U_{it}) \quad (4)$$

Here, U_{it} represents the inefficiency term; smaller values of U_{it} indicate higher efficiency. Thus, when $U_{it}=0$, decision-making unit is operating on the efficiency frontier (TE=1).

SFA estimation employed the frontier package using maximum likelihood estimation (MLE). The inefficiency term in the SFA model was assumed to follow a half-normal distribution.

2.3 Spearman's Rank Correlation

To assess the hypothesis of a significant correlation between the efficiency scores derived from DEA and SFA, Spearman's rank correlation coefficient is used, particularly when the data do not follow a normal distribution (Sirkin 2006). Varabyova & Schreyögg (2013) also applied Spearman's correlation to compare SFA and DEA. This non-parametric test is ideal for comparing the rankings of efficiency scores produced by both methods, as it assesses the strength and direction of the monotonic relationship between the two sets of efficiency rankings.

The Spearman rank correlation coefficient ρ is calculated as follows:

$$\rho = 1 - \frac{6\sum_{i=1}^{n}\sum_{t=1}^{T} d_{it}^2}{nT\left\{(nT)^2 - 1\right\}}$$

where *i* denotes the decision-making unit, *t* represents the time period, d_{it} is the difference between ranks of paired observation, and *nT* is the total number of paired data points. A significant positive correlation would suggest that the efficiency rankings from DEA and SFA are closely aligned. In contrast, a low or negative correlation would indicate differing assessments of efficiency between the two methods. Spearman correlation analysis and visualization were implemented using the corrplot and ggplot2 packages. The complete computational workflow is available upon request to improve transparency and reproducibility.

3. Research Results

3.1 Overview of Descriptive Statistics

Table 1 presents the descriptive statistics of the input and output variables used in the efficiency analysis. The logarithmic transformations of income and cost variables ensure variance stabilization and comparability across banks. The mean of log(interest income) is 14.65, while the mean of log(non-interest income) is 10.94, indicating that interest-based activities dominate the income structure of the sampled banks. Similarly, log(interest cost) and log(labor cost) show relatively balanced input magnitudes (13.55 and 12.94, respectively), suggesting comparable cost structures across decision-making units (DMUs). The observed standard deviations reveal moderate dispersion, implying that the sample banks operate under varying levels of cost and income efficiency, a condition favorable for frontier-based efficiency estimation.

Table 1. Descriptive Statistics of Data

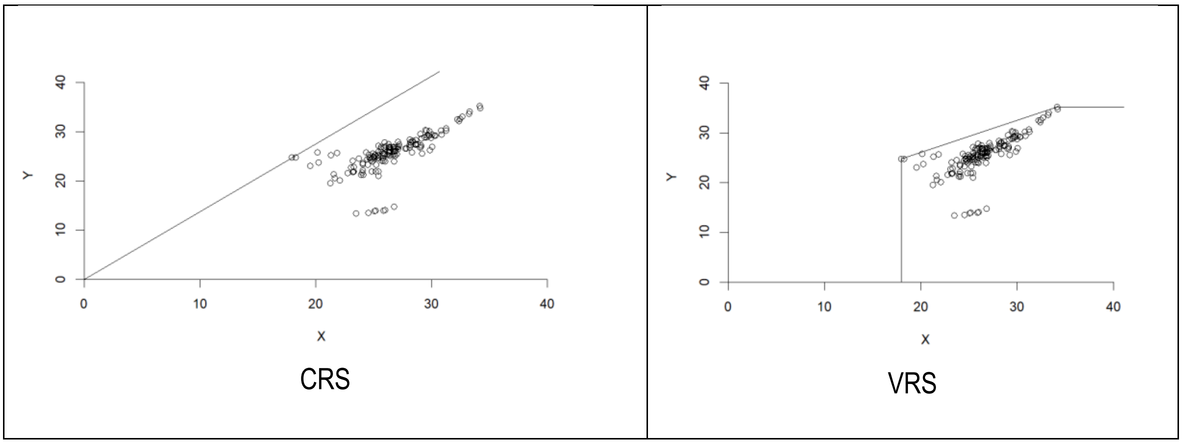
Variable	N	Mean	Std.dev	Min	Max
Ln (interest income)	152	14.65	1.38	11.72	18.63
Ln (non-interest income)	152	10.94	2.96	0.00	16.54
Ln (interest cost)	152	13.55	1.39	9.91	16.99
Ln (labor cost)	152	12.94	1.76	5.12	17.22

