

Determinants of Profitability in Indonesian Commercial Banks: Financial Ratios and Macroeconomic Fluctuations

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ABSTRACT

The COVID-19 pandemic significantly affected the profitability and operational performance of Indonesian commercial banks during changing macroeconomic conditions. This study examines the effects of financial ratios and macroeconomic fluctuations on the profitability of KBMI 3 commercial banks and KBMI 4 commercial banks (excluding Islamic banks) across the pre-pandemic (2018–2019), pandemic (2020–2021), and post-pandemic (2022–2023) periods. A quantitative approach was employed using balanced panel data from 15 banks, analyzed through panel data regression, Data Envelopment Analysis (DEA), and Difference-in-Differences (DiD). The results indicate that BOPO has a significant negative effect on Return on Assets ($b = -0.077$, $p < 0.001$), whereas Net Interest Margin ($b = 0.164$, $p < 0.001$) and exchange rate fluctuations ($b = 0.0008$, $p = 0.013$) have significant positive effects. The regression model achieved an R^2 of 0.857 (Adjusted $R^2 = 0.840$), and DEA results indicate an average technical efficiency of 85.5%. DiD analysis further reveals that KBMI 4 banks experienced a larger decline in profitability during the pandemic than KBMI 3 banks. These findings highlight the importance of improving operational efficiency and resilience to enhance banking performance during periods of economic uncertainty.

Keywords: Bank Profitability; Difference-in-Differences; Financial Ratios; Indonesian Commercial Banks; Macroeconomic Fluctuations; Operational Efficiency; Technical Efficiency

JEL Classification: G21; G1; C23; E32

INTRODUCTION

The banking sector supports financial intermediation, risk management, and capital allocation, making it essential to economic stability and growth (Setiawan & Wisna, 2021). The COVID-19 pandemic disrupted banking performance through higher credit risk, weaker profitability, and operational inefficiencies (Bumantara & Muchtar, 2024; Genoveva et al., 2021; Saputro & Fakhri, 2024). In Indonesia, KBMI 3 and KBMI 4 commercial banks, classified according to core capital under Indonesia's Financial Services Authority (OJK) Regulation No. 12/POJK.03/2021, faced substantial pressure despite relatively strong capital bases. From 2018 to 2023, banking performance can be viewed across pre-pandemic (2018–2019), pandemic (2020–2021), and post-pandemic (2022–2023) periods.

The pandemic weakened profitability through reduced economic activity, increased credit risk, and pressure on interest margins, while exchange-rate volatility and monetary-policy changes also influenced performance (Duncan et al., 2022; Lamablawa et al., 2022; Phan & Narayan, 2020; Ratri et al., 2022; Wuryani et al., 2021). Although profitability gradually recovered after the pandemic, it remained below pre-pandemic levels. The post-pandemic banking environment was also shaped by regulatory developments in digital banking services (Sulistyandari & Sutrisno, 2023). Return on Assets (ROA) measures bank profitability by reflecting how effectively banks use their assets to generate earnings (Marlina, 2022). Previous studies have examined bank-specific factors, including Loan-to-Deposit Ratio (LDR), Operating Expenses to Operating Income (OEOI/BOPO), Non-Performing Loans (NPL), Net Interest Margin (NIM), and Capital Adequacy Ratio (CAR), as well as macroeconomic variables such as Interest Rates (IR) and Exchange Rates (XR), in relation to bank profitability (Dahrani & Nainggolani, 2023; Kamal, 2023; Sari & Indriani, 2023).

However, limited evidence simultaneously examines profitability determinants, technical efficiency, and differences in the pandemic effect between KBMI 3 and KBMI 4 banks across all three periods. Therefore, this study examines Indonesian KBMI 3 and KBMI 4 commercial banks from 2018 to 2023 using panel regression, Data Envelopment Analysis (DEA), and Difference-in-Differences (DiD). This integrated approach provides complementary evidence on profitability determinants, technical efficiency, and the pandemic's differential effects across bank groups. The findings are expected to help bank managers, policymakers, and investors strengthen banking resilience and financial performance during periods of economic uncertainty.

LITERATURE REVIEW

Financial Ratios and Bank Performance

Financial ratios assess key dimensions of bank performance, including profitability, liquidity, credit risk, market risk, solvency, and operational efficiency. These ratios help stakeholders evaluate a bank's ability to generate earnings, manage financial risks, and maintain financial stability (Fakhri & Darmawan, 2021; Widyarini & Marsoem, 2021). Bank profitability is influenced by both internal financial conditions and external macroeconomic factors (Rafid et al., 2024). Accordingly, this study considers seven determinants of profitability: LDR, BOPO, NPL, NIM, CAR, IR, and XR.

Profitability Ratio: Return on Assets (ROA)

ROA is a key measure of bank profitability because it indicates the extent to which a bank generates net income from its asset base (Kamal, 2023; Marlina, 2022). In banking, ROA reflects management's effectiveness in using financial resources to generate income and may be affected by liquidity conditions, credit risk, and changes in the

operating environment (Saleh & Winarso, 2021). This study uses ROA as the principal outcome variable to assess the relationship between bank-specific financial ratios, macroeconomic factors, and bank profitability.

Credit Risk Ratio: Non-Performing Loan (NPL)

Credit risk arises when borrowers fail to meet their repayment obligations. NPL measure asset quality and credit risk; higher NPL levels can increase loan-loss provisions, reduce interest income, and weaken bank profitability. This negative relationship may become more pronounced during economic downturns, when borrowers' repayment capacity deteriorates (Hossain & Ahamed, 2021; Kamal, 2023). Accordingly, this study expects NPL to have a negative relationship with ROA.

Market Risk Ratio: Net Interest Margin (NIM)

NIM measures the income generated from interest-bearing assets relative to the costs of intermediation activities. A higher NIM generally reflects stronger core banking income, pricing power, and potential profitability; therefore, NIM is expected to have a positive relationship with ROA (Setiawan & Wisna, 2021). However, NIM may be affected by competition, interest-rate movements, and changes in funding costs, making it relevant to assessing bank profitability across changing economic conditions.

Liquidity Risk Ratio: Loan-to-Deposit Ratio (LDR)

Liquidity management reflects a bank's ability to meet short-term obligations while maintaining lending, with LDR capturing the trade-off between liquidity and income generation. Optimal LDR balances profitability and liquidity needs, with ratios between 80–90% representing the ideal range for Indonesian banks (Tran et al., 2023). Higher LDR can improve profitability through greater utilization of deposits, while excessively high LDR may create additional liquidity risk (Kamal, 2023).

Solvency Risk Ratio: Capital Adequacy Ratio (CAR)

Capital adequacy represents a bank's capacity to absorb unexpected losses while maintaining stability and intermediation, with CAR measuring capital relative to risk-weighted assets as an indicator of resilience to financial shocks. Adequate capital may support profitability by reducing financial vulnerability and sustaining operations during adverse conditions. Capital adequacy buffers proved crucial during the pandemic, with well-capitalized banks demonstrating greater resilience (Bumantara & Muchtar, 2024). Higher CAR can strengthen risk-absorbing capacity while potentially creating opportunity costs when capital is not deployed productively (Marlina, 2022). Empirical findings on the profitability implications of capital adequacy remain mixed, suggesting the relationship depends on the operating environment and capital management strategies.

Efficiency Ratio: Operating Expense to Operating Income (OEI/BOPO)

Operational efficiency concerns a bank's ability to generate operating income while controlling the resources required for its activities, with BOPO (operating expenses to operating income) serving as a key efficiency indicator—higher BOPO reflects lower efficiency. The BOPO ratio is a key efficiency indicator, with values below 85% indicating optimal operational performance in emerging markets (Hossain & Ahamed, 2021). Consistent with this, effective cost control is essential for profitability, and lower BOPO indicates better operating efficiency (Marlina, 2022). Accordingly, the theoretical relationship between BOPO and profitability is expected to be negative, especially during economic disruption when income may decline while operating expenses remain substantial.

Macroeconomic Fluctuations

Macroeconomic variables, particularly interest rates and exchange rates, significantly influence bank profitability.

