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Efficiency of Conventional Vs Islamic Banks in Indonesia: Pre and Mid-Covid Analysis

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Abstract

This study aims to assess the technical efficiency of Indonesia's conventional and Islamic banks and to examine whether their efficiencies differ between the periods before and during the COVID-19 pandemic. Bank input and output data are obtained from financial statements sourced from the CEIC Global Database for 96 Indonesian banks over the period from 2015 to 2022. The study employs bootstrap Data Envelopment Analysis (DEA) under both production and intermediation approaches to estimate bias-corrected technical efficiency. Independent t-tests are conducted to compare efficiency scores between conventional and Islamic banks, as well as to examine differences in technical efficiency before versus during the COVID-19 pandemic. The empirical findings indicate that Indonesian banks during the pandemic period were generally less efficient than before, and Islamic banks consistently exhibited lower technical efficiency than conventional banks. Although conventional banks outperform Islamic ones overall, the efficiency gap is not statistically significant during the pandemic. Moreover, banks show higher efficiency under the production approach, indicating stronger performance in revenue generation than fund intermediation. This study advises Indonesian banks to increase interest income (or fund disbursements, for Islamic banks), non-interest income, and loans while also considering risk to improve overall technical efficiency.

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INTRODUCTION

The COVID-19 pandemic has shaken the global economy, including the banking industry in Indonesia (Lantara et al., 2022; Susanti et al., 2023). This crisis has raised significant concerns about the banking sector's ability to maintain performance and efficiency, prompting the Financial Services Authority (OJK) to implement counter-cyclical policies since March 2020, as stated in POJK No. 11/POJK.03/2020. Despite regulatory interventions, Indonesia's aggregate cost-to-income ratio still rose from 46.59% to 47.78% in 2020, due to loan restructuring and reduced loan disbursements, according to World Bank data.

While CIR is a commonly used indicator to measure operational efficiency, it merely captures the ratio between costs and income, thereby oversimplifying complex banking processes. A standard financial ratio, such as CIR, does not identify why inefficiencies occur or how managerial and operational factors contribute to them (Belanès et al., 2015). A study by C. Ho & Zhu (2004) also states that no single ratio can adequately represent performance throughout the spectrum of banking activities, as there is no criterion for choosing a ratio relevant to all stakeholders. This has led scholars to call for multi-dimensional approaches that account for operational nuances and managerial decision-making (Belanès et al., 2015; Quaranta et al., 2018).

To address this issue, the present study measure technical efficiency, which is the ability of a decision-making unit (in this case, a bank) to maximize output from given inputs or minimize inputs for a given output (Coelli et al., 2005; Mezzi, 2018; Mohan, 2020). We apply Data Envelopment Analysis (DEA), a non-parametric method introduced by Charnes et al. (1978), which is widely used to evaluate the relative efficiency of units by comparing multiple inputs and outputs. DEA can decompose efficiency into technical, pure technical, and scale components, allowing researchers to identify whether inefficiencies stem from management, operations, or scale effects.

To enhance robustness, this study applies bootstrap DEA, developed by Simar & Wilson (1998), which corrects for bias and enables statistical inference. Previous research shows that bootstrap DEA produces more realistic efficiency assessments, as evidenced by studies on Australian banks (Moradi-Motlagh et al., 2015) and MENA Islamic banks (Bahrini, 2017). Applications in Indonesia, including those by Zhang & Matthews (2012), Defung et al. (2016), and Effendi et al. (2018), further demonstrate its effectiveness.

However, few have applied this method to the COVID-19 context, which this study aims to address. Therefore, this study aims to address the following question: Did the technical efficiency of Indonesian banks, both conventional and Islamic, differ before and during the COVID-19 pandemic? Furthermore, were there significant differences in technical efficiency between these two groups of banks during the pandemic period? By applying DEA and its bootstrap variant, this study aims to provide a robust and bias-corrected measure of bank efficiency and assess whether significant differences exist across time periods and bank types.

Building on the discussion of how crises affect banking performance, extensive research on the 2008 Global Financial Crisis (GFC) provides important insights into the dynamics of bank efficiency under systemic stress. Most studies have found that the crisis substantially reduced efficiency across different regions, although the extent of this reduction varied depending on the structural and institutional contexts. In Europe, Curi et al. (2015) showed that both focused and diversified foreign banks in Luxembourg experienced efficiency declines during the GFC, while Degl'Innocenti, Kourtzidis, et al. (2017) observed a similar downturn among 116 banks of 9 new European Union (EU) members in Central and Eastern European countries. Davidovic et al. (2019) further found a decline in the efficiency of Croatian banks due to the crisis, followed by improvements after EU accession, primarily for both small and large institutions. Degl'Innocenti, Matousek, et al. (2017) found that the GFC widened inefficiency gaps globally, particularly for banks headquartered farther from major financial centers such as London and New York. Similarly, Moradi-Motlagh & Babacan (2015) documented that Australian banks experienced notable deterioration in efficiency during the crisis.