Source: Data processed by the author(s)

3.2 Efficiency Scores from DEA

The efficiency analysis using Data Envelopment Analysis (DEA) was conducted under both Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) assumptions. Figure 1 illustrates the DEA frontiers for both CRS and VRS models. The CRS plot represents the Charnes, Cooper, and Rhodes (CCR) model (Charnes *et al.*, 1978), which assumes proportionality between inputs and outputs. The VRS plot represents the Banker, Charnes, and Cooper (BCC) model, allowing for scale inefficiencies by constructing a convex frontier.

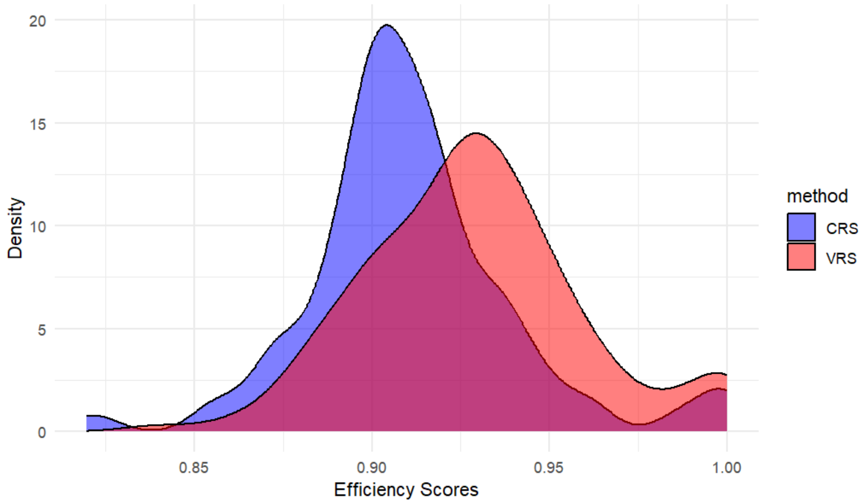
Figure 1. DEA Plot CRS vs VRS



Source: Data processed by the author(s)

As depicted, several banks lie on or near the efficient frontier in both models, indicating high technical efficiency levels. However, the VRS model's frontier lies above the CRS frontier, consistent with the theoretical expectation that VRS efficiency scores are typically equal to or greater than CRS scores (Timothy Coelli *et al.* 2005). This occurs because the VRS specification isolates pure technical efficiency by excluding scale effects.

Figure 2. Density Plot CRS vs VRS



Source: Data processed by the author(s)

Table 2. Descriptive Statistics of Efficiency DEA

Variable	Mean	SD	Min	Max
efficiency_scores_crs	0.91108	0.02976	0.81966	1.00000
efficiency_scores_vrs	0.92874	0.03118	0.83908	1.00000

Source: Data processed by the author(s)

Figure 2 and Table 2 provide the distribution and descriptive summary of the DEA efficiency scores. The mean CRS efficiency is 0.9111, while the mean VRS efficiency is 0.9287, with both exhibiting relatively low standard deviations (0.03). This finding indicates that the majority of banks in the sample operate close to the efficiency frontier, though minor inefficiencies persist. The density plot further reveals that VRS scores are right-skewed, implying that when scale effects are relaxed, banks appear more efficient.