Interest Rates

Interest rates are a key macroeconomic determinant of bank profitability, as monetary policy affects lending rates, funding costs, loan demand, and interest margins. In Indonesia, changes in the Bank Indonesia 7-Day Reverse Repo Rate significantly influence profitability through net interest margins, loan demand elasticity, and funding costs (Setyono et al., 2021). This study expects a negative relationship between interest rates and ROA, since higher rates can raise borrowing and funding costs, dampen loan demand, and compress intermediation profits. Interest rate fluctuations affect lending margins and borrowing costs as the main channel linking monetary conditions to profitability (Hossain & Ahamed, 2021; Kamal, 2023), a dynamic that was especially salient during the pandemic and recovery as policy rates were adjusted to evolving economic conditions.

Exchange Rates

Exchange rate movements can affect bank profitability through valuation changes in foreign-currency-denominated assets and cross-border transaction profitability (Widodo, 2022). Previous findings identify foreign-currency assets and liabilities as the principal channel through which exchange rate volatility may affect profitability and propose a positive relationship between exchange rate movements and ROA (Kamal, 2023). In Indonesia, rupiah depreciation may benefit banks with favorable foreign-currency positions, although the overall effect depends on their foreign-currency exposure and risk management.

Analytical Approaches to Bank Performance

The determinants discussed above capture different dimensions of bank profitability, but profitability alone does not fully describe banking performance. A bank may generate relatively high profits while using resources inefficiently, or it may operate efficiently while experiencing lower profitability because of market conditions or narrower margins. For this reason, the present study complements profitability analysis with multiple panel data regression analyses, technical efficiency measurement, and a quasi-experimental assessment (DiD) of the pandemic effect.

Panel Data Analysis

Panel data analysis combines cross-sectional and time-series dimensions, allowing bank-specific observations to be examined over multiple years while accounting for unobserved heterogeneity across banks and changes over time (Baltagi, 2021; Wooldridge, 2019). This approach is appropriate because Indonesian commercial banks differ in operational characteristics, risk profiles, and financial structures, while their profitability may respond differently to macroeconomic conditions and the COVID-19 pandemic. Hence, this study uses panel regression to examine the simultaneous relationship between bank-specific financial ratios, macroeconomic variables, and ROA across KBMI 3 and KBMI 4 banks from 2018 to 2023.

Data Envelopment Analysis (DEA)

Profitability-based analysis alone does not fully capture how efficiently banks transform resources into outputs. Therefore, DEA is incorporated as a complementary efficiency assessment. Recent applications in Indonesian banking show DEA's effectiveness in benchmarking performance (Ratri et al., 2022). DEA evaluates the relative technical efficiency of decision-making units by comparing their observed inputs and outputs. The CCR (Charnes, Cooper, and Rhodes) model evaluates technical efficiency by

establishing an efficiency frontier, comparing decision-making units (DMUs), and identifying best practices (Charnes et al., 1978). Banks on the frontier are considered technically efficient, while those below it have potential to improve their input-output allocation.

In this study, DEA assesses the technical efficiency of KBMI 3 and KBMI 4 banks across the pre-pandemic, pandemic, and post-pandemic periods. The efficiency scores identify relative efficiency benchmarks and examine differences in average technical efficiency between the two bank groups. Thus, panel regression focuses on the determinants of ROA, while DEA provides an efficiency-based assessment of differences across KBMI classifications.

Difference-in-Differences (DiD) Test

DiD is a quasi-experimental approach that estimates the differential effect of an event by comparing changes in an outcome variable between a treatment group and a control group before and after the event. The approach helps distinguish event-related changes from pre-existing differences between groups (Fredriksson & Oliveira, 2019). In this study, KBMI 4 banks are treated as the treatment group, while KBMI 3 banks serve as the comparison group, with the pandemic period representing the intervention. ROA is used as the outcome variable to assess whether the pandemic produced a differential effect on profitability between the two bank categories.

DiD complements the panel regression by addressing whether the COVID-19 pandemic was associated with a differential change in profitability between KBMI 3 and KBMI 4 banks. This allows the study to assess both the factors associated with bank profitability and whether the pandemic affected the two bank categories differently.

Hypotheses Development

The hypotheses are developed based on the theoretical relationships between bank-specific financial ratios, macroeconomic conditions, the COVID-19 pandemic, technical efficiency, and bank profitability. The hypotheses are organized into four areas: financial-ratio effects, macroeconomic effects, the pandemic-period effect, and differences between KBMI 3 and KBMI 4 banks.

Financial-Ratio Effects: LDR, BOPO, NPL, NIM, CAR

LDR reflects the extent to which banks utilize deposits to finance lending activities. A higher LDR may increase income-generating loans and potentially improve profitability, but an excessively high LDR may also expose banks to liquidity pressures. Kamal (2023) and Parhusip & Cakranegara (2021) examined LDR in relation to bank performance in the Indonesian banking context.

Profitability depends on effective cost control; a larger BOPO indicates inefficiency (Marlina, 2022). The cost-to-income ratio, or BOPO, measures how well a bank manages its operating costs relative to its revenue, with a lower BOPO indicating better efficiency and higher profitability. Parhusip and Cakranegara (2021) also examine BOPO as one of the financial ratios associated with ROA in Indonesian banks. Accordingly, increases in BOPO are expected to reduce bank profitability, making BOPO relevant for examining changes in bank cost structures across the pre-, during, and post-pandemic periods.

Higher NPL ratios indicate increased provisioning expenses and declining asset quality, which lower profitability (Hossain & Ahamed, 2021; Kamal, 2023). High NPL levels signal declining asset quality and greater provisioning requirements, negatively affecting bank profitability. It is also highlighted by Parhusip and Cakranegara (2021) as a critical component impacting ROA.

Banks' ability to earn from interest-bearing assets is reflected in their NIM; a higher NIM increases profitability (Kamal, 2023). NIM represents the difference between interest earned on assets and interest paid on obligations relative to earning assets. A broader NIM indicates a greater capacity to generate profits from lending and investment activities.

A higher CAR boosts profitability by indicating improved financial stability and risk-absorbing capabilities (Marlina, 2022). By measuring capital relative to risk-weighted assets, CAR reflects a bank's ability to absorb unexpected losses and remain stable during economic shocks. However, excessively high capital may indicate that funds are not being deployed into potentially profitable assets. Despite this trade-off, stronger capitalization is generally expected to support bank profitability.

H1: Changes in LDR have a significant positive effect on ROA.

H2: Changes in BOPO have a significant negative effect on ROA.

H3: Changes in NPL have a significant negative effect on ROA.

H4: Changes in NIM have a significant positive effect on ROA.

H5: Changes in CAR have a significant positive effect on ROA.

Macroeconomic Effects: Interest Rate, Exchange Rate, Pandemic-Period Effect

Interest rate fluctuations impact lending margins and borrowing costs, which in turn impact profitability (Hossain & Ahamed, 2021; Kamal, 2023). Higher interest rates can raise funding costs and weaken lending activity, particularly when asset and liability repricing occur at different speeds.

Foreign currency assets and liabilities are impacted by exchange rate volatility, which affects profitability (Kamal, 2023). Exchange-rate movements may generate gains or losses through the revaluation of foreign-currency positions and may influence bank profitability, particularly during periods of economic disruption and heightened credit risk.

The COVID-19 pandemic disrupted economic activity and created major challenges for commercial banks through weaker credit demand, higher credit risk, and pressure on interest margins. Indonesian banking studies similarly report changes in bank performance during the pandemic (Lestari, 2022; Ratri et al., 2022). As economic disruption reduced loan activity and increased credit risk, the pandemic period is expected to be associated with lower ROA than the pre-pandemic period (Kamal, 2023; Lamablawa et al., 2022).

H6: Changes in interest rates have a significant negative effect on ROA.

H7: Changes in the exchange rate have a significant positive effect on ROA.

H8: The COVID-19 pandemic period has a significant negative effect on ROA.

Differential Effects Between KBMI 3 and KBMI 4

Technical Efficiency Differences

Bank size and organizational scale may influence how efficiently financial institutions transform their resources into outputs. Because of economies of scale, larger banks are usually more efficient; however, because of their flexibility, smaller banks might do better in times of crisis (Ratri et al., 2022). Consequently, differences in technical efficiency may emerge between KBMI 3 and KBMI 4 banks, particularly when operating conditions change substantially during an economic disruption.

