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DETERMINANTS OF INDONESIAN STATE-OWNED BANK PROFITABILITY BEFORE, DURING, AND AFTER COVID-19

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ABSTRACT

The profitability of Indonesia's four state-owned banks fluctuated considerably between 2015 and 2025, yet earlier studies of these banks neither cover the post-pandemic period nor combine bank-specific, macroeconomic, and pandemic determinants in one model. This study examines how credit risk, liquidity, capital, operating efficiency, interest margin, bank size, inflation, the BI-rate, GDP growth, and the COVID-19 pandemic are associated with the return on assets (ROA) of these banks. The sample covers BRI, BNI, BTN, and Bank Mandiri over 44 quarters from 2015Q1 to 2025Q4, giving 176 bank-quarter observations drawn from quarterly financial reports, Statistics Indonesia, and Bank Indonesia. A fixed effects model is estimated with bank-clustered standard errors and wild cluster bootstrap p-values, and Driscoll-Kraay standard errors are used as a robustness check. A one percentage point increase in the operating expense to operating income ratio (BOPO) is associated with a 0.077 percentage point lower ROA ($p = 0.022$), and ROA was 0.169 percentage points lower during the core pandemic period ($p = 0.042$). Bank size and GDP growth are also negatively associated with ROA, whereas the positive associations of the BI-rate and net interest margin are significant only under Driscoll-Kraay errors. NPL, LDR, CAR, and inflation show no significant association. Operating efficiency is therefore the most consistent correlate of state-owned bank profitability in this period, which points to cost management as a priority for these banks, although the evidence rests on only four banks.

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1. INTRODUCTION

Indonesia's four state-owned banks held Rp5,928.43 trillion in assets at the end of 2025, or 43.44% of the Rp13,646.42 trillion held by all commercial banks (Otoritas Jasa Keuangan, 2026). Like any bank, they channel savings to borrowers, but they also carry a development mandate, financing micro, small, and medium enterprises (MSMEs), infrastructure, and social programs (Purnamasari & Sitorus, 2023; Wijayani et al., 2022). A sound financial condition is what lets a bank keep performing these functions without weakening the stability of the financial system (Sari & Indriani, 2023), and this study uses return on assets (ROA) as its indicator of that condition.

Profitability has not followed a single path across the four banks. Based on fourth-quarter figures from each bank's financial reports, BRI's ROA fell from 3.50% in 2019 to 1.98% in 2020, recovered to 3.93% in 2023, and eased to 3.26% in 2025. BNI recorded the sharpest decline in the first pandemic year, from 2.42% to 0.54%, and had returned to 2.60% by 2023. Mandiri fell to 1.64% in 2020 but rose to 4.03% in 2023, the highest value among the four banks that year, before declining to 3.19% in 2025. BTN followed a different pattern, as its ROA had already dropped to 0.13% in 2019, before the pandemic, and remained between 0.69% and 1.07% from 2020 to 2025. These paths indicate that the four banks responded differently to common shocks, which motivates the use of quarterly data from 2015Q1 to 2025Q4 to examine the determinants of their profitability.

This study treats ROA as the outcome of financial intermediation. In the Theory of Intermediation proposed by Gurley and Shaw (1956), banks collect funds from parties with a surplus and channel them to parties that need funds. Scholtens and van Wensveen (2003) add that banks also actively earn profit and create value added by managing financial risks. Each determinant here maps onto one part of that process. NPL, LDR, and CAR describe its risk and balance sheet side, which is how much is lent, how much goes bad, and how much capital stands behind it. BOPO, NIM, and SIZE describe its economics, which are the cost of running it, the margin it earns, and the scale it runs at. Inflation, the BI-rate, GDP, and COVID-19 describe the environment around it.

The empirical profitability literature is built the same way. It relates profitability to bank-specific and macroeconomic determinants (Athanasoglou et al., 2008; Demirgüç-Kunt & Huizinga, 1999; Dietrich & Wanzenried, 2011; Molyneux & Thornton, 1992) and shows that profits tend to persist from year to year (Athanasoglou et al., 2008; Goddard et al., 2004). This study follows that structure. Because profits persist and differ systematically across banks, the model controls for stable bank characteristics through bank fixed effects and relies on inference that is robust to serial correlation within banks.

Start with credit risk. Loans are what intermediation produces and also what it puts at risk, and unpaid loans cost a bank interest income and provisions, so a higher NPL should lower ROA. In Greece, credit risk reduced profitability (Athanasoglou et al., 2008), and Priharta & Gani (2023) report a negative NPL effect for Bank BUMN. LDR shows how much of the mobilized funds ends up as loans. Molyneux and Thornton (1992) found that liquidity holdings were weakly and inversely related to profitability and described them as a cost to the bank, so a higher LDR should raise ROA, although a very high ratio also raises funding risk.

CAR is the capital buffer that stands behind lending and absorbs losses when loans fail. Better-capitalized banks tend to be more profitable (Athanasoglou et al., 2008; Demirgüç-Kunt & Huizinga, 1999; Goddard et al., 2004; Molyneux & Thornton, 1992), and Priharta & Gani (2023) find a positive CAR effect for Bank BUMN.

Efficiency, pricing, and scale come next. BOPO compares operating expenses with operating income, so it shows how efficiently the process is run. Operating expenses were strongly and negatively related to profitability in Greece (Athanasoglou et al., 2008), and operationally efficient Swiss banks were more profitable than less efficient ones (Dietrich & Wanzenried, 2011). NIM is the price of intermediation, and because net interest income is the core earnings stream of a lending bank, a wider margin should raise ROA. Both ratios have been included in earlier models of Bank BUMN profitability (Dini & Manda, 2020). SIZE captures the scale of intermediation. Larger banks may gain from economies of scale and from a more diversified loan and funding base, which supports a positive expectation. The evidence is weak, however, as size was the only bank-specific determinant without a significant effect on profitability in Greece (Athanasoglou et al., 2008), and European banks showed no consistent relationship between size and profitability (Goddard et al., 2004).

The environment works through the demand for credit and the cost of funds. Inflation can help or hurt, depending on whether banks anticipate it and reprice loans faster than their costs rise, as Athanasoglou et al. (2008) discuss. Demirgüç-Kunt and Huizinga (1999) report that inflation goes together with higher margins and profitability, and the Greek evidence agrees when inflation is expected, so this study expects a positive association.