This pattern is consistent with findings by (Sufian, Kamarudin, and Nassir 2016) and (Silva, Tabak, and Oliveira 2016), who observed that larger banks benefit less from the VRS assumption compared to smaller ones. The results also echo (Akandekumtiim and Moyo 2024), who emphasized the suitability of DEA-VRS for analyzing heterogeneous banking environments. However, DEA's deterministic nature implies that all deviations from the frontier are treated as inefficiency, disregarding random shocks - a limitation acknowledged by (Fare, Grosskopf, and Lovell 1994) and (Benbachir 2025).

3.3 Efficiency Scores from SFA

Table 3 presents the estimation results from Stochastic Frontier Analysis (SFA) using both Cobb–Douglas and Translog production functions. The Cobb–Douglas specification provides significant parameter estimates for both input variables (interest cost and labor cost), suggesting that these inputs positively and significantly influence output efficiency ($p < 0.01$). The translog specification, while more flexible, yields statistically insignificant coefficients for the second-order and interaction terms, indicating that the Cobb–Douglas function sufficiently captures the input-output relationship for this dataset.

Table 3. Estimation of SFA (Cobb-Douglas vs Translog)

Variable	Cobb-Douglass		Translog	
	Estimate	p-value	Estimate	p-value
(Intercept)	2.530	4.0e-07	14.54130	< 2e-16
Ln interest cost	0.719	< 2e-16	-0.92950	0.35
Ln labor interest	0.191	1.1e-10	0.03400	0.97
Ln interest cost2			0.0966	0.95
Ln labor interest2			0.0627	0.93
Ln interest cost* Ln labor interest			-0.0915	0.93
sigmaSq	0.179	< 2e-16	0.08480	0.93
Gamma	0.000007	1	0.05000	0.96

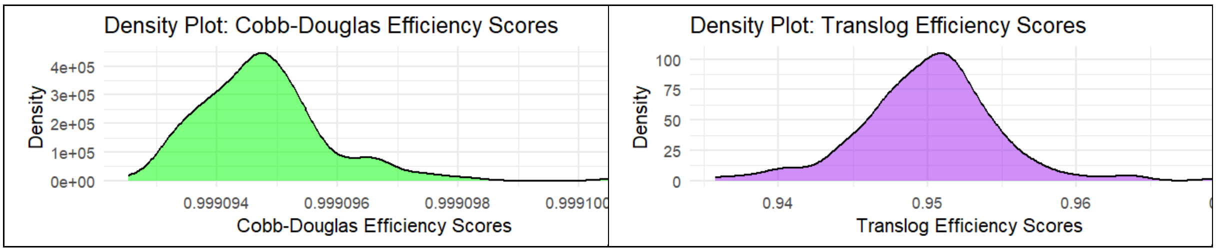
Source: Data processed by the author(s)

The estimated γ (gamma) parameter in the Cobb–Douglas model is close to zero ($\gamma = 0.000007$), indicating that random noise dominates over inefficiency. This suggests a relatively high operational consistency among banks, where most deviations from the frontier stem from stochastic disturbances rather than managerial inefficiency. Conversely, the Translog model reports $\gamma = 0.05$, still implying limited inefficiency variance.

The extremely low gamma values obtained in both SFA specifications indicate that the variance of inefficiency is relatively small compared to statistical noise. This finding suggests that Indonesian banks in the sample operated under relatively homogeneous efficiency conditions during 2020–2021, or alternatively, that the selected input-output structure may not fully capture managerial inefficiency variation. Consequently, the SFA model may possess limited discriminatory power in distinguishing inefficient banks within this dataset.

This result also implies that external shocks, regulatory adjustments, and macroeconomic uncertainty during the post-pandemic period may have contributed more strongly to performance variation than internal managerial inefficiency. Similar observations were reported by Ariefianto *et al.* (2026), who found that Indonesian banking inefficiency is highly responsive to macroeconomic disturbances. Therefore, future studies may benefit from incorporating environmental variables, risk indicators, or panel stochastic frontier models to improve inefficiency identification.