H9: There is a statistically significant difference in the average technical efficiency scores between KBMI 3 and KBMI 4 banks across the pre-pandemic, pandemic, and post-pandemic periods.

Differential Pandemic Effect on KBMI 3 and KBMI 4 Profitability

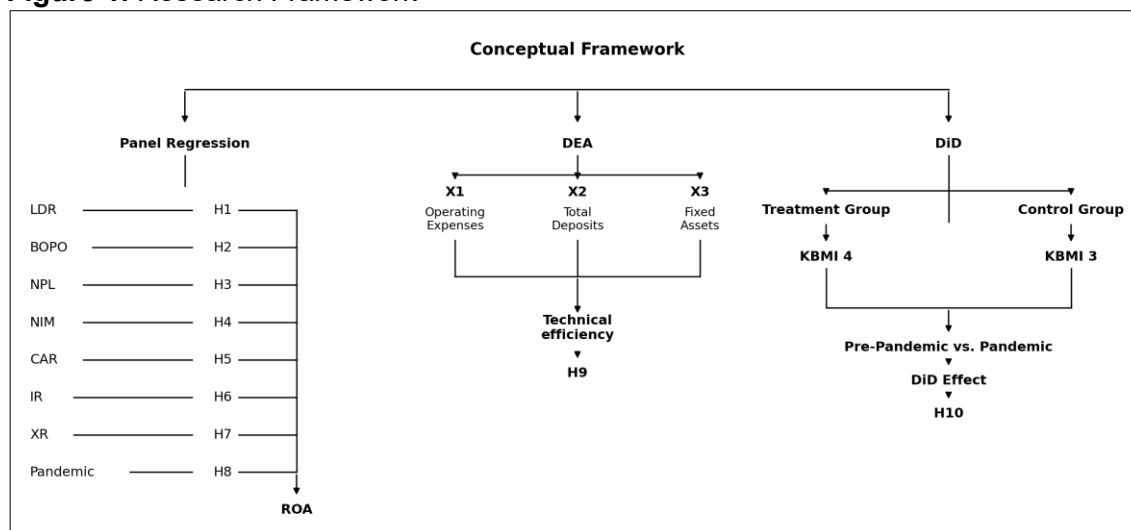
The effect of the COVID-19 pandemic may not have been similar across bank groups. This is particularly relevant because the KBMI classification separates banks by core-capital scale and therefore provides a meaningful basis for comparing institutions of different sizes and operational capacities. This matters because KBMI 4 banks may face different exposure to economic disruptions than KBMI 3 banks, despite having stronger capital bases. Accordingly, the pandemic is expected to produce a differential effect on the profitability of the two bank groups.

H10: The COVID-19 pandemic has a significantly different effect on ROA between KBMI 4 and KBMI 3 commercial banks.

Conceptual Framework

The research theoretical framework illustrates the conceptual relationships that visually represent theoretical causal links between independent variables (e.g., BOPO, NIM, etc.) and the dependent variable (ROA). The aim is to define the conceptual basis for this study and to show how independent variables theoretically affect the dependent variable (ROA). The study framework model is depicted in Figure 1.

Figure 1. Research Framework



RESEARCH METHOD

Research Design

This study investigated the effects of financial ratios and macroeconomic variations on the profitability of Indonesian commercial banks during the pre-pandemic (2018–2019), pandemic (2020–2021), and post-pandemic (2022–2023) eras using a quantitative research design. ROA measured profitability, and financial ratios and macroeconomic indicators served as explanatory variables. The study combined panel data regression, DEA, and DiD to provide a comprehensive assessment of bank performance. Panel regression estimates the relationship between bank-specific and macroeconomic determinants and ROA; DEA assesses relative technical efficiency based on multiple inputs and outputs; and DiD examines whether the COVID-19 period was associated with a differential change in profitability between KBMI 4 and KBMI 3 banks. Thus, the three methods address distinct but complementary dimensions of bank performance.

Sampling

According to OJK Regulation No. 12/POJK.03/2021, the population consisted of Indonesian conventional commercial banks that were categorized as KBMI 3 and KBMI 4. To guarantee the availability and consistency of financial data during the observation period, purposive sampling was used. Table 1 summarizes the sample-selection process and the final composition of the bank sample.

Table 1. Sample Selection Table

Selection Criteria	Result	
Target population	Indonesian conventional commercial banks classified as KBMI 3 and KBMI 4	
Inclusion criteria	1	Classified as KBMI 3 or KBMI 4
	2	Operated continuously during 2018–2023
	3	Published audited annual reports containing the required financial information
Exclusion criteria	1	Islamic banks
	2	Banks involved in mergers or acquisitions
	3	Banks with incomplete financial disclosures
Final KBMI 3 banks	11 banks	
Final KBMI 4 banks	4 banks	
Final sample	15 banks	
Observation period	2018–2023	
Observation frequency	Annual	
Years per bank	6 years	
Final bank-year observations	90 observations (15 × 6)	

Data Collection and Measures

All secondary data used in this investigation came from publicly accessible sources. The Federal Reserve Economic Data (FRED) database and Bank Indonesia provided macroeconomic indicators, while audited annual reports covering the 2018–2023 period provided bank-specific financial data. Prior to analysis, no missing observations were identified in the final dataset; consequently, no observations were interpolated or excluded due to missing values. The final dataset therefore comprised 90 complete bank-year observations from 15 banks over six annual periods, forming a balanced panel with banks as the cross-sectional units and years as the time dimension.

ROA was used to assess bank profitability. Meanwhile, LDR, BOPO, NIM, the BI 7-Day Reverse Repo Rate (IR), and the IDR/USD exchange rate were the explanatory variables. The operational definitions and measurement formulas of all variables are presented in Table 2.

Table 2. Variable Definitions and Measurement

Variable	Operational Definition	Scale	Analytical Method	Data Source
ROA	$(\text{Net Income} / \text{Total Assets}) \times 100\%$	Ratio (%)	Panel Regression; DiD	Bank annual reports
LDR	$(\text{Total Loans} / \text{Total Deposits}) \times 100\%$	Ratio (%)	Panel Regression	Bank annual reports
BOPO	$(\text{Operating Expenses} / \text{Operating Income}) \times 100\%$	Ratio (%)	Panel Regression	Bank annual reports
NPL	$(\text{Non-Performing Loans} / \text{Total Loans}) \times 100\%$	Ratio (%)	Panel Regression	Bank annual reports
NIM	$(\text{Interest Income} - \text{Interest Expense}) / \text{Average Earning Assets} \times 100\%$	Ratio (%)	Panel Regression	Bank annual reports

CAR	(Tier 1 + Tier 2 Capital) / Risk-Weighted Assets × 100%	Ratio (%)	Panel Regression	Bank annual reports
IR	BI 7-Day Reverse Repo Rate	Percentage (%)	Panel Regression	Bank Indonesia
XR	Quarterly average IDR/USD exchange rate	IDR per USD	Panel Regression	FRED Database (RBIDBIS)
Operating Expenses	Total operating expenses incurred by the bank	IDR Million	DEA Input	Bank annual reports
Total Deposits	Total customer deposits	IDR Million	DEA Input	Bank annual reports
Fixed Assets	Total fixed assets employed in banking operations	IDR Million	DEA Input	Bank annual reports
Total Loans	Total loans extended by the bank	IDR Million	DEA Output	Bank annual reports
Net Profit	Net profit generated by the bank	IDR Million	DEA Output	Bank annual reports
KBMI4	Dummy variable coded 1 for KBMI 4 banks and 0 for KBMI 3 banks	Dummy (0/1)	Group/treatment indicator DiD Analysis	OJK classification/ bank annual reports
DURING_COVID	Dummy variable coded 1 for 2020–2021 and 0 otherwise	Dummy (0/1)	DiD Analysis	Study period
POST_COVID	Dummy variable coded 1 for 2022–2023 and 0 otherwise	Dummy (0/1)	DiD Analysis	Study period
DURING_COVID × KBMI4	Interaction between the DURING_COVID dummy and the KBMI4 dummy. It captures the additional change in ROA experienced by KBMI 4 banks during the COVID-19 period (2020–2021), relative to KBMI 3 banks.	Dummy (0/1)	DiD Analysis	Derived variable
POST_COVID × KBMI4	Interaction between the POST_COVID dummy and the KBMI4 dummy. It captures the additional change in ROA experienced by KBMI 4 banks during the post-pandemic period (2022–2023), relative to KBMI 3 banks.	Dummy (0/1)	DiD Analysis	Derived variable

Data Analysis

The empirical analysis consisted of four sequential stages, corresponding to the descriptive stage and the three analytical techniques introduced in the Research Design. First, descriptive statistics were computed for the dependent variable and all explanatory variables to summarize their central tendency, dispersion, and range, providing an initial characterization of the panel dataset prior to inferential testing.