In the Middle East and Southeast Asia, the effects of the GFC were also evident, though Islamic banks often showed greater resilience. Abdul-Wahab & Haron (2017) found that while efficiency in Qatari banks declined from 2007 to 2011, Islamic banks were less affected than conventional ones. Hafez & Halim (2019) similarly reported that Egyptian Islamic banks outperformed conventional banks after the crisis, suggesting stronger post-crisis recovery. In the GCC region, Parsa (2022) noted a temporary drop in efficiency during the GFC, with a faster recovery among Islamic banks. In Indonesia, findings were mixed. Anwar (2019) observed only a slight decline in efficiency during 2008 using SFA, whereas Effendi et al. (2018) found a significant post-crisis efficiency decrease, particularly among regionally operating banks. Ngo & Le (2019) further demonstrated that the 2008 crisis lowered efficiency in Vietnamese banks and highlighted its positive link with capital market development.

Despite the general trend of declining efficiency, several studies found that banks maintained stability during the GFC. Mobarek & Kalonov (2014) found no significant impact of the crisis on banks in 18 OIC countries. Mezzi (2018) and Rosman et al. (2014) also reported that Islamic banks were largely unaffected, effectively converting inputs into outputs even amid financial turmoil. Bahrini (2017) confirmed that the GCC Islamic bank maintained stable efficiency during and after the crisis. However, a subsequent decline in efficiency occurred in 2011–2012 when financial shocks spread to the real economy.

While the literature on the GFC is extensive, studies on banking technical efficiency during the COVID-19 pandemic remain relatively limited, yielding mixed findings. Gulati et al. (2023) found that Indian banks maintained stable efficiency, while Mai et al. (2023) reported no significant impact on 76 Islamic banks across countries. Similarly, Sang (2022) noted a slight improvement among Vietnamese banks. In contrast, Mateev et al. (2023) and Lassoued et al. (2025) found significant efficiency declines in MENA banks, with differing conclusions regarding the relative resilience of Islamic and conventional banks. These divergent results suggest that efficiency outcomes are shaped by regional, institutional, and structural differences, underscoring the need for further comparative research.

Comparisons between Islamic and conventional banks are particularly relevant due to their differing theoretical and operational foundations. Islamic banks, operating under Shariah principles, emphasize risk-sharing and asset-backed financing, while conventional banks rely on interest-based, risk-transfer mechanisms (Azad et al., 2017; Eyceyurt Batir et al., 2017; Hafez & Halim, 2019). Following the 2008 crisis, Islamic banks were often perceived as more stable due to their limited exposure to speculative assets (M. I. Haque et al., 2020; Lassoued et al., 2025). However, more recent evidence is mixed, with efficiency gaps between the two systems varying across countries, regulatory environments, and technological developments (Safiullah & Shamsuddin, 2022).

During the COVID-19 pandemic, these contrasts became even more relevant. Because the pandemic originated in the real sector, it directly disrupted the asset-backed transactions that underpin Islamic banking, potentially exposing Islamic banks to unique vulnerabilities (Lassoued et al., 2025). In the Indonesian context, for example, Lantara et al. (2022) examined 14 Islamic banks using the conventional DEA approach and found declines in technical, pure technical, and scale efficiencies during the COVID-19 period. However, their analysis was limited in scope. It focused solely on Islamic banks, lacked a comparison with conventional banks, and used a standard DEA model without bootstrap correction, which may result in biased efficiency estimates.

To address these limitations, the present study extends the existing literature by applying a bootstrap DEA approach to obtain more robust and bias-corrected efficiency estimates. It also offers a comparative analysis between conventional and Islamic banks in Indonesia, thereby providing a comprehensive understanding of how these two banking models responded to the COVID-19 shock. Furthermore, independent t-tests are employed to compare the bias-corrected efficiency scores, providing policymakers and bank managers with valuable insights to identify operational gaps and benchmark performance during periods of crisis. Building on these objectives, we hypothesize that there is a significant difference in bias-corrected efficiency between banks before and during the COVID-19 pandemic. We also hypothesize that there is a significant difference in bias-corrected efficiency between Islamic and conventional banks. Furthermore, we hypothesize that this difference persists during the COVID-19 pandemic period, indicating possible resilience or vulnerability differences between the two banking systems.

The remainder of this paper is organized as follows: the next section details the methodology and the input-output variables used; the following section presents the descriptive statistics of the data and the analysis of the efficiency scores; and finally, the paper concludes with a summary of the main findings and suggestions for future research.

