

Growth: Journal Management and Business
Volume 04 No 02 October 2026
E ISSN : 3031-7959

https://lenteranusa.id/

Bank Profitability Across Disruption and Recovery: Credit Risk, Capital Adequacy, and Funding in Listed Indonesian Banks

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Received: 19-10-2026 Revised : 14-11-2026 Accepted : 16-11-2026 Published : 21-11-2026

Abstract
Bank profitability during 2020-2024 was shaped by an unusual disruption recovery cycle, making it important to distinguish persistent bank-level associations from specification sensitive results. This study examines how credit risk, capital adequacy, and third-party funding are associated with return on assets among banks listed on the Indonesia Stock Exchange. The sample comprises 27 eligible banks. Of 135 potential bank year observations, two were excluded because zero market capitalization values made the logarithmic transformation undefined, yielding an unbalanced panel of 133 observations. Panel regressions were estimated using common, fixed, and random effects specifications, followed by diagnostic tests and reviewer-requested sensitivity checks for common shocks, serial correlation, extreme observations, winsorization, multicollinearity, and alternative timing. The fixed-effects specification was selected as the baseline, while robust least squares Mestimation was treated as a separate sensitivity estimator rather than as a fixed effects covariance correction. Results are specification sensitive: the baseline fixed effects model associates higher non-performing loans with lower profitability and higher third-party funding with higher profitability, whereas robust Mestimation weakens those relationships and produces a positive association for capital adequacy. Operating inefficiency shows the most stable negative association, although its mechanical overlap with profitability measures requires cautious interpretation. Severe redundancy between third-party funding and bank size and residual dependence across banks further limit strong coefficient level conclusions. The evidence therefore supports cautious, associative rather than causal interpretation. The contribution lies in evaluating familiar banking determinants across the pandemic to recovery period while explicitly documenting model dependence, sample boundaries, and robustness limitations for selected listed Indonesian banks in this specific setting.

Keywords: bank profitability, credit risk, capital adequacy, third-party funding, panel data regression

Introduction

Profitability is one of the key indicators used to assess a bank's ability to sustain its intermediation function, absorb risk, and generate returns from the assets under management. In the banking industry, profit not only reflects operating performance but also determines a bank's capacity to strengthen its capital position and maintain business continuity. Accordingly, Return on Assets (ROA) is widely used to evaluate how effectively banks utilize their assets to generate earnings. The literature indicates that bank profitability is influenced by internal factors related to credit quality, bank size, cost efficiency, funding

structure, and capital adequacy (Kumar & Bird, 2022). In the Indonesian context, the relationship among asset quality, capitalization, and profitability has also received considerable attention because changes in these factors may have different implications for banks' ability to generate ROA (Masdjojo et al., 2023; Priharta & Gani, 2023).

The issue of profitability becomes more complex because stronger capital positions and larger funding sources do not necessarily lead to higher earnings. Masdjojo et al., (2023) show that credit quality is closely associated with bank profitability in Indonesia, while Oppusunggu and Simbolon, (2024) find that the Capital Adequacy Ratio is significantly related to ROA among BUKU IV banks. On the other hand, evidence regarding funding sources suggests that growth in deposits does not automatically translate into higher profits. Handoyo et al., (2023) for example, find that the growth of Third-Party Funds has no effect on ROA in Regional Development Banks, whereas Amimakmur et al., (2024) report that Third-Party Funds positively affect the financial performance of banks listed on the Indonesia Stock Exchange. These differences indicate that a bank's ability to generate profit depends not only on the amount of funds it mobilizes but also on how effectively those funds and its capital are converted into productive assets.

The 2020-2024 observation window spans the pandemic shock, reopening, and subsequent normalization, conditions that could simultaneously affect borrower repayment capacity, deposit flows, capitalization, and bank earnings. Fiscal and macroeconomic developments are therefore treated as contextual channels rather than explanatory variables in the estimated model. Prior evidence suggests that fiscal pressure can affect credit quality through borrowers' repayment capacity, while government-related fund flows may also influence deposit conditions in some Indonesian banks (Handoyo et al., 2023; Rahman & Adda, 2023). Because such system-wide shocks can be shared across banks, the empirical analysis supplements bank fixed effects with period-effect and cross-sectional-dependence sensitivity checks rather than attributing these macroeconomic mechanisms directly to the bank-level coefficients.

Within this framework, Non-Performing Loans, the Capital Adequacy Ratio, and Third-Party Funds can be viewed as three interrelated dimensions in explaining profitability. NPL represents asset quality and exposure to credit risk. An increase in problem loans may reduce income from productive assets while simultaneously increasing the need for loan-loss provisions. Empirical evidence from Indonesia shows that NPL negatively affects profitability (Handoyo et al., 2023; Masdjojo et al., 2023; Tangngisalu et al., 2020), while Gurung et al., (2024) also find that deteriorating asset quality is negatively associated with bank profitability. However, this relationship is not entirely consistent. Madugu et al., (2020) show that the relationship between credit risk and profitability may vary according to bank characteristics. These findings suggest that the effect of NPL on ROA depends on credit portfolio structure, risk management capability, and the institutional characteristics of each bank.