Second, panel data regression was conducted to estimate the effects of financial ratios and macroeconomic variables on bank profitability. The regression model is specified as:

$$ROA_{it} = \beta_0 + \beta_1 BOPO_{it} + \beta_2 CAR_{it} + \beta_3 LDR_{it} + \beta_4 NIM_{it} + \beta_5 NPL_{it} + \beta_6 IR_t + \beta_7 XR_t + \beta_8 PANDEMIC_t + \beta_9 POST_t + \varepsilon_{it}$$

where *i* indexes the 15 sample banks, and *t* indexes the six sample years (2018–2023); PANDEMIC and POST are dummy variables coded 1 for the 2020–2021 and 2022–2023

periods, respectively, and 0 otherwise. The Chow, Hausman, and Lagrange Multiplier tests were used to determine which of the three possible specifications, ranging from the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM), was the most suitable (Baltagi, 2021; Wooldridge, 2019).

Third, DEA based on the Charnes–Cooper–Rhodes (CCR) model was employed to evaluate the relative technical efficiency of each bank, treated as a decision-making unit (DMU), for each sample year. Operating expenses, total deposits, and fixed assets were specified as inputs, and total loans and net profit as outputs. The CCR specification assumes constant returns to scale (CRS), and the model was run with an output orientation. This means that, while holding inputs constant, the model assesses how far each bank's observed output could be expanded to reach the efficiency frontier, consistent with the study's objective of evaluating how effectively banks convert a given resource base into loans and profit. All 15 sample banks across the six sample years (90 bank-year DMUs) were scored using the DEA Frontier Excel add-in developed by Zhu (1999), which produces an efficiency score bounded between 0 (fully inefficient) and 1 (efficient, i.e., located on the frontier).

Fourth, a DiD approach was applied to estimate the differential effect of the COVID-19 pandemic on the profitability of KBMI 3 and KBMI 4 banks. COVID-19 was treated as the intervention/shock, while KBMI 4 banks were designated as the treatment group and KBMI 3 banks as the control group. The grouping was based on the banks' KBMI classification, which provides a regulatory capital-based distinction between the two groups. In line with the research hypothesis, KBMI 4 banks were expected to experience greater deterioration in profitability during the pandemic, while KBMI 3 banks served as the comparison group. The DiD model therefore estimates whether the change in ROA for KBMI 4 banks during the pandemic differed significantly from the corresponding change for KBMI 3 banks. The DiD model is specified as:

$$ROA_{it} = \beta_0 + \beta_1 KBMI4_i + \beta_2 DURING_COVID_t + \beta_3 POST_COVID_t + \beta_4 (DURING_COVID_t \times KBMI4_i) + \beta_5 (POST_COVID_t \times KBMI4_i) + \epsilon_{it}$$

where KBMI4 identifies the treatment group (1 = KBMI 4, 0 = KBMI 3); DURING_COVID and POST_COVID identify the pandemic (2020–2021) and post-pandemic (2022–2023) periods; and the two interaction terms, DURING_COVID × KBMI4 and POST_COVID × KBMI4, are the DiD estimators of interest, capturing the additional change in ROA experienced by KBMI 4 banks relative to KBMI 3 banks during and after the pandemic, respectively.

The validity of the DiD identification strategy depends on the parallel-trends assumption, which requires that, absent the pandemic, ROA for KBMI 3 and KBMI 4 banks would have followed similar trends. The assessment was conducted descriptively by comparing the groups' pre-pandemic ROA trajectories in 2018–2019. However, because only two pre-pandemic observations are available, a formal pre-trend test, such as an event-study specification with multiple pre-treatment leads, could not be reliably performed. Therefore, the assessment is treated as a qualitative diagnostic rather than formal confirmation of the parallel-trends assumption, and the limited pre-pandemic period is acknowledged as a limitation. Together, panel regression, DEA, and DiD provide complementary evidence on profitability determinants, operational efficiency, and banks' differential resilience to the COVID-19 shock.

RESULTS

Descriptive Statistics and Data Characteristics

Table 3. Key Financial Indicators (2018-2023)

Variable	Mean	Range	SD	Interpretation
BOPO	77.48%	43.80%-98.12%	12.34%	High-cost structure variability
CAR	25.45%	10.34%-130.40%	13.82%	Overcapitalization in some banks
LDR	86.42%	45.60%-163.10%	18.76%	Divergent liquidity strategies
NIM	5.13%	3.06%-11.30%	1.89%	Competitive interest margins
ROA	2.01%	0.13%-4.22%	1.12%	Bimodal performance distribution

Table 3 presents descriptive analysis and key findings. BOPO ranges from 43.80% to 98.12% (a 54.3-percentage-point spread), and CAR ranges from 10.34% to 130.40%, with the upper extreme reflecting a small number of heavily overcapitalized banks rather than the sample as a whole. LDR is similarly dispersed (45.60%–163.10%), pointing to markedly different liquidity and lending strategies across banks. Second, profitability itself is unevenly distributed: ROA ranges from 0.13% to 4.22% around a mean of 2.01%, with a standard deviation (1.12%) that is large relative to the mean, indicating that some sample banks operated close to break-even while others generated substantially higher returns during 2018–2023. These patterns motivate the panel regression, DEA, and DiD analyses that follow, which examine, respectively, which financial and macroeconomic factors are associated with this variation in ROA, how much of the variation reflects operational efficiency, and how the COVID-19 pandemic affected the two bank groups differently.

Classical Assumption Tests

Normality Test

Table 4. Normality Test

Statistic	Value
Mean	6.27e-16
Median	-0.038206
Maximum	0.862925
Minimum	-0.962010
Std. Dev.	0.335297
Skewness	0.105157
Kurtosis	4.218298
Jarque-Bera	5.731806
Probability	0.056932

Table 4 shows that the Jarque-Bera probability value ($0.06 > 0.05$) already confirms a normal distribution.

Multicollinearity Test

Table 5. Multicollinearity Test

Variable	BOPO	CAR	IR	LDR	NIM	NPL	XR
BOPO	1.000	-0.024	-0.199	0.277	-0.267	0.497	-0.182
CAR	-0.024	1.000	0.073	-0.305	-0.069	-0.033	0.272
IR	-0.199	0.073	1.000	0.170	0.146	-0.280	0.343
LDR	0.277	-0.305	0.170	1.000	0.322	-0.158	-0.218
NIM	-0.267	-0.069	0.146	0.322	1.000	-0.344	-0.088
NPL	0.497	-0.033	-0.280	-0.158	-0.344	1.000	-0.071
XR	-0.182	0.272	0.343	-0.218	-0.088	-0.071	1.000

Table 5 shows that no correlation coefficients exceeded 0.7 (highest: NPL-BOPO at 0.497). According to Gujarati and Porter (2009), multicollinearity can be significant if the correlation coefficient between two regressors has an absolute value greater than 0.7.

Heteroscedasticity Test

Table 6. Heteroscedasticity Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.488892	1.575066	-1.579675	0.1182
BOPO	-0.004657	0.003213	-1.449512	0.1512
CAR	-0.0000738	0.000935	-0.078910	0.9373
IR	-0.086923	0.045918	-1.893019	0.0620
LDR	-0.000393	0.000926	-0.424002	0.6727
NIM	0.001216	0.013057	0.093133	0.9260
NPL	0.005871	0.018150	0.323502	0.7472
PANDEMIC	-0.221702	0.122082	-1.816017	0.0732
POST	-0.191583	0.112552	-1.702172	0.0927
XR	0.000244	0.000126	1.926822	0.0576

Table 6 indicates that the significance values of all independent variables exceeded 0.05, so there is no heteroscedasticity.