BI-rate is Bank Indonesia's policy rate. Molyneux and Thornton (1992) found that interest rates were positively related to bank profitability, and Borio et al. (2017) show that higher short-term rates go with higher ROA among 109 large banks in advanced economies, because the gain in net interest income outweighs the losses in provisions and non-interest income. GDP works through the business cycle, with expansions lifting credit demand and loan quality and slowdowns doing the opposite. Athanasoglou et al. (2008) find that profitability is procyclical, although the effect is clearer when output is above its trend.

The pandemic hit all of these links at once. It can be read as an external shock that disrupted intermediation, worsened asset quality, and pressured profitability (Buchory, 2023; Tran et al., 2022), and global evidence shows that bank performance and stability deteriorated after the outbreak (Elnahass et al., 2021). Khalifaturofi'ah et al. (2023) find a negative pandemic effect for Indonesian banks, and Bank BUMN faced a particularly demanding task, because they had to protect performance while supporting the national recovery. Because the pandemic was a shock common to all four banks, this study represents it with a dummy for the core pandemic quarters from 2020Q2 to 2021Q4 rather than with time effects or a pandemic intensity measure. Time effects would absorb inflation, the BI-rate, and GDP growth, which vary only over time, and an intensity measure such as case counts would likewise vary only over time and would be difficult to separate from the contraction in GDP growth during 2020.

Indonesian evidence is mixed, but not randomly so. Priharta and Gani (2023), who study Bank BUMN from 2011 to 2020, find the conventional pattern. Studies centered on the pandemic window report a less tidy picture. Khalifaturofi'ah et al. (2024) find positive NPL and LDR effects among 52 conventional banks and link them to lower interest rates and credit subsidies. Meidi and Tannia (2025) find no LDR or CAR effect among listed banks from 2020 to 2023, and Khalifaturofi'ah et al. (2023) find no NPL, LDR, or inflation effect. Signs and significance thus appear to shift with the policy regime and the bank sample, which pooled samples of conventional or listed banks cannot easily separate.

Ownership matters too. In Switzerland during the 2007 to 2009 crisis, state-owned banks were more profitable than privately owned banks, which Dietrich and Wanzenried (2011) attribute to their image as safer institutions. Whether state ownership cushions or amplifies a shock is therefore an open question for Bank BUMN. Existing studies of these banks end before or within the first year of the pandemic, as Dini and Manda (2020) cover 2009 to 2018 and Priharta & Gani (2023), the study closest to this one, cover 2011 to 2020. This study extends that evidence in three ways. First, extending the sample to 2025 brings in the recovery after 2020 and a full monetary cycle, in which the BI-rate stayed at 3.50% until mid-2022, rose to 6.25% in 2024, and was lowered to 4.75% in 2025, so that the association between the policy rate and profitability is observed under both easing and tightening. Second, the COVID-19 dummy separates the pandemic quarters from the rest of the period within one model, rather than leaving them at the end of a sample that stops in 2020. Third, the model combines credit risk, liquidity, and capital with efficiency, margin, size, and GDP growth, and is estimated on 176 bank-quarter observations with inference suited to a panel of only four banks. To our knowledge, no study of Bank BUMN combines these bank-specific, macroeconomic, and pandemic determinants in one model through 2025.

Drawing on the theoretical foundations, empirical evidence from previous studies, and the research gap identified above, this study tests ten hypotheses. NPL is expected to be negatively associated with ROA (H1), while LDR (H2), CAR (H3), and NIM (H5) are expected to be positively associated with it, and BOPO is expected to be negatively associated with it (H4). SIZE is expected to be positively associated with ROA (H6), as are inflation (H7), the BI-rate (H8), and GDP growth (H9). Finally, the COVID-19 pandemic is expected to be negatively associated with ROA (H10).

2. RESEARCH METHODS

This research adopts a quantitative associative approach. The dataset comprises numerical figures, along with qualitative information that has been converted into numerical values. Based on the method of acquisition, the data used in this study are classified as secondary data.

In its implementation, this study utilized various instruments to measure the variables under investigation. Statistical methods were then used to analyze the collected data.

This research encompasses state-owned banks that are publicly traded on the Indonesia Stock Exchange (IDX) throughout 2015Q1 to 2025Q4. This object was chosen given that these banks held 43.44% of total commercial bank assets at the end of 2025 and hold a strategic position in transmitting monetary policy on behalf of the government, alongside displaying risk and performance profiles distinct from private banks. A saturation sampling approach was applied for this research, meaning that all four state-owned banks within the population, namely BRI, BNI, BTN, and Bank Mandiri, were included as the research sample. Observing four banks over 44 quarters yields a balanced panel of 176 bank-quarter observations.

Documentation served as the data collection technique employed for this research. Figures for bank-specific variables, namely NPL, LDR, CAR, BOPO, NIM, SIZE and ROA, were sourced from the bank-only quarterly published financial reports available on the IDX and OJK websites as well as each bank's respective website. Data on inflation and GDP growth came from the Central Statistics Agency (Badan Pusat Statistik/BPS), while BI-rate figures were sourced from Bank Indonesia. This research also incorporates a COVID-19 dummy variable to account for the pandemic period.

The variables in this study consist of one dependent variable, namely bank profitability as proxied by ROA, and ten independent variables, namely NPL, LDR, CAR, BOPO, NIM, SIZE, inflation, BI-rate, GDP growth, and a COVID-19 dummy variable. Return on Assets (ROA) is a financial ratio that measures a bank's management's ability to generate pre-tax profit by utilizing all of the total assets under its management (Kasmir, 2021). This ratio is calculated using the following formula:

$$Return\ on\ Assets = \frac{Profit\ Before\ Taxes}{Average\ Total\ Assets}\ x\ 100\% \quad \text{.....(1)}$$

NPL is a ratio that indicates how effectively a bank manages non-performing credit risk (Kasmir, 2021). Loans that remain in default beyond the tolerance limit are classified as NPL, and this study uses the gross NPL ratio. According to BI Regulation No. 15/2/PBI/2013, a net NPL ratio above 5% is one of the criteria for placing a bank under intensive supervision. This ratio is calculated using the following formula:

$$Non\text{-}Performing\ Loan = \frac{Problem\ Loans}{Total\ Loans}\ x\ 100\% \quad \text{.....(2)}$$

LDR reflects the proportion of funds collected from the public that are subsequently disbursed as loans (Kasmir, 2021). Bank Indonesia Regulation No. 15/15/PBI/2013 establishes a healthy LDR range of 78% to 92%. This threshold is designed to prevent banks from distributing funds excessively or insufficiently, thereby maintaining a balance between profitability and liquidity stability. This ratio is calculated using the following formula:

$$Loan\ to\ Deposit\ Ratio = \frac{Total\ Loans}{Total\ Deposits}\ x\ 100\% \quad \text{.....(3)}$$