RESEARCH METHODS

Data Envelopment Analysis (DEA) is a non-parametric approach with a linear program that measures the relative efficiency of a Decision Making Unit (DMU) with other DMUs, thereby producing a frontier that shows the efficient point of all DMUs by projecting the inefficient DMUs to the frontier directly (Setiawan et al., 2019). If a DMU is on the frontier, then it represents the best practice among other DMUs, i.e., it has reached an efficient level. If the DMU is not on the frontier, then the DMU has not reached an efficient level. The efficiency score of these DMUs ranges from 0 to 1, or 0% to 100%. An efficient DMU has a score of 1 or 100%, while a score below that indicates an inefficient DMU. DEA is the most widely used method in the non-parametric approach due to its many advantages, which include its flexibility in handling a variety of data and its deterministic approach, which does not need the assumption of data distribution prior to estimation (Fethi et al., 2011; T. H. Ho et al., 2021; Ngo & Le, 2019; Vidal-García et al., 2018).

There are two assumptions for using DEA. The first assumption is the constant return to scale (CRS), which assumes that the ratio of additional input to output remains constant (Najmah & Sihaloho, 2025). For example, if there is an increase in input by a factor of t, then the output will increase by the same factor, t. This model assumes that each DMU operates at an optimal scale. The mathematical programming problem can be seen:

$$\begin{aligned} & max_{\theta,\lambda}\ \theta \\ & st \qquad -\theta y_{it} + Y\lambda \geq 0 \\ & x_{it} - X\lambda \geq 0 \\ & \lambda \geq 0 \end{aligned} \qquad \text{.......................} \ (1)$$

Where X and Y are matrices with all outputs and inputs, and λ is a vector of parameters (DMU weights), the weights for each output and input are determined so that each DMU maximizes its own efficiency ratio. Adopting the method by Setiawan et al. (2012), the efficiency score is calculated using $1/\theta$, assuming values within the unit interval.

The other assumption is variable return to scale (VRS), which assumes that the ratio of additional input and output is not necessarily the same (Najmah & Sihaloho, 2025). For example, if there is an increase in input by a factor of t, it does not mean that the output will increase by the same factor. The output can grow larger or smaller than t times. This model assumes that the DMU is not operating at optimal scale. The mathematical programming problem can be seen:

$$max_{\theta,\lambda}\ \theta$$
$$st \quad -\theta y_{it} + Y\lambda \geq 0 \ \dots\dots\dots\dots\dots\dots\dots\dots (2)$$
$$x_{it} - X\lambda \geq 0$$
$$\lambda'1 = 1$$
$$\lambda \geq 0$$

Where X and Y are matrices with all outputs and inputs, and λ is a vector of parameters (DMU weights), the weights for each output and input are determined so that each DMU maximizes its own efficiency ratio. The efficiency score is finally calculated using $1/\theta$, assuming values within the unit interval. The only difference between this mathematical programming problem and the CRS mathematical programming problem is that there is a convexity constraint indicated by $\lambda'1 = 1$, which states that inefficient units are only compared with units of the same size. Therefore, since the size of banks varies, using the VRS assumption would be more appropriate (Effendi et al., 2018).

Both mathematical programming problems shown above are output-oriented. Output-oriented technical efficiency refers to the ability of the DMU to produce potential output from a given set of inputs (Septiani & Setiawan, 2023). Effendi et al. (2018) stated that the output-oriented assumption may hold for Indonesian banks because bank inputs, such as labor and deposits, can be rigidly constrained. The efficiency score under the CRS assumption represents overall technical efficiency, whereas the efficiency score under the VRS assumption represents pure technical efficiency. The efficiency scores of these two models allow us to find scale efficiency, which is computed as:

$$SE = TE_{CRS}/TE_{VRS} \ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3)$$

Where SE is the scale efficiency score, TE_{CRS} is the overall technical efficiency score, and TE_{VRS} is the pure technical efficiency score. Scale efficiency is a measure of the distance between the CRS and VRS frontiers. The larger the distance, the lower the scale efficiency.

As we mentioned previously, in this study, we not only use conventional DEA but also bootstrap DEA. Using the bootstrap approach, the data-generating process is iteratively simulated, the original estimate is applied to the simulated sample, and the results are compared to the original estimator's sampling distribution (Effendi et al., 2018; Setiawan, 2019a, 2019b; Setiawan et al., 2019; Simar & Wilson, 1998). We also use bootstrap DEA because conventional DEA has several limitations. These include finite sample bias and inconsistent results from a slow convergence rate, especially when there are several inputs and outputs, which raises the problem's dimensionality (Charles et al., 2019; Y. Chen et al., 2021; Kneip et al., 1998; Lee & Cai, 2020; Zhang & Matthews, 2012). According to Kneip et al. (1998), unless a very large quantity of data is provided, large bias, large variance, and very wide confidence intervals may be produced when the number of inputs and outputs is huge. Furthermore, the efficiency measure exhibits an upward bias due to construction and is sensitive to outliers (Biener et al., 2016; Vidal-García et al., 2018).