Autocorrelation Test

Table 7. Autocorrelation Test

Statistic	Value	Statistic	Value
Root MSE	0.217	R-squared	0.857
Mean dependent var	0.579	Adjusted R-squared	0.840
S.D. dependent var	0.576	S.E. of regression	0.230
Sum squared resid	4.239	F-statistic	53.078
Durbin-Watson stat	1.692	Prob(F-statistic)	0.000

Table 7 shows that the Durbin–Watson statistic is 1.692. Compared against the Durbin–Watson critical bounds for $n = 90$ and $k = 9$ at $\alpha = 0.05$, the statistic ($dL = 1.45 < d = 1.692 < dU = 1.88$) is in the inconclusive range. However, as a rule of thumb, a Durbin–Watson value near 2 indicates a lack of autocorrelation (values near 0 or 4 indicate positive or negative autocorrelation, respectively); the statistic is fairly close to this benchmark at 1.692.

Panel Regression Analysis

Table 8. Model Selection Tests

Test	p-value	Conclusion
Chow Test	0.0000	Fixed Effects preferred over Pooled OLS
Hausman Test	0.5053	Random Effects preferred
Lagrange Multiplier	0.0000	Significant individual effects

Table 8 shows that the Random Effects Model (REM) is more effective and consistent than the Fixed Effects Model since the Hausman test does not reject the null hypothesis that the individual effects are uncorrelated with the explanatory variables ($p = 0.505$). Together, the three tests support the Random Effects Model as the best specification for interpreting the determinants of ROA.

Determinants of Bank Profitability

Table 9. Significant Determinants of ROA

Variable	Coefficient	p-value	Economic Interpretation
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BOPO	-0.077***	0.000	A 1-percentage-point increase in BOPO reduces ROA by 0.077 percentage points (7.7 bps)
NIM	+0.164***	0.0002	Primary profitability driver
XR	+0.0008**	0.013	Currency depreciation benefits

The large negative impact of BOPO on ROA ($\beta = -0.077$, $p < 0.001$) in Table 9 suggests that operational efficiency is the most important factor influencing bank profitability. This result implies that lower profitability is linked to higher operating costs in relation to operating income. Additionally, NIM significantly increases ROA ($\beta = 0.164$, $p < 0.001$), emphasizing the significance of interest margins as a major factor in bank profitability. Meanwhile, the exchange rate has a statistically significant but negligible positive impact on ROA ($\beta = 0.0008$, $p = 0.013$), suggesting that changes in the currency rate also affect bank profitability.

Model Summary

Table 10. Goodness-of-Fit Statistics

Weighted Statistics			
Root MSE	0.217019	R-squared	0.856553
Mean dependent var	0.579276	Adjusted R-squared	0.840416
S.D. dependent var	0.576208	S.E. of regression	0.230184
Sum squared resid	4.238759	F-statistic	53.07765
Durbin-Watson stat	1.692006	Prob(F-statistic)	0.000000

Table 10 offers important metrics for assessing the overall fit and explanatory power of the regression model. The F-test is one of these statistics and determines whether all independent variables, taken together, have a substantial impact on ROA, the dependent variable. The F-test compares the probability value linked to the F-statistic to a significance threshold of 0.05. BOPO, LDR, NPL, CAR, NIM, Interest Rate, Exchange Rate, Pandemic, and Post-Pandemic variables all simultaneously have a statistically significant impact on ROA for banks in categories KBMI 3 & 4 during 2018–2023, according to this study's F-test probability value of 0.000000, which is significantly below 0.05.

The degree to which the independent variables account for the variation in the dependent variable is measured by the coefficient of determination, also known as modified R-squared. The Adjusted R², which accounts for the number of predictors in the model, is 0.840416, and the coefficient of determination, R², is 0.856553. This shows that, after accounting for the number of explanatory variables, the model accounts for about 84.0% of the variation in ROA, with the remaining variation being due to factors not covered in this study.

Result of Panel Data Analysis: Final Regression Equation

$$\text{ROA} = -2.593 - 0.077 \cdot \text{BOPO} - 0.002 \cdot \text{CAR} - 0.002 \cdot \text{LDR} + 0.164 \cdot \text{NIM} \\ - 0.033 \cdot \text{NPL} - 0.178 \cdot \text{IR} + 0.001 \cdot \text{XR} - 0.909 \cdot \text{PANDEMIC} - \\ 1.058 \cdot \text{POST}$$

The constant term of -2.593 represents the estimated ROA when all explanatory variables are equal to zero. However, because a simultaneous zero value for all predictors is not economically meaningful within the context of banking operations, the constant should be interpreted primarily as a model intercept rather than as evidence of intrinsic profitability challenges.

Among the statistically significant coefficients, BOPO (-0.077) indicates that a one-percentage-point increase in operating expenses relative to operating income reduces ROA by 0.077 percentage points, while NIM ($+0.164$) indicates that a wider interest margin is associated with higher profitability. XR has a small but significant positive coefficient ($+0.0008$), consistent with the earlier discussion of currency depreciation. The PANDEMIC (-0.909) and POST (-1.058) dummies indicate that, controlling for other regressors, ROA remained below its pre-pandemic baseline throughout 2020–2023, with the model-adjusted shortfall slightly larger in the post-pandemic period. CAR, LDR, NPL, and IR carry theoretically expected signs in most cases but are not statistically significant at conventional levels and are therefore not interpreted as reliable determinants of ROA in this sample.

Overall, the equation captures the simultaneous effects of operational efficiency, capital and liquidity ratios, interest margins, asset quality, macroeconomic factors, and the pandemic and post-pandemic periods on Indonesian banks' profitability.

Result of DEA Technical Efficiency

Table 11. DEA Efficiency Scores by Bank Group

Period	KBMI 3 Mean	KBMI 4 Mean	Efficiency Gap
Pre-Pandemic	0.861	0.920	-5.9%
Pandemic	0.849	0.706	+14.3%
Post-Pandemic	0.862	0.901	+3.9%

Table 12. Result of DEA

KBMI Category	Bank	Pre-Pandemic	Pandemic	Post-Pandemic
KBMI 4	BCA	1.000	1.000	1.000
KBMI 3	BTN	1.000	1.000	1.000
KBMI 3	HSBC	1.000	1.000	1.000
KBMI 3	OCBC	1.000	0.950	0.995
KBMI 3	Danamon	0.931	1.000	1.000
KBMI 4	Mandiri	0.929	0.625	0.912
KBMI 3	PANIN	0.910	0.663	0.756
KBMI 4	BRI	0.909	0.627	0.862
KBMI 3	UOB	0.889	0.894	0.686
KBMI 4	BNI	0.843	0.573	0.832
KBMI 3	BTPN	0.841	1.000	1.000
KBMI 3	Permata	0.786	0.665	0.663
KBMI 4	CIMB	0.757	0.652	0.798
KBMI 3	Maybank	0.711	0.582	0.649
KBMI 3	Mega	0.643	0.932	0.932

Table 13. Technical Efficiency Scores For Each Period

Measure	Pre-Pandemic	Pandemic	Post-Pandemic
Average technical efficiency	0.877	0.811	0.873
KBMI 4 average	0.921	0.707	0.901
KBMI 3 average	0.861	0.849	0.862
Total Average for all periods	0.855		

Table 11, 12, and 13 show differences in technical efficiency across KBMI 3 and KBMI 4 banks and across the three observation periods. The most notable pattern is the efficiency reversal during the pandemic: the efficiency gap shifted from 5.9 percentage points in favor of KBMI 4 before the pandemic to 14.3 percentage points in favor of KBMI 3 during the pandemic, before narrowing to 3.9 percentage points in favor of KBMI 4 after the pandemic. At the bank level, BCA, BTN, and HSBC maintained 100% efficiency throughout the three periods, while Mandiri's efficiency declined by 30.4 percentage points from the pre-pandemic to the pandemic period.

The lowest efficiency scores were recorded during the COVID-19 pandemic (2020–2021), with KBMI 4 banks averaging 0.707, lower than KBMI 3 banks, indicating that larger banks were more affected by the pandemic. After the pandemic, both groups improved, with KBMI 4 rebounding to 0.901 and KBMI 3 to 0.862, nearly returning to pre-pandemic levels. Generally, KBMI 4 banks are more efficient than KBMI 3 banks in both pre- and post-pandemic periods, but less efficient during the pandemic.