CAR represents a measure of how capably a bank handles its assets while absorbing risks stemming from its operational activities (Kasmir, 2021). Bank Indonesia Regulation No. 15/12/PBI/2013 mandates that banks maintain this ratio at a minimum threshold of 8%. With a ratio above this threshold, a bank is considered sound and has greater flexibility in managing its capital. This ratio is calculated using the following formula:

$$Capital\ Adequacy\ Ratio = \frac{Tier\ 1\ Capital + Tier\ 2\ Capital}{Risk\ Weighted\ Assets}\ x\ 100\% \quad \text{.....(4)}$$

Net Interest Margin (NIM) measures a bank's ability to generate net interest income from its interest-earning assets, reflecting how effectively it manages the spread between interest income and interest expenses. A higher NIM generally indicates greater efficiency in generating interest-based returns from the bank's assets. Based on OJK Circular Letter No. 11/SEOJK.03/2015, this ratio is calculated using the following formula:

$$Net\ Interest\ Margin = \frac{Net\ Interest\ Income}{Average\ Productive\ Assets}\ x\ 100\% \quad (5)$$

Operating Expenses to Operating Income Ratio (BOPO) measures a bank's operational efficiency by comparing its operating expenses with its operating income. A lower BOPO indicates that a bank can generate operating income at a lower cost, reflecting more efficient cost management and stronger operational performance. This ratio is calculated in accordance with Financial Services Authority (OJK) Circular Letter No. 11/SEOJK.03/2015 using the following formula:

$$Operating\ Expenses\ to\ Operating\ Income = \frac{Total\ Operating\ Expenses}{Total\ Operating\ Revenue}\ x\ 100\% \quad (6)$$

Bank Size represents the scale of a bank's operations and is measured as the natural logarithm of its bank-only total assets in rupiah. This transformation helps reduce data dispersion and facilitates comparisons across banks of different sizes, while capturing differences in their financial capacity and operational scale. It is calculated using the following formula:

$$Bank\ Size = ln\ (Total\ Assets) \quad (7)$$

Inflation denotes a sustained increase in what consumers pay for goods and services throughout a country, a condition capable of diminishing purchasing power (Mankiw, 2007). This study uses year-on-year consumer price inflation in the last month of each quarter, as published by BPS, which is calculated using the following formula, where m denotes the last month of the quarter:

$$Inflation = \frac{CPI_m - CPI_{m-12}}{CPI_{m-12}}\ x\ 100\% \quad (8)$$

BI-rate is Bank Indonesia's policy interest rate, used as a benchmark in implementing monetary policy to keep inflation under control and maintain economic stability (Saragih et al., 2021). To achieve the operational targets of monetary policy, the policy rate is set and announced by Bank Indonesia's Board of Governors during its monthly meeting, and it serves as a benchmark in the conduct of monetary operations, particularly in controlling liquidity in the money market. This study uses the policy rate prevailing at the end of each quarter. The series is not a single instrument throughout the period. From 2015Q1 to 2016Q2 it is the BI Rate, which was replaced on 19 August 2016 by the BI 7-Day Reverse Repo Rate (BI7DRR) as part of a strengthening of the monetary operations framework, so that the BI7DRR is used from 2016Q3 onward (Bank Indonesia, 2026). Since 21 December 2023, Bank Indonesia has used the name BI-Rate for its policy rate in place of BI7DRR, a change of name that does not alter the meaning, purpose, or seven-day reverse repo operation of the rate (Bank Indonesia, 2023). The series from 2016Q3 to 2025Q4 therefore refers to one instrument, and the six quarters under the earlier BI Rate are examined in a robustness check that adds a dummy variable for that regime.

Gross Domestic Product (GDP) growth measures the rate at which a country's economic output changes over time, reflecting the overall pace of economic expansion or contraction. It is commonly used to assess macroeconomic conditions that may influence banking performance, as changes in economic activity can affect credit demand, borrowers' repayment capacity, and banks' income generation. This study uses quarter-on-quarter growth of real GDP at constant 2010 prices, as published by BPS, which is calculated using the following formula, where q denotes the quarter:

$$GDP\ Growth = \frac{GDP_q - GDP_{q-1}}{GDP_{q-1}}\ x\ 100\% \quad (9)$$

The last factor is COVID-19. COVID-19 was a global health crisis that affected the Indonesian economy, triggering shifts in consumer behavior and adjustments in monetary policy (Kartika & Riadi, 2022; Sari & Indriani, 2023). This pandemic has caused a contraction in economic growth and a slowdown in credit growth, which could affect banking financial performance. This dummy variable takes a value of 1 from 2020Q2 to 2021Q4, representing the core pandemic period, and 0 for all other quarters.

Panel data analysis is employed in this study in accordance with the econometric guidelines established by Gujarati and Porter (2012). Panel data estimation offers three alternative approaches, specifically Pooled Least Square (PLS), Fixed Effect Model (FEM), and Random Effect Model (REM). Drawing on the approach recommended by Pindyck & Rubinfeld (1998) and Wooldridge (2010), the Chow, Hausman (1978), and Breusch & Pagan (1980) Lagrange Multiplier (LM) tests were applied in selecting the estimation model best suited for this research. Because the panel contains only four banks, the asymptotic foundations of the Hausman and LM tests are weak, and their results are read as indicative rather than decisive. The fixed effects specification is also favored on a priori grounds, since the four banks constitute the whole population of interest rather than a random draw from a larger population, which makes it natural to treat their bank-specific intercepts as fixed parameters. The estimated model is:

$$ROA_{it} = \alpha_i + \beta_1 NPL_{it} + \beta_2 LDR_{it} + \beta_3 CAR_{it} + \beta_4 BOPO_{it} + \beta_5 NIM_{it} + \beta_6 SIZE_{it} + \beta_7 INF_t + \beta_8 BIR_t + \beta_9 GDP_t + \beta_{10} DC_t + \varepsilon_{it} \quad (10)$$

where i denotes the bank, t denotes the quarter, and α_i is the bank fixed effect. Inflation, the BI-rate, GDP growth, and the COVID-19 dummy vary only over time and take the same value for all four banks in a given quarter. Quarter fixed effects would therefore be perfectly collinear with these variables, so they are not included, and the coefficients of the macroeconomic variables are identified from their movements across the 44 quarters. This also means that any other shock common to all banks in a quarter is not absorbed separately and may be partly reflected in these coefficients.