The idea behind the bootstrap is to use the Data Generating Process (DGP) as a model to approximate the sample distributions of interest (Efron, 1979). This approximated distribution can then be used to quantify the bias in the DEA estimator and construct confidence intervals. Additionally, it is projected that this approach can lessen the issue of serial correlation in the efficiency score of the DMUs (Septiani & Setiawan, 2023). Following Setiawan et al. (2012), the bias-corrected efficiency score can be estimated using the following formula:

$$\hat{\hat{\delta}}(x,y) = \hat{\delta}(x,y) - bias_B[\hat{\delta}(x,y)]$$
$$= 2\hat{\delta}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\delta}_b^*(x,y) \ \dots\dots\dots (4)$$

with the condition of the sample variance,

$$\hat{\delta}_b^*(x,y) < \frac{1}{3}\left(\widehat{bias}_B[\hat{\delta}(x,y)]\right)^2 \quad \dots\dots\dots\dots (5)$$

For the last two relations, the original and bias-corrected efficiency scores are denoted by $\hat{\delta}(x,y)$ and $\hat{\hat{\delta}}(x,y)$, respectively, and $\hat{\delta}_b^*(x,y)$ represents the bootstrap estimate of the efficiency score in the bth out of B bootstrap repetitions. To compare and gain insight into the correction and trend of the efficiency scores of the two methods, this study presents the results of both the original and bias-corrected pure technical efficiency scores.

There are different views on determining the most appropriate input and output variables for banks. The two most frequently used approaches are the production approach and the intermediation approach. According to the production approach introduced by Benston (1965), banks are viewed as producers of loan and deposit accounts, employing their labor and capital as inputs and the quantity of accounts they service as their output. The production approach assumes that the primary objective of banks is to maximize revenue. As a result, the best output measure is the quantity and type of transactions, along with the associated documents. At the same time, inputs are defined as physical assets, such as labor and capital.

On the other hand, the intermediation approach views banks as financial intermediaries that receive purchased funds and convert them into services provided to debtors, such as loans and other assets, using labor and capital (Ahn & Le, 2014). Bhatia et al. (2018) argue that the intermediation approach is more suitable for assessing bank efficiency, as the primary role of banks is to facilitate the transfer of funds between surplus and deficit units. Berger & Humphrey (1997) point out that both approaches have their own weaknesses, as they fall short of capturing the dual function of financial institutions as both financial intermediaries and providers of transaction or document processing services. They argue that the intermediation approach may be more suitable for evaluating financial institutions as a whole. In contrast, the production approach may be slightly more effective for assessing the efficiency of financial institutions' branches.

In the DEA approach, the number of inputs and outputs is determined by the number of DMUs in the sample. In the present context, the DMUs are banks. The DEA's ability to distinguish between efficient and inefficient DMUs depends on several inputs and outputs incorporated into the DEA model. As a general rule of thumb, the product of the inputs and outputs should not exceed the total number of DMUs in the sample (Cooper et al., 2007). Khezrimotlagh et al. (2021) state that the accuracy and discriminating power of DEA concerning DMU performance decline as the number of DMUs reduces (or as the number of inputs and outputs rises).

We decided to use both the production approach and the intermediation approach to compare and analyze the results of both approaches. We followed the study from Du & Sim (2016) for the production approach. This study uses fixed assets, other operational expenses, interest expenses, and capital as the input variables. Meanwhile, the output variables are interest income and other operational income. For the intermediation approach, we adopt the study from H. T. H. Nguyen & Nguyen (2022) and Sang (2022). The input variables are deposits, interest expenses, and other operational expenses. Loans, interest income, and other operational income are used as the output variables in this approach. Islamic banks do not provide loans in the same manner as conventional banks, as Islamic law forbids the charging of interest (Doumpos et al., 2017; M. I. Haque et al., 2020). Rather than charging interest, Islamic banks earn a profit through equity participation (Abdul-Majid et al., 2017; Doumpos et al., 2017; M. I. Haque et al., 2020; Hoque & Liu, 2022; Ozdincer & Yuce, 2018). Moreover, Islamic banks give their savers profits instead of interest. For Islamic banks, the interest expense variable is replaced by profit sharing for investment fund owners, and interest income is replaced by income from fund disbursements. All variables are measured in millions of Indonesian Rupiah (IDR).

Table 1. Input-output variables of each approach

Approach	Inputs	Outputs	References
Production	Fixed assets	Interest income	Du & Sim (2016)
	Other operational expenses	Other operational income	
	Interest expenses		
	Capital		
Intermediation	Deposits	Loans	H. T. H. Nguyen & Nguyen (2022) and Sang (2022)
	Interest expenses	Interest income	
	Other operational expenses	Other operational income	

Source: Data Processed, 2025

After measuring the bias-corrected pure technical efficiency scores of Indonesian banks using bootstrap data envelopment analysis, we compared these scores between conventional banks and Islamic banks, as well as between banks before and during the pandemic, using independent t-tests based on the work of Ganga-Contreras et al. (2025), Pham et al. (2021), Sufian & Kamarudin (2015), and Hisham Yahya et al. (2012). There are three null and alternative hypotheses stated as follows:

Hypothesis 1:

H0: There is no difference between banks before and during the COVID-19 pandemic periods in the level of bias-corrected pure technical efficiency. $E(\theta_{\text{banks before the pandemic}}) = E(\theta_{\text{banks during the pandemic}})$

H1: There is a difference between banks before and during the COVID-19 pandemic periods in the level of bias-corrected pure technical efficiency. $E(\theta_{\text{banks before the pandemic}}) \neq E(\theta_{\text{banks during the pandemic}})$

Hypothesis 2:

H0: There is no difference in the level of bias-corrected pure technical efficiency between Islamic banks and conventional banks. $E(\theta_{\text{Conventional banks}}) = E(\theta_{\text{Islamic banks}})$

H1: There is a difference in the level of bias-corrected pure technical efficiency between Islamic banks and conventional banks. $E(\theta_{\text{Conventional banks}}) \neq E(\theta_{\text{Islamic banks}})$

Hypothesis 3:

H0: There is no difference in the level of bias-corrected pure technical efficiency between Islamic banks and conventional Banks during the pandemic. $E(\theta_{\text{Islamic banks during the pandemic}}) = E(\theta_{\text{Conventional banks during the pandemic}})$

H1: There is a difference in the level of bias-corrected pure technical efficiency between Islamic banks and conventional banks during the pandemic. $E(\theta_{\text{Conventional banks during pandemic}}) \neq E(\theta_{\text{Islamic banks during pandemic}})$

Where $E(\theta)$ is the bias-corrected pure technical efficiency score. To test the hypotheses, we gather specified input-output variables from the financial statements of 96 conventional and Islamic banks each month, from January 2015 to April 2022, in Indonesia. We use monthly data to examine the changes in efficiency levels in more depth due to the pandemic, which began in March 2020. The main data source is the Financial Services Authority database compiled by CEIC.

RESULTS AND DISCUSSION

From Table 2, it is evident that all variables exhibit high variation. For all banks, non-interest income exhibits the highest variance at 3.063, followed by fixed assets at 2.950. Capital at 2.533, deposits at 2.530, loans at 2.485, interest income at 2.463, non-interest expenses at 2.446, and the lowest variance is observed in interest expenses at 2.048. The order of variables with the highest variance for conventional banks is almost the same as for all banks, with a different order only in capital and deposits. Non-interest income remains the variable with the highest variance, at 2.924, followed by fixed assets at 2.860, then deposits at 2.469, capital at 2.440, loans at 2.417, interest income at 2.415, non-interest expenses at 2.382, and the lowest is interest expenses at 2.005. For Islamic banks, the order of variables with the highest variance differs significantly from that of all banks and conventional banks. However, the variable with the highest variance is still held by non-interest income at 3.443, followed by non-interest expenses at 1.501, then fixed assets at 1.453, deposits at 1.251, loans at 1.172, interest income at 1.045, interest expenses at 0.907, and the lowest is capital at 0.905.

The Islamic banks have lower coefficients of variation for almost all variables compared to the conventional banks. For example, the coefficients of variation of capital are 0.950 and 2.440 for Islamic and conventional banks, respectively. The relatively lower coefficient of variation of Islamic banks can be attributed to the smaller variation in the size of Islamic banks compared to conventionally operating banks.

Table 2. Descriptive Statistics of the Input-Output Variables from January 2015 to April 2022 for All Banks (Million Rp)

Variable	Mean	Standard deviation	Coefficient of variation	Minimum	Maximum
Fixed assets	2,423.847	7,149.860	2.950	0.545	58,679.730
Capital	10,655.390	26,987.190	2.533	0.321	287,077.900
Deposits	56,296.190	142,424.300	2.530	0.663	1,136,124.000
Interest expenses	181.430	371.560	2.048	0.040	3,404.907
Non-interest expenses	362.271	886.148	2.446	0.001	11,559.840
Loans	49,266.860	122,403.300	2.485	16.388	989,527.800
Interest income	497.777	1,226.180	2.463	1.195	11,718.850
Non-interest income	192.308	589.016	3.063	0.001	13,246.580
Conventional Banks					
Fixed assets	2,645.616	7,565.956	2.860	10.188	58,679.730
Capital	11,690.720	28,524.140	2.440	0.321	287,077.900
Deposits	60,982.030	150,550.700	2.469	0.663	1,136,124.000
Interest expenses	195.573	392.212	2.005	0.040	3,404.907
Non-interest expenses	392.720	935.484	2.382	0.001	11,559.840
Loans	53,517.200	129,375.600	2.417	16.388	989,527.800
Interest income	536.937	1,296.743	2.415	1.195	11,718.850
Non-interest income	212.679	621.852	2.924	0.001	13,246.580
Islamic Banks					
Fixed assets	730.342	1,060.933	1.453	0.545	5,073.734
Capital	2,749.250	2,487.839	0.905	117.575	13,160.530