Results of DiD (Difference-in-Differences)

By comparing changes in ROA throughout the pre-pandemic (2018–2019), pandemic (2020–2021), and post-pandemic (2022–2023) periods, the DiD analysis evaluates the effect of the COVID-19 pandemic on the profitability of Indonesian banks categorized as KBMI 3 and KBMI 4.

The DiD framework compares KBMI 4 banks as the treatment group with KBMI 3 banks as the control group to evaluate the pandemic's differential impact on ROA. Previous DEA results showed that KBMI 4 banks had lower efficiency during the pandemic (0.7062) than KBMI 3 banks, indicating greater operational impact. This finding is consistent with the concept of “Differential exposure” in DiD studies, where the treatment group experiences a more intense effect of the intervention. However, the treatment and control groups were defined ex ante based on structural capitalization, rather than on observed DEA or ROA outcomes. Under OJK Regulation No. 12/POJK.03/2021, KBMI classification distinguishes conventional commercial banks by core capital levels. KBMI 4 banks were therefore designated as the treatment group, while KBMI 3 banks served as the control group.

This assignment is theoretically motivated by the expectation that banks with different capitalization and operational scales may respond differently to economy-wide shocks such as COVID-19. Larger, more highly capitalized banks generally have greater balance-sheet capacity and operational scale but may also have greater exposure to complex lending and market activities, while smaller banks may differ in flexibility and exposure to economic disruptions. Accordingly, the KBMI classification provides a structural basis for examining differential changes in profitability between the two groups, with the treatment designation determined independently of observed ROA changes and DEA efficiency scores.

Table 14. Result of DID

Variable	Coefficient	Standard Error	T-Statistic	P-value
c (Constant)	1.88	0.1918	9.7983	0
DURING_COVID	-0.386	0.1452	-2.6607	0.0077
POST_COVID	-0.0009	0.1501	-0.0061	0.9949
KBMI4	1.34	0.4961	2.7009	0.0063
DURING_COVID_X_KBMI4	-0.799	0.2715	-2.9462	0.0045
POST_COVID_X_KBMI4	-0.204	0.2775	-0.7353	0.4583

As presented in Table 14, the constant (1.880, $p = 0.0000$) represents the estimated average ROA for KBMI 3 banks (the control group) in the pre-pandemic baseline period. The DURING_COVID coefficient (-0.386, $p = 0.0077$) indicates that KBMI 3 banks experienced a statistically significant average ROA decline of 0.39 percentage points during 2020–2021 relative to the pre-pandemic baseline, while the non-significant POST_COVID coefficient (-0.0009, $p = 0.9949$) indicates that this decline was not sustained into 2022–2023 for KBMI 3 banks.

The KBMI4 coefficient (1.340, $p = 0.0063$) shows that, before the pandemic, KBMI 4 banks had a significantly higher average ROA than KBMI 3 banks, by 1.34 percentage points, confirming a clear pre-existing profitability gap between the two groups that the DiD design controls for. The key DiD estimator, DURING_COVID $\times$ KBMI4 (-0.799, $p = 0.0045$), is statistically significant and indicates that KBMI 4 banks experienced an additional ROA decline of 0.80 percentage points during the pandemic, beyond the decline already experienced by KBMI 3 banks; the profitability decline was significantly more negative for KBMI 4 banks than for KBMI 3 banks. By contrast, the POST_COVID $\times$ KBMI4 estimator (-0.204, $p = 0.4583$) shows that KBMI 4 banks' profitability decreased by 0.2% compared to KBMI 3 banks. However, this result is not statistically significant ($0.5 > 0.05$), suggesting that the decline in KBMI 4 banks' profitability during the post-pandemic period was temporary.

Figure 2. Average ROA Trends: KBMI 3 vs. KBMI 4, 2018–2023

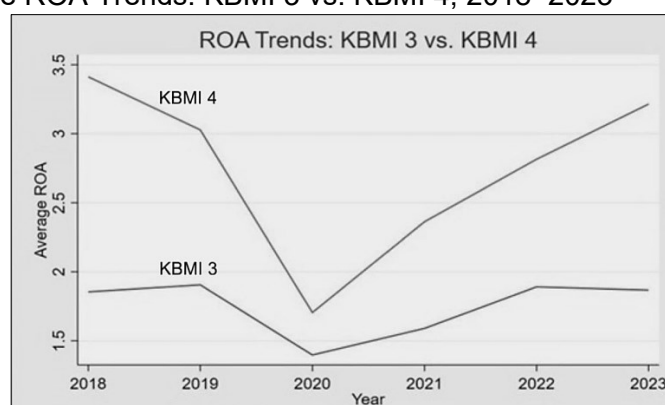


Figure 2 presents the annual average ROA of KBMI 3 and KBMI 4 banks over the 2018–2023 period and also provides the basis for the qualitative pre-trends assessment outlined in the Data Analysis section. KBMI 4 banks' average ROA fell from approximately 3.4% in 2018 to approximately 3.0% in 2019, while KBMI 3 banks' average ROA was essentially flat over the same two years. Because the two groups' pre-pandemic trajectories were not strictly parallel, and because only two pre-pandemic data points are available, this study treats the parallel-trends assumption as plausible; this is addressed further in the Limitations section. Both groups' ROA fell sharply in 2020, with KBMI 4 banks falling from a higher starting point and by a larger margin, before both

groups recovered gradually through 2023; KBMI 4 banks' average ROA remained above that of KBMI 3 banks.

Hypothesis Testing

Table 15 summarizes the hypothesis-testing results based on the panel regression, DEA comparison, and DiD analysis.

Table 15. Hypothesis Testing

	Hypothesis	Coefficient	p-value	Decision
H1	LDR → ROA (+)	-0.002	> 0.05	Not Supported
H2	BOPO → ROA (-)	-0.077	< 0.001	Supported
H3	NPL → ROA (-)	-0.033	> 0.05	Not Supported
H4	NIM → ROA (+)	+0.164	0.0002	Supported
H5	CAR → ROA (+)	-0.002	> 0.05	Not Supported
H6	Interest Rate → ROA (-)	-0.178	> 0.05*	Not Supported
H7	Exchange Rate → ROA (+)	+0.0008	0.013	Supported
H8	COVID-19 Pandemic → ROA (-)	-0.909	0.0027	Supported
H9	KBMI 3 and KBMI 4 banks exhibit different average technical efficiency across the pre-pandemic, pandemic, and post-pandemic periods.	Pre = -0.059; Pandemic = +0.143; Post = +0.039	Not applicable	Descriptively supported
H10	COVID-19 caused a larger decline in ROA for KBMI 4 than KBMI 3	DiD = -0.799	0.0045	Supported

DISCUSSION

H1: Loan-to-Deposit Ratio (LDR) and ROA

For LDR, the panel regression reveals a tiny, statistically insignificant negative coefficient ($\beta = -0.002$, $p = 0.471$). H1 is therefore not supported. This result is in line with earlier research, indicating that the link between LDR and bank profitability may differ based on the loan quality, operating conditions, and liquidity-management strategies used by banks. Although a higher LDR can increase interest-generating assets, an excessively high LDR may also heighten liquidity risk and constrain banks' ability to meet funding obligations, thereby offsetting potential profitability gains (Kamal, 2023; Parhusip & Cakranegara, 2021; Saleh & Winarso, 2021).

H2: Operating Efficiency (BOPO) and ROA

BOPO has a strong, statistically significant negative effect on ROA ($\beta = -0.076831$, $p = 0.0000$). Therefore, H2 is supported. This finding aligns with the principle that minimizing operating expenses relative to operating income is central to maximizing profitability. This pattern is consistent with evidence from other pandemic-affected sectors: Reddy et al. (2021) found that AirAsia's survival during the COVID-19 pandemic depended heavily on aggressive operational cost control, echoing the centrality of cost efficiency to firm performance during periods of crisis.