Figure 3. Density Cobb-Douglas vs Translog



Source: Data processed by the author(s)

Table 4. Descriptive Statistics of Efficiency SFA

Variable	Mean	SD	Min	Max
efisiensi_sfa_cd	0.99909	0.00000	0.99909	0.99910
efisiensi_sfa_translog	0.95012	0.00471	0.93574	0.96998

Source: Data processed by the author(s)

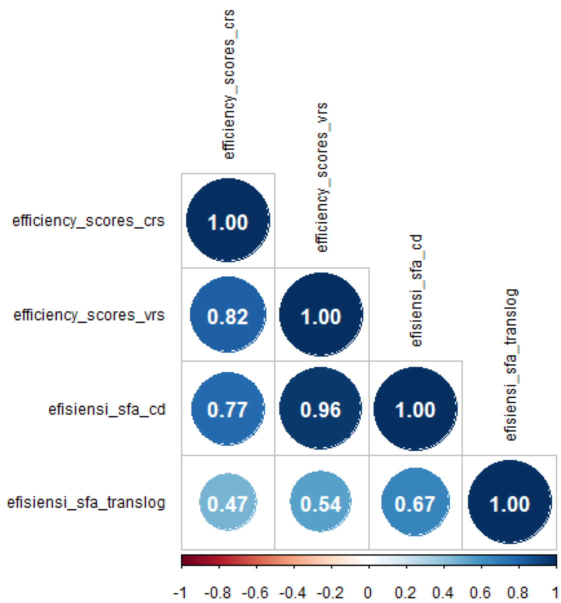
Figure 3 and Table 4 further illustrate the density of efficiency scores derived from both functional forms. The Cobb–Douglas model produces efficiency scores tightly clustered near unity (mean = 0.99909), signifying almost perfect efficiency under its restrictive assumptions. In contrast, the Translog model shows a broader distribution (mean = 0.95012, SD = 0.0047), reflecting its greater flexibility in accommodating input substitution and curvature effects.

These findings are in line with (Nguyen, Thi, and Pham 2025) and (Raju 2018), who highlighted that SFA's stochastic structure captures noise more effectively, resulting in a more dispersed but realistic efficiency distribution. Similarly, (Silva, Tabak, and Oliveira 2016) argued that the Translog specification, despite being more complex, better represents efficiency variations under uncertain market conditions.

3.4 Spearman's Rank Correlation Analysis

To examine the relationship between efficiency measures from DEA and SFA, Spearman's rank correlation was computed (Figure 4). The results reveal strong and significant positive correlations between most efficiency indicators. The correlation between CRS and VRS scores is 0.82, confirming consistency across DEA scale assumptions. Additionally, the correlation between DEA-VRS and SFA-Cobb–Douglas is notably high (ρ = 0.96), suggesting that both methods rank banks similarly in terms of efficiency, despite their methodological differences.

Figure 4. Spearman's Correlation Plot



Source: Data processed by the author(s)

The correlation between SFA-Translog and DEA efficiency scores is weaker (ρ = 0.47–0.67), implying that the flexible functional form captures different aspects of inefficiency, possibly due to non-linearities and random shocks. This aligns with (Vu, Nguyen, and Dinh 2019) and (Akandekumtiim and Moyo 2024), who observed that while DEA and SFA generally yield consistent efficiency rankings, SFA tends to produce lower efficiency levels because it adjusts for noise.

4. Discussions

DEA and SFA are complementary not substitutive, approaches for evaluating bank efficiency. As (Timothy Coelli *et al.* 2005) and (Shaik 2022) noted, DEA excels in benchmarking and identifying best-practice frontiers, whereas SFA provides a deeper understanding of inefficiency sources by decomposing error components. The high correlation between DEA-VRS and SFA-Cobb–Douglas implies that, in relatively stable banking environments, deterministic and stochastic frontiers yield convergent efficiency rankings. However, under greater environmental volatility - as modeled by the Translog SFA - efficiency estimates diverge, emphasizing the need for context-specific methodological selection.