Deposits	20,513.400	25,668.770	1.251	10.195	123,739.900
Interest expenses	73.433	66.622	0.907	0.742	264.522
Non-interest expenses	129.753	194.816	1.501	0.229	2,190.733
Loans	16,809.760	19,693.490	1.172	471.759	95,911.600
Interest income	198.738	207.702	1.045	4.002	1,255.552
Non-interest income	36.748	126.519	3.443	0.057	2,119.465

Source: Data Processed (2025)

Table 3 presents the estimation results for pure technical efficiency, bias-corrected technical efficiency, and scale efficiency, respectively, using the production approach. This estimate reveals a significant difference when using the bootstrapping approach. For example, all banks using the ordinary approach (pure technical efficiency) have an average of 0.829, while those using the bootstrapping approach (bias-corrected pure technical efficiency) have an average of 0.744. This demonstrates that the bootstrapping approach yields more robust results. This estimation also shows that the scale efficiency of Indonesian banks, as measured by the production approach, is greater than their pure technical efficiency. The scale efficiency scores average 0.899, 0.895, and 0.931 for all consecutive, conventional, and Islamic banks across all observation periods. These are higher than the pure technical efficiencies, reaching averages of 0.829, 0.831, and 0.811 for the bank groups, respectively. This result suggests that pure technical inefficiency is the primary source of overall technical inefficiency, rather than scale inefficiency, for Indonesian banks during the study period.

Table 3. The efficiency scores of conventional and Islamic banks before and during the COVID-19 pandemic, with the production approach

Period	**PTE**	**Bias-corrected PTE**	**SE**
All Banks			
Before pandemic	0.836	0.755	0.894
During pandemic	0.811	0.717	0.911
All observation period	0.829	0.744	0.899
Conventional Banks			
Before pandemic	0.840	0.758	0.890
During pandemic	0.810	0.716	0.906
All observation period	0.831	0.746	0.895
Islamic Banks			
Before pandemic	0.809	0.734	0.925
During pandemic	0.818	0.718	0.946
All observation period	0.811	0.729	0.931

Source: Data Processed (2025)

For the intermediation approach, the results are presented in Table 4. Like the production approach, the intermediation approach also reveals a significant difference when using the bootstrapping approach. For example, all banks following the ordinary approach (pure technical efficiency) have an average of 0.793, while those following the bootstrapping approach (bias-corrected pure technical efficiency) have an average of 0.706. Once again, these results further demonstrate that the bootstrapping approach enhances the robustness of the estimation results. In this table, the scale efficiency scores average 0.853, 0.849, and 0.885 for the consecutive all, conventional, and Islamic banks across all observation periods. These are higher than the pure technical efficiencies, reaching averages of 0.793, 0.798, and 0.757 for the bank groups, respectively. Similar to the production approach, the scale efficiency of Indonesian banks using the intermediation approach is also greater than their pure technical efficiency. This indicates that pure technical inefficiency is the primary source of overall technical inefficiency, rather than scale inefficiency, for Indonesian banks during the study period.

Table 4. The efficiency scores of conventional and Islamic banks before and during the COVID-19 pandemic, with the intermediation approach

Period	PTE	Bias-corrected PTE	SE
All Banks			
Before pandemic	0.793	0.707	0.876
During pandemic	0.793	0.702	0.796
All observation period	0.793	0.706	0.853
Conventional Banks			
Before pandemic	0.799	0.712	0.872
During pandemic	0.795	0.703	0.791
All observation period	0.798	0.710	0.849
Islamic Banks			
Before pandemic	0.748	0.672	0.904
During pandemic	0.778	0.693	0.837
All observation period	0.757	0.678	0.885

Source: Data Processed (2025)

The difference tests of the bias-corrected pure technical efficiencies, using an independent t-test for all banks, between the periods before and during the COVID-19 pandemic, are reported in Table 5. The null hypothesis of no difference in the level of bias-corrected pure technical efficiency between banks before and during the COVID-19 pandemic periods is rejected: $E(\theta_{\text{banks before the pandemic}}) \neq E(\theta_{\text{banks during the pandemic}})$. The results suggest that, regardless of the bank roles, banks were more efficient before the pandemic than during the pandemic, with significance levels of 1% and 10% for the production approach and intermediation approach, respectively. These results are in line with research by Effendi et al. (2018), Lassoued et al. (2025), Hafez & Halim (2019), Lantara et al. (2022), Degl'Innocenti, Kourtzidis, et al. (2017), Ngo & Le (2019), Parsa (2022), Moradi-Motlagh & Babacan (2015), Mateev et al. (2023), Abdul-Wahab & Haron (2017), Degl'Innocenti, Matousek, et al. (2017), Davidovic et al. (2019), Anwar (2019), Řepková (2013), and Curi et al. (2015), which identify that banks during crises or pandemic periods convert input into output less efficiently than other periods.