H3: Non-Performing Loans (NPL) and ROA

Although NPL has the theoretically predicted negative sign, the coefficient ($\beta = -0.033352$, $p = 0.5487$) is not statistically significant. H3 is therefore not supported. This result contrasts with earlier research that found a strong negative NPL–ROA association in Indonesian banking data (e.g., Hossain & Ahamed, 2021; Kamal, 2023). This

discrepancy may be due to differences in sample composition (the KBMI 3/4 focus of this investigation) or the time period studied.

H4: Net Interest Margin (NIM) and ROA

NIM positively affects ROA in a statistically significant way ($\beta = 0.163989$, $p = 0.0002$). As a result, NIM has the highest positive coefficient of any explanatory variable in the model, supporting H4. According to [Hossain and Ahamed \(2021\)](#), this demonstrates that a key factor influencing profitability is the difference between interest revenue and interest expense in relation to generating assets. The finding also implies that in a low-interest-rate or highly competitive lending environment, where widening NIM becomes harder, banks may need to rely more heavily on non-interest income sources to sustain profitability ([Parhusip & Cakranegara, 2021](#)).

H5: Capital Adequacy Ratio (CAR) and ROA

CAR has a small negative, statistically insignificant coefficient ($\beta = -0.001675$, $p = 0.5288$), the opposite sign to what was hypothesized. Therefore, H5 is not supported. One plausible explanation is that most sample banks already held capital well in excess of the level at which additional capital meaningfully strengthens loss-absorbing capacity, so that further increases in CAR were not associated with additional ROA gains within this sample.

H6: Interest Rate and ROA

The BI 7-Day Reverse Repo Rate (IR) is not statistically significant at the 5% level ($\beta = -0.177715$, $p = 0.1180$), but it has a negative coefficient consistent with the proposed trend. The narrow range of IR observed during the study period may have limited the model's ability to detect a statistically distinguishable effect, which is why H6 is not supported at conventional significance levels, even though the p-value is closer to the 10% threshold than most of the other non-significant variables.

H7: Exchange Rate and ROA

ROA is positively impacted by the exchange rate in a statistically significant way ($\beta = 0.000794$, $p = 0.0131$). H7 is therefore supported. Banks are impacted by changes in exchange rates through their foreign exchange transactions and the revaluation of assets and liabilities denominated in foreign currencies. This largely aligns with the findings of [Marlissa and Mamengko \(2024\)](#), who found that the rupiah's exchange rate against the US dollar is strongly influenced by macroeconomic fundamentals such as interest rates and economic growth, supporting exchange-rate fluctuations as an important macroeconomic channel for the Indonesian banking industry.

H8: COVID-19 Pandemic Period and ROA

The PANDEMIC dummy has a negative and statistically significant coefficient ($\beta = -0.908925$, $p = 0.0027$), indicating that, after controlling for the financial-ratio and macroeconomic variables in the model, ROA was significantly lower during the COVID-19 pandemic period (2020–2021) than during the pre-pandemic baseline period (2018–2019). Therefore, H8 is supported. This result is consistent with evidence that the COVID-19 shock disrupted bank operations, increased credit risk, and created substantial macroeconomic uncertainty in the banking sector ([Duncan et al., 2022](#); [Ratri et al., 2022](#)).

H9: Technical Efficiency Differences Between KBMI 3 and KBMI 4

The DEA result in [Table 12](#) shows that KBMI 4 banks were, on average, more technically efficient than KBMI 3 banks before the pandemic (0.921 vs. 0.861) and after it (0.901 vs. 0.862), but markedly less efficient during the pandemic itself (0.706 vs. 0.849). The pattern is broadly consistent with the direction of H9.

The pandemic-period efficiency reversal is concentrated in three of the four KBMI 4 banks: Mandiri, BNI, and BRI, all state-owned, while BCA (another KBMI 4 bank) maintained a perfect efficiency score throughout. Larger banks may face additional constraints during a crisis, including directed lending or policy support obligations, legacy operational systems, and more complex decision-making structures, that can slow their ability to adjust operations relative to smaller or more agile competitors. However, it is important to distinguish this efficiency finding from the profitability finding. DEA technical efficiency measures how well a bank converts operating expenses, deposits, and fixed assets into loans and net profit. A bank can therefore be highly efficient without being the most profitable, and vice versa. This study's design does not test a causal link between the efficiency scores and ROA; the two are presented as complementary, not substitutable.

H10: Differential Pandemic Effect on KBMI 3 vs. KBMI 4 Profitability (DiD)

The DURING_COVID $\times$ KBMI4 interaction term is negative and statistically significant ($\beta = -0.799$, $p = 0.0045$; Table 14), indicating that KBMI 4 banks experienced a significantly larger decline in ROA than KBMI 3 banks during the pandemic. Therefore, H10 is supported for the pandemic period.

The larger pandemic-period decline among KBMI 4 banks is consistent with, and reinforces, the DEA finding under H9 that three of the four KBMI 4 banks became markedly less efficient during 2020–2021. Larger banks' potentially greater exposure to pandemic-sensitive sectors, higher fixed-cost bases relative to smaller banks, and more complex internal structures are plausible contributing channels discussed in prior literature (Fakhri & Darmawan, 2021). Despite their larger relative decline, KBMI 4 banks' average ROA remained above that of KBMI 3 banks throughout 2018–2023, indicating that KBMI 4 banks' pre-existing profitability advantage, while eroded, was not reversed by the pandemic shock.

CONCLUSION

Using panel regression, DEA, and DiD analysis, this study examined the profitability and technical-efficiency performance of Indonesian KBMI 3 and KBMI 4 commercial banks during the pre-pandemic, pandemic, and post-pandemic periods from 2018 to 2023.

According to the panel-regression results, the sample's primary profitability-related characteristics were interest-margin management and operational cost efficiency. While exchange-rate fluctuations and higher NIM were positively correlated with ROA, larger BOPO was linked to lower ROA. Compared with the pre-pandemic baseline, ROA was also lower during the pandemic.

The DEA results indicate an overall average technical efficiency of 0.855, or 85.5%, across all the bank-period observations. Descriptively, KBMI 4 banks recorded slightly higher average efficiency than KBMI 3 banks before and after the pandemic, but lower average efficiency during the pandemic. The DiD analysis further indicates that KBMI 4 banks experienced a significantly larger decline in ROA than KBMI 3 banks during 2020–2021, whereas the post-pandemic difference in the change in ROA was not statistically significant.

By integrating panel regression, DEA, and DiD, this study provides complementary evidence on profitability determinants, relative technical efficiency, and differences in the pandemic-period profitability response across Indonesian bank groups. The findings suggest that bank management should prioritize cost control and sustainable interest-

margin management. For regulators, the greater pandemic-period profitability decline among KBMI 4 banks indicates that capital scale alone should not be treated as a sufficient indicator of resilience during systemic shocks.

LIMITATION

This study has several limitations. First, although no missing observations were identified in the final dataset and linear interpolation was therefore unnecessary, no winsorization or other outlier-adjustment procedures were applied; consequently, the reported coefficients may be sensitive to extreme observations.

Second, the DEA results are specific to the CCR model and the three inputs and two outputs selected for the analysis. Alternative specifications, such as the BCC model with variable returns to scale, may produce different efficiency rankings.

Third, the DiD analysis relies on the parallel-trends assumption, which could only be assessed qualitatively because the study contains only two pre-pandemic years (2018–2019), preventing a reliable formal pre-trend test.

Finally, the sample is purposively selected and relatively small, comprising 15 banks (11 KBMI 3 and 4 KBMI 4) over six years, or 90 bank-year observations. The 2018–2023 observation window also limits the ability to determine whether the post-pandemic profitability gap identified in the panel regression would eventually close over a longer period. Future research could address these limitations by using a longer observation period and a larger sample.

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DECLARATION OF CONFLICTING INTERESTS

The authors affirm that none of the research, writing, or publication of this paper was influenced by any known competing financial or non-financial interests. Strict confidentiality was upheld throughout the collection, management, and analysis of all data for academic purposes.