The regressors are screened for multicollinearity using variance inflation factors (VIF), with values above 10 taken as a sign of serious collinearity. The residuals of the fixed effects model are then tested for groupwise heteroskedasticity with the modified Wald test (Baum, 2001), for first-order serial correlation with the Wooldridge test (Drukker, 2003; Wooldridge, 2010), and for cross-sectional dependence with the Pesaran (2004) CD test. Inference accounts for the small number of banks. Standard errors are clustered by bank, which makes them robust to heteroskedasticity and to serial correlation within each bank. Because conventional cluster-robust inference over-rejects when clusters are few (Cameron et al., 2008), the t statistics are compared with a t distribution with $G - 1 = 3$ degrees of freedom, and p-values are obtained from a wild cluster bootstrap with the null hypothesis imposed and Webb six-point weights, which are designed for very few clusters (Webb, 2023). With four clusters, the bootstrap enumerates all $6^4 = 1{,}296$ possible weight combinations, and it is implemented with the boottest procedure (Roodman et al., 2019). These bootstrap p-values form the main basis for inference. As a robustness check, the model is also estimated with Driscoll-Kraay standard errors with a lag length of three quarters, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence and rely on the time dimension of the panel (Driscoll & Kraay, 1998; Hoechle, 2007).

Three further robustness checks are carried out. First, BTN is excluded, because its mortgage-focused business model differs from that of the other three banks. With only three banks left, cluster-based inference is unreliable, so Driscoll-Kraay standard errors are used for this sample. Second, all regressors except the COVID-19 dummy are lagged by one quarter, which reduces the scope for profitability in a quarter to feed back into the regressors measured in the same quarter.

Third, a dummy for the quarters under the earlier BI Rate, from 2015Q1 to 2016Q2, is added to the main model to check that the change of policy rate instrument does not drive the BI-rate result. Hypotheses are tested at the 5% significance level, and p-values between 0.05 and 0.10 are reported as weak evidence. To compare the economic importance of the regressors, standardized coefficients are calculated by multiplying each coefficient by the ratio of the standard deviation of the regressor to the standard deviation of ROA.

3. RESULTS AND DISCUSSION

3.1. RESULTS

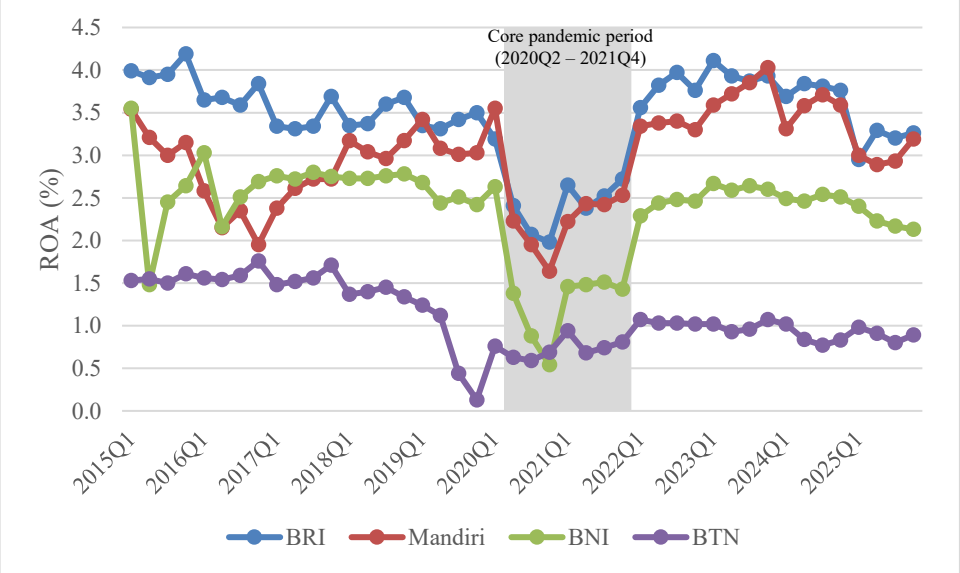


Figure 1. Quarterly ROA of Indonesian State-Owned Banks, 2015Q1 to 2025Q4
Source: Data Processed, 2026

Figure 1 shows the quarterly ROA of the four banks over the study period. BRI recorded the highest ROA in 39 of the 44 quarters, while BTN recorded the lowest in 42 quarters, so the ranking of the banks was largely stable over time. All four banks reached their lowest pandemic-era values in the second half of 2020, with ROA falling to 1.98% at BRI, 1.64% at Mandiri, and 0.54% at BNI in 2020Q4, and to 0.59% at BTN in 2020Q3. BTN's lowest value in the whole period, however, was recorded before the pandemic, at 0.13% in 2019Q4. By 2022Q1, the first quarter after the core pandemic period, ROA had returned to 3.56% at BRI, 3.34% at Mandiri, 2.29% at BNI, and 1.07% at BTN. The series also shows a recurring rise in the first quarter of several years, which reflects the annualized, year-to-date basis on which ROA is reported in quarterly financial statements.

Descriptive statistical analysis was conducted to determine the mean, maximum, minimum, and standard deviation values for each variable examined in this study. Table 1 displays descriptive statistics covering every variable examined in this research. The descriptive statistics are based on 176 bank-quarter observations. Profitability, measured by ROA, averages 2.46 percent with a standard deviation of 1.02, which indicates generally healthy earnings across the sample. The spread is wide, however. The lowest value of 0.13 percent was recorded by BTN in 2019Q4, while the highest value of 4.19 percent belongs to BRI in 2015Q4. Asset quality, measured by NPL, averages 2.85 percent with a standard deviation of 0.82, comfortably below the 5 percent regulatory ceiling. Even so, the maximum of 4.91 percent, recorded by

BTN in 2020Q1, came close to that threshold, whereas Mandiri reached the cleanest portfolio at 0.96 percent in 2025Q4.