Compared with studies in Southeast Asia, the efficiency scores observed in Indonesian banks appear relatively high under both DEA and SFA approaches. Vietnamese banking studies by Nguyen *et al.* (2025) and Vu *et al.* (2019) reported greater efficiency dispersion, reflecting stronger heterogeneity in operational environments and ownership structures. Similarly, Malaysian banks analyzed by Sufian *et al.* (2016) exhibited wider variation in scale efficiency. The relatively concentrated efficiency scores in this study may indicate that Indonesian banks experienced convergence in operational strategies during the post-pandemic recovery period, particularly through digitalization and cost restructuring initiatives.

The combined DEA–SFA approach provides a robust dual-lens assessment of Indonesian banks' efficiency. DEA reveals that most banks operate close to the efficiency frontier, with minor deviations attributed to scale inefficiencies. SFA corroborates these findings, highlighting that random noise plays a dominant role in explaining efficiency variation. The high correlation between DEA-VRS and SFA-Cobb–Douglas suggests that both methods yield compatible efficiency rankings when banking operations are relatively homogenous.

From a policy perspective, the findings imply that Indonesian banking regulators should not only focus on improving managerial efficiency but also strengthen resilience against macroeconomic and stochastic shocks. Since DEA and SFA indicate that banks generally operate near the efficiency frontier, future efficiency gains may depend more heavily on technological innovation, digital transformation, and risk management improvements rather than traditional cost minimization strategies alone. For bank management, the results highlight the importance of balancing operational expansion with scale optimization. Banks operating efficiently under the VRS framework may still experience scale inefficiencies under CRS assumptions, suggesting that strategic growth decisions should consider operational scale sustainability. Furthermore, the stronger efficiency consistency between DEA-VRS and SFA-Cobb-Douglas indicates that stable operational structures remain critical for maintaining efficiency during uncertain economic conditions.

Overall, these results confirm that integrating non-parametric and parametric frontier methods enhances the robustness of efficiency evaluations. As recommended by Alrafadi *et al.* (2016), combining DEA and SFA allows researchers to cross-validate results and capture both deterministic and stochastic dimensions of inefficiency, thus offering a more comprehensive understanding of banking performance dynamics in Indonesia.

Conclusions and Further Research

In conclusion, the combined application of DEA and SFA provides a comprehensive understanding of banking efficiency by integrating non-parametric benchmarking and parametric stochastic modeling. The DEA results indicate that Indonesian banks generally operate near the efficient frontier, with higher efficiency under VRS assumptions reflecting the role of scale differences. Meanwhile, SFA results suggest that random shocks, rather than managerial inefficiency, predominantly explain variations in performance - especially under the Cobb-Douglas specification. The strong correlation between DEA-VRS and SFA-Cobb-Douglas efficiency scores confirms the consistency of both methods in ranking bank performance, while the weaker correlation with the Translog model highlights the sensitivity of efficiency estimates to functional form assumptions. Overall, this study reinforces the complementarity of DEA and SFA: DEA effectively identifies best-practice frontiers and relative performance, whereas SFA provides deeper insights into inefficiency drivers under stochastic conditions, making their combined use essential for robust efficiency evaluation in the banking sector.

In order to capture efficiency changes over time, future research may expand on this study by utilizing productivity indexes like the Malmquist index and dynamic efficiency analysis using panel data approaches. Furthermore, incorporating environmental factors - such as the degree of digitization, the quality of governance, credit risk, and macroeconomic conditions - may offer more profound insights into the roots of inefficiency that DEA and SFA are unable to fully capture. To improve the reliability and thoroughness of banking efficiency evaluations, future research may also investigate hybrid or alternative frontier approaches and perform comparison analysis across various bank groupings (e.g., large vs. small banks, conventional vs. Islamic banks).

Declarations

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