REFERENCES

- Baltagi, B. H. (2021). *Econometric Analysis of Panel Data*. Springer.
<https://doi.org/10.1007/978-3-030-53953-5>
- Bumantara, T. S., & Muchtar, S. (2024). Pengaruh macroeconomy dan bank specific terhadap non-performing loans pada bank KBMI 3 yang terdaftar di Bursa Efek Indonesia. *El-Mal Jurnal Kajian Ekonomi & Bisnis Islam*, 5(3), 1216–1222.
<https://doi.org/10.47467/elmal.v5i3.5656>
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444.
[https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
- Dahrani, D., & Nainggolan, E. P. (2023). Profitability review of Islamic banks in Indonesia. *Journal of International Conference Proceedings*, 6(3), 260–270.
<https://doi.org/10.32535/jicp.v6i3.2480>
- Duncan, E., Horváth, Á., Iercosan, D., Loudis, B., Maddrey, A., Martinez, F., ..., & Wix, C. (2022). COVID-19 as a stress test: Assessing the bank regulatory framework. *Journal of Financial Stability*, 61, 101016.
<https://doi.org/10.1016/j.jfs.2022.101016>
- Fakhri, U. N., & Darmawan, A. (2021). Comparison of Islamic and conventional banking financial performance during the COVID-19 period. *International Journal of*

- Islamic Economics and Finance*, 4(SI), 19–40.
<https://doi.org/10.18196/ijief.v4i0.10080>
- Fredriksson, A., & Oliveira, G. M. D. (2019). Impact evaluation using difference-in-differences. *RAUSP Management Journal*, 54(4), 519–532.
<https://doi.org/10.1108/rausp-05-2019-0112>
- Genoveva, G., Syahrivar, J., & Sonny, S. (2021). Economizing behavior during the COVID-19 pandemic. *European Journal of Business Management and Research*, 6(6), 247–252. <https://doi.org/10.24018/ejbmr.2021.6.6.234>
- Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics* (5th ed). McGraw-Hill Irwin.
- Hossain, M. S., & Ahamed, F. (2021). Comprehensive analysis on determinants of bank profitability in Bangladesh [Preprint]. *arXiv*, 2105.14198.
<https://ideas.repec.org/p/arx/papers/2105.14198.html>
- Kamal, A. G. (2023). The impact of financial ratios on bank performance before and during COVID-19: Evidence from bank business activities category 3 and 4 in Indonesia. *European Journal of Business Management and Research*, 8(3), 305–315. <https://doi.org/10.24018/ejbmr.2023.8.3.1995>
- Lamablawa, A., Prihantono, E. Y., & Pratama, D. E. (2022). The effect of income on net profit of banks before and during the COVID-19 pandemic. *Jurnal Penelitian*, 19(2), 127–135. <https://doi.org/10.26905/jp.v19i2.9303>
- Lestari, F. (2022). Performance analysis of conventional commercial banks in Indonesia during the COVID-19 pandemic (2019-2020). In *International Conference on Economics, Management and Accounting* (pp. 436–441). Atlantis Press.
<https://doi.org/10.2991/aebmr.k.220204.049>
- Marlina, R. (2022). Determinants of bank profitability in Indonesia based on commercial bank business activities (Buku). *Journal of Business & Finance in Emerging Markets*, 5(1), 31–46. <https://doi.org/10.32770/jbfem.vol531-46>
- Marlissa, E. R., & Mamengko, Z. R. R. (2024). Factors of BPD deposit interest rate, government bank deposit interest rate, inflation rate, economic growth (GDP), and money supply to the rupiah exchange rate per US dollar in Indonesia for 2004–2021 period. *International Journal of Accounting and Finance in Asia Pacific*, 7(1), 79–91. <https://doi.org/10.32535/ijafap.v7i1.2882>
- Parhusip, G., & Cakranegara, P. A. (2021). The influence of NIM, BOPO, LDR, and size toward return on assets (ROA) and its relations with technical efficiency on banks (Buku 4) in Indonesia. *IDEAS Journal of Management & Technology*, 1(2), 47–61. <https://doi.org/10.33021/ideas.v1i2.3426>
- Phan, D. H. B., & Narayan, P. K. (2020). Country responses and the reaction of the stock market to COVID-19—A preliminary exposition. *Emerging Markets Finance and Trade*, 56(10), 2138–2150. <https://doi.org/10.1080/1540496X.2020.1784719>
- Rafid, M., Soukotta, A., Cakranegara, P. A., Sutiyan, O. S. J., & Nurriqli, A. (2024). Analysis of liquidity ratios, profitability ratios, and capital structures on financial distress conditions in service companies during the COVID-19 period. *Jurnal Darma Agung*, 30(3), 614–622. <http://doi.org/10.46930/ojsuda.v30i2.2280>
- Ratri, A. M., Suwandaru, A., Brimantyo, H., Nugraha, G. I. K., & Rasyid, A. (2022). Comparison of Indonesian banking performance pre and post pandemic Covid-19. *Jurnal Bisnis dan Manajemen*, 9(1), 109–118.
<https://doi.org/10.26905/jbm.v9i1.7637>
- Reddy, L. S., Ranjith, P. V., Lim, Y. C., Kee, D. M. H., Loo, W. T., Cheah, K. T., & Mak, S. Y. (2021). The survival of AirAsia during the Covid-19 pandemic. *International Journal of Tourism and Hospitality in Asia Pacific*, 4(2), 42–56.
<https://doi.org/10.32535/ijthap.v4i2.1058>
- Saleh, D. S., & Winarso, E. (2021). Analysis of non performing loan (NPL) and loan to deposit ratio (LDR) towards profitability. *International Journal of Multicultural and Multireligious Understanding*, 8(1), 423–436.
<https://doi.org/10.18415/ijmmu.v8i1.2387>

- Saputro, M. V. G. N., & Fakhri, M. G. A. (2024). Kebijakan moneter dalam pemulihan ekonomi Indonesia pada masa pandemi Covid-19. *Journal of Economics and Social Sciences*, 3(1), 44–53. <https://doi.org/10.59525/jess.v3i1.407>
- Sari, P., & Indriani, P. (2023). Determinan profitabilitas perbankan sebelum dan masa pandemic COVID-19 di BEI periode 2018-2021. *Jurnal Media Wahana Ekonomika*, 20(1), 176–186. <https://doi.org/10.31851/jmwe.v20i1.11255>
- Setiawan, C., & Wisna, N. M. M. M. (2021). The determinants of net interest margin: An empirical study of Indonesia category-IV banks for the period of 2014-2017. *Studies of Applied Economics*, 39(12), 1–14. <http://repository.president.ac.id/xmlui/handle/123456789/10674>
- Setyono, F., Istiqomah, Y. N. A., Ilmundhita, S., & Mujib, A. (2021). Analisis efisiensi perbankan syariah pada masa pandemi Covid-19 menggunakan Data Envelopment Analysis (DEA). *I-Finance: A Research Journal on Islamic Finance*, 7(1), 11–30. <https://doi.org/10.19109/ifinance.v7i1.8434>
- Sulistiyandari, S., & Sutrisno, P. A. (2023). Legal aspects and role of OJK in Bank Digital by Digital banking Services during Post-COVID-19 pandemic in Indonesia. *Journal of Law and Sustainable Development*, 11(12), e2364. <https://doi.org/10.55908/sdgs.v11i12.2364>
- Tran, D. V., Bui, D. G., Nguyen, C., & Hoang, H. V. (2023). Bank liquidity hoarding during the COVID-19 pandemic. *Finance Research Letters*, 55, 104021. <https://doi.org/10.1016/j.frl.2023.104021>
- Widodo, P. (2022). Is the volatility of the Islamic stock index lower than the conventional stock index during COVID-19 pandemic? Empirical evidence in Indonesia Stock Exchange. *Journal of Islamic Economics and Finance Studies*, 3(1), 24–42. <https://doi.org/10.47700/jiefes.v3i1.4364>
- Widyarini, R., & Marsoem, B. S. (2021). Determinants of banking profitability listed on the Indonesia Stock Exchange before and during Covid-19. *Jurnal Syntax Admiration*, 2(12), 2394–2411. <https://doi.org/10.46799/jsa.v2i12.355>
- Wooldridge, J. M. (2019). *Introductory Econometrics: A Modern Approach* (7th ed.). Cengage Learning.
- Wuryani, E., Handayani, S., & Mariana, M. (2021). The effect of financial performance and bank size on banking stock prices. In *International Joint Conference on Arts and Humanities 2021* (pp. 975–979). Atlantis Press. <https://doi.org/10.2991/assehr.k.211223.170>

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