Table 1. Descriptive Statistics and Variance Inflation Factors

Variable	Obs	Mean	Std. Dev.	Min	Max	VIF	1/VIF
ROA	176	2.46	1.02	0.13	4.19	-	-
NPL	176	2.85	0.82	0.96	4.91	2.83	0.35
LDR	176	91.61	7.87	77.61	114.24	2.83	0.35
CAR	176	19.86	2.07	14.78	25.28	2.15	0.47
BOPO	176	74.21	9.95	51.88	98.12	5.26	0.19
NIM	176	5.34	1.33	2.86	8.43	1.86	0.54
SIZE	176	34.30	0.65	32.64	35.34	6.54	0.15
INF	176	3.20	1.46	1.03	7.26	2.60	0.38
BIR	176	5.23	1.17	3.50	7.50	1.75	0.57
GDP	176	1.11	2.30	−4.19	5.05	1.04	0.96
DC	176	0.16	0.37	0	1	2.51	0.40

Source: Data Processed, 2026

LDR averages 91.61 percent and sits near the upper end of the range typically viewed as prudent, with a standard deviation of 7.87. The minimum of 77.61 percent was observed at Mandiri in 2022Q4, while BTN reached 114.24 percent in 2019Q2, meaning its lending exceeded its deposit base and signaling considerable funding strain. In contrast, capital buffers are strong. CAR averages 19.86 percent with a standard deviation of 2.07, far above the minimum requirement. Even the weakest reading of 14.78 percent, recorded by BTN in 2015Q2, remains well within safe territory, while BRI posted the strongest capitalization at 25.28 percent in 2021Q4.

BOPO averages 74.21 percent with a standard deviation of 9.95, which is the largest dispersion among the bank-specific ratios. Mandiri was the most efficient at 51.88 percent in 2023Q4, whereas BTN reached 98.12 percent in 2019Q4, meaning almost all operating income was absorbed by operating costs. This is consistent with the very low ROA that BTN recorded in the same quarter. NIM averages 5.34 percent with a standard deviation of 1.33, ranging from 2.86 percent at BTN in 2024Q4 to 8.43 percent at BRI in 2016Q2, which likely reflects differences in business models and loan portfolios. Bank size, measured on a logarithmic scale, averages 34.30 with a relatively small standard deviation of 0.65. The values run from 32.64 at BTN in 2015Q1 to 35.34 at Mandiri in 2025Q4, suggesting that the sample consists of large banks of broadly comparable scale.

Turning to the macroeconomic environment, inflation averages 3.20 percent with a standard deviation of 1.46. It peaked at 7.26 percent in 2015Q2 and fell to a low of 1.03 percent in 2025Q1, showing a markedly more stable price environment in recent years. The policy rate averages 5.23 percent with a standard deviation of 1.17, ranging from 7.50 percent in 2015 to a low of 3.50 percent from 2021Q1 to 2022Q2, in line with monetary easing during the pandemic. Economic growth averages 1.11 percent and is the most volatile macro variable, with a standard deviation of 2.30. It contracted by 4.19 percent in 2020Q2 and rebounded to 5.05 percent in 2020Q3, which captures the shock and recovery of the pandemic period. Finally, the COVID-19 dummy has a mean of 0.16, reflecting the seven quarters from 2020Q2 to 2021Q4 out of the 44 quarters in the sample.

Table 1 also reports variance inflation factors (VIF) and tolerance values (1/VIF), which allow the regressors to be screened for multicollinearity before estimation. No VIF value exceeds the conventional cutoff of 10, and no tolerance value falls below 0.10. The highest values belong to SIZE (6.54) and BOPO (5.26), which remain well below the cutoff. Multicollinearity is therefore not a serious concern for the coefficient estimates.

Table 2 summarizes the model selection procedure. The Chow test yields an F statistic of 30.849 with a probability below 0.001, indicating that bank-specific intercepts differ meaningfully and that a pooled specification is too restrictive. The Breusch-Pagan LM test,

computed from the pooled residuals, also rejects the pooled specification ($\chi^2 = 11.514$, $p < 0.001$), so the two tests agree that unobserved bank heterogeneity is present.

The random effects model cannot be estimated separately from the pooled model in this panel, because the variance of the random effect is not identified when only four bank means are available to estimate it, and the Hausman test ($\chi^2 = 123.289$, $p < 0.001$) favors the fixed effects model. Together with the fact that the four banks form the whole population of interest, the evidence supports the fixed effects model as the most appropriate specification.

Table 2. Selection of the Estimation Model

Test	Statistic	Probability	Decision
Chow test	F(3, 162) = 30.849	<0.001	FEM preferred to PLS
Hausman test	$\chi^2(10) = 123.289$	<0.001	FEM preferred to REM
Breusch-Pagan LM test	$\chi^2(1) = 11.514$	<0.001	Bank effects present, PLS rejected

Notes: With only four banks and ten regressors, the between-bank regression used to estimate the random effect variance is not identified, so that variance is estimated at zero and the REM coincides with PLS. The Hausman test therefore compares FEM with this estimator, and because the difference of the covariance matrices is not positive definite, the statistic is computed with a generalized inverse. The LM statistic is computed from PLS residuals following Breusch and Pagan (1980). Given N = 4, the asymptotic foundations of the Hausman and LM tests are weak, and the results are read as indicative evidence.
Source: Data Processed, 2026

Table 3 shows that the Wooldridge test detects first-order serial correlation in the panel errors ($p = 0.013$), whereas the modified Wald test finds no evidence of groupwise heteroskedasticity ($p = 0.709$). The Pesaran CD test does not reject the absence of cross-sectional dependence at the 5% level, although its probability of 0.059 is close to that threshold. Given these diagnostics, the main inference relies on standard errors clustered by bank, which are robust to within-bank autocorrelation, with p-values from a wild cluster bootstrap because the panel contains only four clusters. Driscoll-Kraay standard errors, which are also robust to cross-sectional dependence, are reported as a robustness check.

Table 3. Diagnostic Tests on the Fixed Effects Residuals

Test	H0	Statistic	Probability	Conclusion
Modified Wald	Homoskedasticity across banks	$\chi^2(4) = 2.148$	0.709	H0 not rejected
Wooldridge	No first-order serial correlation	F(1, 3) = 27.889	0.013	H0 rejected
Pesaran CD	No cross-sectional dependence	CD = 1.887	0.059	H0 not rejected

Source: Data Processed, 2026

Table 4 presents the fixed effects estimates. Under the wild bootstrap inference, four regressors are significant at the 5% level. BOPO has a coefficient of −0.077 ($p = 0.022$), meaning that a one percentage point increase in BOPO is associated with a 0.077 percentage point decrease in ROA. SIZE has a coefficient of −0.414 ($p = 0.047$), meaning that an increase of one unit in the natural logarithm of total assets is associated with a 0.414 percentage point decrease in ROA. GDP growth has a coefficient of −0.008 ($p = 0.044$), meaning that a one percentage point increase in quarterly GDP growth is associated with a 0.008 percentage point decrease in ROA. The COVID-19 dummy has a coefficient of −0.169 ($p = 0.042$), meaning that ROA was 0.169 percentage points lower in the core pandemic quarters than in the other quarters. The BI-rate has a coefficient of 0.066 and is significant only at the 10% level ($p = 0.059$). NIM (0.097) and the BI-rate are significant at the 1% level under Driscoll-Kraay standard errors ($p = 0.002$ and $p < 0.001$, respectively) but not under the bootstrap, and inflation is close to significance under Driscoll-Kraay standard errors ($p = 0.051$). NPL, LDR, and CAR are not significant under any of the three methods of inference. The within R-squared of 0.947 indicates that the regressors explain 94.7% of the variation in ROA within banks over time.