Table 5 also shows that the efficiency scores obtained with the production approach are higher than those obtained with the intermediation approach, implying that Indonesian banks are more efficient at optimizing revenue than distributing credit. The studies of Lutfi & Suyatno (2019), Řepková (2015), and Kočišová (2013) show a positive and significant relationship between loan-to-deposit ratio and the efficiency level of banks using the intermediation approach, which may indicate the cause of suboptimal intermediation activities, with Indonesian banks' loan-to-deposit ratio only reaching 77.13% in December 2021 (OJK, 2024), still below the lower limit set in Bank Indonesia regulation number 15/7/PBI/2013 of 78%. The study by Kočišová (2013) also shows that there is no significant relationship between the loan-to-deposit ratio and the efficiency level of banks under the production approach, which may explain why the efficiency score under the production approach is higher than the efficiency score under the intermediation approach.

Table 5. Difference test of bias-corrected technical efficiency of all banks before and during the pandemic

	Production approach	**Intermediation approach**
Mean Efficiency Before the Pandemic	0.755	0.707
Mean Efficiency During the Pandemic	0.717	0.702
Difference	0.038	0.005
t-statistic	10.243	1.496
Probability (p-value)	0.000	0.067

Source: Data Processed (2025)

Table 6 tests the difference in bias-corrected pure technical efficiencies between conventional and Islamic banks in all observation periods. The null hypothesis of no difference in the level of bias-corrected pure technical efficiency between Islamic banks and conventional banks is rejected: $E(\theta_{\text{banks before the pandemic}}) \neq E(\theta_{\text{banks during the pandemic}})$. The research results suggest that conventional banks have significantly higher efficiency scores than Islamic banks at the 1% critical level. This is in line with the studies by Alsharif (2021), Mobarek & Kalonov (2014), M. I. Haque et al. (2020), Sulaeman et al. (2019), Doumpos et al. (2017), Kaffash et al. (2018), Abdul-Wahab & Haron (2017), R. Haque & Sohel (2019), and Chaffai & Hassan (2019), which find that conventional banks are more efficient than Islamic banks. This may be caused by conventional banks having several advantages over Islamic banks, like accepting interest on loans that represent a major source of the banks' revenue, not sharing losses with clients, having a long history and experience, using more developed technologies, and enjoying huge capital (Hoque & Liu, 2022; Safiullah & Shamsuddin, 2022). This may also be caused by the strict application of Shariah laws, which make many Islamic banking products distinctive and raise operational expenses. In addition, Islamic banks are generally smaller than conventional banks, and there is evidence that banks' size has a positive impact on their efficiency (see, for example, Abdulahi et al., 2023; Antunes et al., 2022; Anwar, 2019; Boubaker et al., 2022; Defung et al., 2016; Mezzi, 2018; Mobarek & Kalonov, 2014; Nair & Vinod, 2019; Okuda & Aiba, 2016; Otero et al., 2020; Parsa, 2022; Patra et al., 2023). Like the previous difference test, the results also show that the efficiency scores obtained with the production approach were higher than those obtained with the intermediation approach.

Table 6. Difference test of bias-corrected technical efficiency between conventional and Islamic banks across all observation periods

	Production approach	**Intermediation approach**
Mean Efficiency of Conventional Banks	0.746	0.710
Mean Efficiency of Islamic Banks	0.729	0.678
Difference	0.017	0.032
t-statistic	3.224	6.518
Probability (p-value)	0.001	0.000

Source: Data Processed (2025)

Lastly, Table 7 provides the tests of the bias-corrected pure technical efficiency difference between conventional banks and Islamic banks in the pandemic period. The results show that the bias-corrected pure technical efficiency between conventional banks and Islamic banks was not significantly different during the pandemic; hence, the null hypothesis cannot be rejected: $E(\theta_{\text{Islamic banks during the pandemic}}) = E(\theta_{\text{Conventional banks during the pandemic}})$. This implies that both banking streams have no significant differences in converting input into output during the pandemic, regardless of which approach is used. Once again, the results show that the efficiency scores obtained with the production approach are higher than those obtained with the intermediation approach.

Table 7. Difference test of bias-corrected technical efficiency between conventional and Islamic banks during the pandemic

	Production approach	**Intermediation approach**
Mean Efficiency of Conventional Banks	0.716	0.703
Mean Efficiency of Islamic Banks	0.718	0.693
Difference	-0.002	0.010
t-statistic	-0.185	1.112
Probability	0.573	0.133

Source: Data Processed (2025)