Table 4. Fixed Effects Estimation Results

Variable	Coefficient	Conventional SE	p-value	Cluster SE	Wild bootstrap p-value	Driscoll-Kraay SE	Driscoll-Kraay p-value
NPL	0.020	0.020	0.316	0.057	0.934	0.038	0.606
LDR	−0.001	0.002	0.604	0.002	0.604	0.004	0.743
CAR	0.008	0.007	0.226	0.011	0.515	0.008	0.290
BOPO	−0.077	0.003	<0.001	0.005	0.022	0.004	<0.001
NIM	0.097	0.029	0.001	0.034	0.126	0.030	0.002
SIZE	−0.414	0.075	<0.001	0.118	0.047	0.105	<0.001
INF	−0.027	0.011	0.013	0.011	0.167	0.013	0.051
BIR	0.066	0.011	<0.001	0.029	0.059	0.017	<0.001
GDP	−0.008	0.004	0.060	0.003	0.044	0.004	0.048
DC	−0.169	0.048	0.001	0.047	0.042	0.055	0.004
Observations	176						
Banks	4						
Bank fixed effects	Yes						
R-squared within	0.947						
R-squared between	0.893						
R-squared overall	0.845						

Notes: The dependent variable is ROA. All three columns share the same fixed effects coefficients and differ only in the standard errors. Cluster standard errors are clustered by bank, and with four clusters (G = 4) the wild cluster bootstrap p-values are obtained with the null hypothesis imposed and Webb six-point weights, enumerating all 1,296 weight combinations. Driscoll-Kraay standard errors use a lag length of three quarters. The wild bootstrap p-values form the main basis for inference.
Source: Data Processed, 2026

The standardized coefficients, calculated from the coefficients in Table 4 and the standard deviations in Table 1, allow the magnitudes of these associations to be compared. A one standard deviation increase in BOPO is associated with a decrease in ROA of 0.757 standard deviations, followed by SIZE (−0.265), NIM (0.127), the BI-rate (0.075), the COVID-19 dummy (−0.061), inflation (−0.038), and GDP growth (−0.018), while the standardized coefficients of NPL, LDR, and CAR are below 0.02 in absolute value.

Table 5 reports three robustness checks. BOPO remains negative and significant in all three, with a coefficient between −0.057 and −0.079. The COVID-19 dummy remains negative in all three and is significant when BTN is excluded and when the old BI Rate dummy is added, while it is larger and close to significance in the lagged model (p = 0.052). SIZE remains negative and significant when BTN is excluded and when the old BI Rate dummy is added, but it loses significance in the lagged model. The BI-rate coefficient is essentially unchanged when the old BI Rate dummy is added (0.074, p = 0.057), and that dummy itself is not significant (p = 0.686), so the change of policy rate instrument in 2016 does not drive the BI-rate result. The BI-rate, NIM, and GDP growth all lose significance when the regressors are lagged. NPL, LDR, CAR, and inflation remain insignificant in every specification.

Table 5. Robustness Checks

Variable	Excluding BTN	p-value	Lagged regressors	p-value	Old BI Rate dummy	p-value
NPL	0.051 (0.036)	0.163	0.062 (0.066)	0.468	0.022 (0.056)	0.928
LDR	0.004 (0.005)	0.434	−0.006 (0.002)	0.174	−0.002 (0.003)	0.569
CAR	0.002 (0.010)	0.814	0.013 (0.017)	0.555	0.007 (0.012)	0.586
BOPO	−0.079 (0.005)	<0.001	−0.057 (0.011)	0.049	−0.078 (0.005)	0.021
NIM	0.088 (0.041)	0.034	0.013 (0.080)	0.840	0.098 (0.034)	0.133
SIZE	−0.422 (0.145)	0.006	−0.417 (0.252)	0.306	−0.433 (0.144)	0.049
INF	−0.019 (0.014)	0.187	−0.011 (0.022)	0.629	−0.026 (0.010)	0.163
BIR	0.084 (0.020)	<0.001	−0.007 (0.020)	0.683	0.074 (0.019)	0.057
GDP	−0.010 (0.004)	0.017	0.013 (0.009)	0.310	−0.008 (0.003)	0.042
DC	−0.189 (0.076)	0.016	−0.531 (0.166)	0.052	−0.159 (0.049)	0.047
Old BI Rate dummy	-	-	-	-	−0.045 (0.071)	0.686
Observations	132		172		176	
Banks	3		4		4	
R-squared within	0.955		0.720		0.947	
Inference	Driscoll-Kraay		Cluster, wild bootstrap		Cluster, wild bootstrap	

Notes: Coefficients with standard errors in parentheses. All models include bank fixed effects. The first column excludes BTN, a mortgage-focused bank, which leaves only three banks, so Driscoll-Kraay standard errors with a lag length of three quarters, relying on the time dimension (T = 44), are used instead of cluster-based inference. In the second column, all regressors except the COVID-19 dummy are lagged by one quarter. The third column adds a dummy equal to 1 for 2015Q1 to 2016Q2, the quarters in which the BI Rate was the policy rate before the BI7DRR took effect on 19 August 2016. Wild bootstrap p-values use Webb six-point weights with the null hypothesis imposed.
Source: Data Processed, 2026

3.2. DISCUSSION

Under the wild cluster bootstrap inference in Table 4, four regressors are significantly associated with ROA at the 5% level, namely BOPO, SIZE, GDP growth, and the COVID-19 dummy, while the BI-rate is significant only at the 10% level (p = 0.059). NIM and the BI-rate are significant at the 1% level under Driscoll-Kraay standard errors but not under the bootstrap, so the evidence for them is weaker. NPL, LDR, CAR, and inflation show no significant association under either method. Of the ten hypotheses, H4 and H10 are therefore supported, H5 and H8 receive only partial support, H6 and H9 are rejected because the associations run opposite to the expected sign, and H1, H2, H3, and H7 are not supported. Statistical significance, however, says little about economic importance. The standardized coefficients show that a one standard deviation increase in BOPO is associated with a decline in ROA of 0.757 standard deviations, compared with 0.265 for SIZE, 0.127 for NIM, 0.075 for the BI-rate, and 0.061 for the COVID-19 dummy, so the association of operating efficiency with ROA is by far the largest in magnitude.

BOPO is negatively associated with ROA (coefficient −0.077, p = 0.022), so that a one percentage point higher BOPO goes together with a 0.077 percentage point lower ROA. This is the most stable association in the study, as it keeps almost the same size when BTN is excluded (−0.079, p < 0.001) and remains significant when the regressors are lagged by one quarter (−0.057, p = 0.049). The result supports H4 and agrees with evidence that operating expenses are strongly and negatively related to profitability (Athanasoglou et al., 2008), that operationally efficient banks are more profitable (Dietrich & Wanzenried, 2011), and that BOPO weakens the profitability of Indonesian Islamic banks (Ajizah & Widarjono, 2023). Part of this association is close to an accounting relationship, because BOPO and pre-tax profit are both built from operating income and operating expenses, so the coefficient is best read as a measure of how closely profitability tracks cost control rather than as an independent cause of it.

NPL shows no significant association with ROA (coefficient 0.020, p = 0.934), so H1 is not supported, which departs from the negative relationship reported by Athanasoglou et al. (2008) and Priharta & Gani (2023). This result should not be taken to mean that credit risk is irrelevant to the profitability of state-owned banks. Within banks, NPL is negatively correlated with ROA (r = −0.56), but it is also correlated with BOPO (r = 0.62) and with the COVID-19 dummy (r = 0.45). In Indonesian bank reporting, impairment losses on loans are recorded as operating expenses and therefore enter BOPO, so the cost of rising NPL reaches profitability largely through BOPO, in line with the provisioning mechanism described by Fauziah (2021), Meidi & Tannia (2025), and Priharta & Gani (2023). Once BOPO and the pandemic dummy are held constant, little independent variation in NPL remains to explain ROA.

LDR shows no significant association with the profitability of Indonesian state-owned banks (coefficient −0.001, p = 0.604), so H2 is not supported. This ratio essentially reflects the proportion of third-party funds successfully channeled into loans, and thus captures liquidity and lending aggressiveness rather than a bank's direct capacity to generate profit. In practice, a high LDR may indicate that a bank is more actively performing its intermediation function, but an increase in lending is not necessarily followed by an increase in profit if credit quality declines, operating costs rise, or interest margins remain insufficiently large (Asysidiq & Sudiyatno, 2022; Meidi & Tannia, 2025). Conversely, a lower LDR does not necessarily indicate reduced profitability, as banks can generate income from other sources, such as fee-based income, investments in securities, or the management of other earning assets.

CAR is not significantly associated with ROA (coefficient 0.008, p = 0.515), so H3 is not supported, unlike the positive CAR effect that Priharta & Gani (2023) report for the same banks. The result agrees with Meidi & Tannia (2025), who find no CAR effect among listed Indonesian banks. During the study period, CAR never fell below 14.78%, well above the 8% minimum, so capital was not a binding constraint on lending, and changes in CAR within that comfortable range add little to the explanation of profitability. The direction of the relationship is also uncertain, because retained earnings raise capital, so higher profitability can raise CAR rather than the reverse.

NIM is positively associated with ROA (coefficient 0.097), which is consistent with H5, but the association is significant only under Driscoll-Kraay standard errors (p = 0.002) and not under the bootstrap (p = 0.126), so H5 receives only partial support. Its precision is limited by its close relationship with bank size, as NIM and SIZE are strongly and negatively correlated within banks (r = −0.78), reflecting margins that narrowed as the banks grew. With only four banks, the two variables are difficult to separate. The association is also absent when NIM is lagged by one quarter, which further limits the weight that can be placed on it.

SIZE is negatively associated with ROA (coefficient −0.414, p = 0.047), so H6 is rejected. Because the model includes bank fixed effects, this coefficient reflects changes in size within each bank over time rather than differences in scale across banks. Between 2015Q1 and 2025Q4, the total assets of each bank grew by a factor of between 2.5 and 3.4, while the ROA

of all four banks was lower at the end of the period than at the beginning. The negative coefficient therefore indicates that profits did not keep pace with balance sheet expansion, rather than that larger banks are inherently less profitable. This interpretation is consistent with the weak evidence on size and profitability in the literature (Athanasoglou et al., 2008; Goddard et al., 2004). The association also loses significance under the bootstrap when the regressors are lagged ($p = 0.306$), so it should be read with caution.

Inflation (INF) is not significantly associated with the profitability of Indonesian state-owned banks (coefficient −0.027, $p = 0.167$), so H7 is not supported, although its negative coefficient is close to significance under Driscoll-Kraay standard errors ($p = 0.051$). Low and relatively stable inflation means that price pressures on the public and businesses are not particularly severe, meaning inflation does not serve as a major driver of increased credit demand. Furthermore, Bank Indonesia implements an Inflation Targeting Framework (ITF) to keep inflation within its target range, so that inflationary pressures during the study period tended to be predictable and did not generate significant uncertainty affecting banking financial performance. This study is also consistent with Khalifaturofi'ah et al. (2023, 2024) who found that inflation has no effect on bank profitability in Indonesia.

The BI-rate is positively associated with ROA (coefficient 0.066), so that a one percentage point higher policy rate goes together with a 0.066 percentage point higher ROA, but the association is significant only at the 10% level under the bootstrap ($p = 0.059$), while it is significant under Driscoll-Kraay standard errors ($p < 0.001$). H8 therefore receives partial support. The coefficient is essentially unchanged when a dummy for the quarters under the earlier BI Rate is added (0.074, $p = 0.057$) and when BTN is excluded (0.084, $p < 0.001$), so neither the change of policy rate instrument in 2016 nor the inclusion of the mortgage-focused bank drives it. The direction agrees with Borio et al. (2017) and Molyneux & Thornton (1992), who show that higher short-term rates go with higher bank profitability because the gain in net interest income outweighs the losses in provisions and non-interest income. A higher policy rate also raises the cost of deposits, however, so its net association with profit depends on how quickly asset yields reprice relative to funding costs. Since NIM is already held constant in the model, the remaining association may reflect income outside the measured margin or differences in repricing within the quarter, and the data do not identify which channel operates. The association also disappears when the regressors are lagged by one quarter, so it does not indicate a delayed transmission of monetary policy to profitability.