Overall, this research finds that banks were more efficient before the pandemic than during the pandemic, and banks operating conventionally were more efficient than Islamic banks in all observation periods, regardless of the approach used. Since this study employs an output-oriented DEA, it places greater emphasis on output-related variables. In this context, efficiency scores improve when output values increase. Therefore, to enhance technical efficiency under the production approach, Indonesian banks are advised to increase their interest income (or fund disbursement, in the case of Islamic banks) as well as non-interest income, both of which constitute the output components of the production approach. To increase non-interest income, banks can diversify their revenue streams by optimizing digital banking solutions. This strategy has been shown to enhance non-interest income by developing new innovative products and digital services (Mainrai & Mohania, 2021; Q. T. T. Nguyen et al., 2023). Data from Bank Indonesia also shows a 92% growth in the number of transactions with digital banks in April 2022 compared to April 2019, indicating a shift in people's behavior that increasingly embraces digital banking services, coupled with the pandemic that has made activities outside the home more limited. For conventional banks seeking to boost interest income, increasing lending rates to enhance the net interest margin (NIM) can be a viable option (Agiomirgianakis et al., 2024). However, this must be balanced with prudent risk management, as high levels of non-performing loans (NPLs) can reduce the ability to expand loans and are a significant source of inefficiency in many banks (M. J. Chen et al., 2015; Chun & Ardaaragchaa, 2024; Phung et al., 2022; Takahashi & Vasconcelos, 2024).

To improve efficiency under the intermediation approach, banks should focus on expanding their loan portfolios while managing credit risk effectively. One promising strategy is offering green financing, which has been shown to lower credit risk while benefiting both lenders and borrowers (Umar et al., 2021). Additionally, the adoption of financial technologies such as Big Data, artificial intelligence, blockchain, and cloud computing can further mitigate risks (Chai & Sun, 2024; Liang et al., 2023; Wu et al., 2024). Financial technology, such as digital banking, can also contribute to increased loan activities by enhancing its ability to gather, evaluate, and process data (Liang et al., 2023). For Islamic banks, enhancing fund disbursements can be achieved by improving Islamic financial literacy and simplifying access to financing for institutions such as mosques and community organizations, which can lead to more customers preferring Islamic banks over conventional banks (Al-Awlaqi & Aamer, 2023). Islamic banks can also increase their income by better identifying and targeting more specific market segments. For instance, focusing on policies that support micro, small, and medium enterprises (MSMEs) can be effective, as Islamic banks tend to generate higher revenues from serving this sector (Disli et al., 2023). Furthermore, expanding the range of Shariah-compliant financing products can enable Islamic banks to meet the diverse needs of their customers better, increase their income, and thereby improve their efficiency scores.

CONCLUSION

In the present study, we estimated the bias-corrected pure technical efficiencies of conventional banks and Islamic banks before and during the COVID-19 pandemic using bootstrap DEA with both production and intermediation approaches. This research also measures pure technical efficiency and scale efficiency using conventional DEA to compare the results. The difference in bias-corrected technical efficiency between the two banking streams and between banks before and during the pandemic is also examined using an independent t-test.

We draw several conclusions from this study. The first finding is that Indonesian banks are more scale-efficient than purely technically efficient. This finding suggests that overall technical inefficiency is primarily due to pure technical inefficiency rather than scale inefficiency. The second finding is that banks were more efficient before the pandemic than during the COVID-19 pandemic, regardless of the input-output approach used. This suggests that banks during the pandemic period convert input into output less efficiently than before the pandemic.

Furthermore, in both production and intermediation approaches, the conventional banks are more efficient than the Islamic banks. This could be because conventional banks are typically larger and more technically loose than Islamic banks. We also find that the bias-corrected pure technical efficiencies are not significantly different between conventional banks and Islamic banks during the pandemic period, indicating that both banking streams exhibit no significant differences in converting inputs into outputs during this time. Additionally, the bias-corrected pure technical efficiency in the production approach is consistently higher than that in the intermediation approach. This finding suggests that Indonesian banks are more effective in generating revenues from expenses than in lending deposits.

This research recommends that Indonesian banks increase their interest income (or fund disbursements for Islamic banks) and non-interest income, adopting prudent risk management, to become more efficient in their production approach. Increasing loans while also considering risk is also necessary to become more efficient in the intermediation approach. Indonesian banks can consider various strategies, such as optimizing financial technologies like digital banking, especially during pandemic, increasing lending rates, and green financing (Agiomirgianakis et al., 2024; Chai & Sun, 2024; Liang et al., 2023; Mainrai & Mohania, 2021; Q. T. T. Nguyen et al., 2023; Umar et al., 2021; Wu et al., 2024). Islamic banks can also consider enhancing Islamic financial literacy, targeting specific market segments, and expanding the range of Shariah-compliant financing products to increase fund disbursement and other revenue streams (Al-Awlaqi & Aamer, 2023; Disli et al., 2023). Since this research only captures the observation period up to April 2022, further research is needed to extend the sample in the aftermath of the pandemic. Future researchers may consider enriching the analysis by employing a two-stage bootstrap DEA analysis to identify macro-level, bank-level, or country-level factors that influence the efficiency of conventional and Islamic banks. Moreover, further research employing other methods is also recommended to reinforce the findings.

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