GDP growth is negatively associated with ROA (coefficient −0.008, $p = 0.044$), so H9 is rejected, but the association is economically negligible, with a standardized coefficient of only −0.018. This result most likely reflects a seasonal mismatch rather than countercyclical profitability. Quarter-on-quarter GDP growth that is not seasonally adjusted follows a strong seasonal pattern, averaging −0.81% in the first quarter, 3.16% in the second, 2.61% in the third, and −0.54% in the fourth, whereas ROA in quarterly published reports is computed on an annualized, year-to-date basis and is highest in the first quarter within each bank. The association also loses significance when the regressors are lagged ($p = 0.310$). The procyclicality reported by Athanasoglou et al. (2008) therefore cannot be tested reliably with this measure.

The COVID-19 dummy is negatively associated with ROA (coefficient −0.169, $p = 0.042$), which supports H10. Holding the other regressors constant, ROA was 0.169 percentage points lower in the quarters from 2020Q2 to 2021Q4 than in the rest of the period. This is in line with global evidence that bank performance and stability deteriorated after the outbreak (Elnahass et al., 2021) and with the negative pandemic effect that Khalifaturofi'ah et al. (2023) report for Indonesian banks. It differs from Ajizah and Widarjono (2023), who found no significant association between the pandemic and the ROA of Indonesian Islamic banks, although their sample ended in 2020 and covered only the first quarters of the pandemic. The dummy captures only part of the pandemic's association with profitability, since the pandemic also worked through the other regressors. During the pandemic quarters, NPL averaged 3.58%

compared with 2.71% in the other quarters, and BOPO averaged 81.31% compared with 72.87%. The credit restructuring relaxation under POJK No. 48/POJK.03/2020 allowed restructured loans to remain in performing categories, which may have kept recorded NPL lower than it would otherwise have been. The negative association is larger when the regressors are lagged (−0.531, p = 0.052), so the finding does not depend on the timing assumption of the main model.

The dummy also overlaps with the policy rate, which averaged 3.71% in the pandemic quarters compared with 5.51% in the other quarters (r = −0.57), but its VIF of 2.51 indicates that this overlap does not prevent the two from being estimated separately, and the COVID-19 coefficient remains negative and significant when the dummy for the earlier BI Rate is added (−0.159, p = 0.047).

These results should be read in light of the small number of banks. With four clusters, p-values close to 0.05 are fragile, so associations that hold under both the bootstrap and Driscoll-Kraay inference, namely those of BOPO, SIZE, GDP growth, and the COVID-19 dummy, are more credible than those of NIM and the BI-rate, which hold only under Driscoll-Kraay inference. In addition, the model identifies associations rather than causal effects, because several regressors, including CAR and BOPO, are themselves shaped by profitability.

4. CONCLUSION

This study examined the bank-specific, macroeconomic, and pandemic determinants of the profitability of Indonesia's four state-owned banks, namely BRI, BNI, BTN, and Bank Mandiri, using 176 bank-quarter observations from 2015Q1 to 2025Q4. ROA was regressed on NPL, LDR, CAR, BOPO, NIM, bank size, inflation, the BI-rate, GDP growth, and a COVID-19 dummy in a fixed effects model. The fixed effects specification was chosen because the Chow and Breusch-Pagan LM tests both rejected pooled estimation, the Hausman test favored fixed over random effects, and the four banks form the whole population of interest. Given that the panel contains only four banks, inference relied on bank-clustered standard errors with wild cluster bootstrap p-values, with Driscoll-Kraay standard errors as a robustness check.

Operating efficiency is the most consistent correlate of profitability. A higher BOPO is associated with a lower ROA, and this association is the largest in magnitude and holds across every specification examined. ROA is also lower in larger banks, as measured within each bank over time, and in the core pandemic quarters, and it shows a small negative association with GDP growth that most likely reflects the seasonal pattern of the growth measure. The positive associations of NIM and the BI-rate are significant only under Driscoll-Kraay inference, so the evidence for them is weaker. NPL, LDR, CAR, and inflation show no significant association with ROA once the other regressors are held constant. The insignificant NPL coefficient does not indicate that credit risk is unimportant, because the cost of problem loans reaches profitability largely through the impairment expenses recorded in BOPO. These findings extend the evidence on Indonesian state-owned banks beyond the first pandemic year, cover a full cycle of monetary easing and tightening, and show that the pandemic quarters were associated with lower profitability even after asset quality, efficiency, and the macroeconomic environment are taken into account.

The findings carry implications for bank management. Because BOPO is the most consistent correlate of ROA and also carries the cost of impairment losses, the management of operating costs and of credit quality, which feeds into those costs, are the areas most closely tied to the profitability of these banks. The negative association between asset growth and ROA within banks indicates that balance sheet expansion over the period was not matched by proportional growth in profit, so growth targets for these banks are more closely tied to profitability when they are set together with targets for efficiency and returns. For supervisors, the lower ROA in the pandemic quarters, alongside higher NPL and BOPO in the same period, indicates that profitability under a systemic shock is better assessed jointly with asset quality and cost indicators. The evidence on the BI-rate is not strong enough to support conclusions about the transmission of monetary policy to state-owned bank profitability.

This study has several limitations. First, the panel contains only four banks, so inference rests on very few clusters, p-values close to conventional thresholds are fragile, and the results cannot be generalized to other bank groups or other countries. Second, the model identifies associations rather than causal effects, because several regressors, including CAR and BOPO, are themselves shaped by profitability, and the macroeconomic variables and the COVID-19 dummy vary only over time, so they cannot be separated from other shocks common to all banks in the same quarter. Third, profitability is measured only by ROA, and the associations reported here may differ under alternative measures such as ROE. Fourth, GDP growth is measured quarter on quarter without seasonal adjustment, which limits the test of the business cycle hypothesis, and the policy rate series combines two instruments, although the main result for the BI-rate is unchanged when the earlier instrument is controlled for. Fifth, the pandemic is represented by a single dummy, which cannot distinguish the severity of the shock across quarters.

Future research can address these limitations in several ways. Extending the sample to a larger set of Indonesian banks, such as regional development banks or all banks within a supervisory group, would allow more reliable cluster-based inference and a direct comparison between state-owned and other banks. Using alternative profitability measures, such as ROE and pre-provision operating profit, would show whether the associations depend on how profitability is measured. Using year-on-year or seasonally adjusted GDP growth would allow a cleaner test of the procyclicality of bank profitability. Measures that vary across banks during the pandemic, such as the share of restructured loans in each bank's portfolio, would make it possible to separate the effect of the shock from that of the regulatory relaxation. Finally, a longer time dimension would support dynamic panel estimators that model the persistence of profitability directly.

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