CAR also exhibits a complex relationship with profitability. Conceptually, capital adequacy provides banks with a buffer to absorb risk and sustain intermediation activities. However, excessively high capital may also indicate that some resources are not being used optimally to generate productive assets. This divergence is reflected in previous empirical findings. Handoyo et al., (2023) find that CAR has a positive and significant effect on ROA, while Oppusunggu and Simbolon, (2024) likewise report a significant relationship between CAR and ROA. In contrast, Madugu et al., (2020) find that the effect of CAR differs between

domestic and foreign banks, while research on profitability and capital buffers in Indonesia shows that the relationship among profitability, credit risk, and capital buffers is shaped by banks' financial structure Masdjojo et al., (2023) These inconsistencies point to a trade-off between risk-absorbing capacity and the efficiency of capital utilization.

The third dimension is Third-Party Funds, which constitute one of the main funding sources for banking intermediation. Theoretically, higher DPK increases a bank's capacity to extend credit and create productive assets. However, mobilized funds also carry funding costs, meaning that their effect on profitability depends on the bank's ability to deploy them productively. Empirical findings remain mixed. Amimakmur et al., (2024) find that Third-Party Funds positively affect bank financial performance, whereas Handoyo et al., (2023) show that DPK growth does not affect ROA. Nugroho et al., (2021) also demonstrate that DPK is related to banks' capital structure, while Amimakmur et al., (2026) show that Third-Party Funds can affect market performance through the mediating role of financial performance. These differing results indicate that increasing DPK is not an end in itself; rather, it is a resource whose effectiveness depends on the bank's ability to convert funds into income after accounting for costs and risks.

These findings reveal a clear research gap. Evidence on the relationships of credit risk, capital adequacy, and third-party funding with profitability remains mixed, while prior studies often focus on regional, state owned, Islamic, large bank, or non-Indonesian settings (Handoyo et al., 2023; Oppusunggu & Simbolon, 2024; Priharta & Gani, 2023). The 2020-2024 period also combines a major common shock with a recovery phase, making it important to distinguish bank specific associations from period-wide disturbances. Accordingly, this study reassesses the three banking dimensions within one listed bank panel while explicitly controlling for bank size, leverage, market capitalization, and operating efficiency and examining the sensitivity of inference to model specification, common shocks, extreme observations, and alternative data treatments.

The directional expectations follow the underlying banking mechanisms. Higher non-performing loans are expected to be negatively associated with return on assets because impaired credit reduces interest realization and increases provisioning and recovery costs (H1). Higher capital adequacy is expected to be positively associated with return on assets because a stronger capital buffer can absorb losses and support continuity of productive intermediation, although excessive capitalization may weaken this benefit (H2). Higher third-party funding is expected to be positively associated with return on assets when deposits are converted into productive earning assets at margins that exceed funding costs (H3). These hypotheses are tested as contemporaneous associations rather than causal effects.

In addition to the main explanatory variables, this study controls for bank size (SIZE), leverage (LEV), market capitalization (MCAP), and operating efficiency (BOPO). SIZE captures the scale of bank assets, while LEV represents the share of total assets financed by liabilities and is interpreted as balance-sheet liability intensity rather than industrial firm indebtedness because deposit-taking banks naturally operate with liability heavy funding structures. MCAP captures the market-valuation dimension, whereas BOPO reflects operating expenses relative to operating income. Including these controls helps separate the associations of credit risk, capital adequacy, and funding from other observable bank characteristics. Prior evidence also indicates that bank size and operating efficiency can be associated differently with bank performance (Junaeni et al., 2023; Nurkhin et al., 2023).

The incremental contribution of this study does not rest on combining familiar banking ratios alone. It lies in evaluating credit risk, capital adequacy, and third-party funding during the 2020-2024 disruption to recovery period for selected banks listed on the Indonesia Stock Exchange, while simultaneously controlling for bank scale, liability intensity, market valuation, and operating efficiency and documenting how conclusions change across panel and robustness specifications. Non-performing loans represent credit risk, capital adequacy represents loss-absorbing capacity, and third-party funds represent funding capacity. The study therefore asks whether these dimensions retain stable associations with return on assets once bank heterogeneity, shared period shocks, data treatment, and specification sensitivity are considered. Consistent with the additive regression actually estimated, the objective is to assess the separate associations of credit risk, capital adequacy, and third-party funding with profitability rather than to claim statistical interaction among them.

Method

This study employs a quantitative explanatory design to examine the associations of Non-Performing Loans (NPL), the Capital Adequacy Ratio (CAR), and Third-Party Funds (DPK) with Return on Assets (ROA) among banking issuers listed on the Indonesia Stock Exchange during 2020 2024. The period covers pandemic disruption, reopening, and normalization, making both bank heterogeneity and common time shocks empirically relevant. The initial sampling frame comprised banking issuers observable on the exchange during the study window, and purposive screening retained 27 issuers that satisfied the continuous-listing and data-availability criteria (Casteel & Bridier, 2021; Ghoniem, 2024). The retained identifiers are AGRO, ARTO, BANK, BBCA, BBKP, BBMD, BBNI, BBRI, BBTN, BBYB, BCIC, BEKS, BGTG, BJBR, BJTM, BMRI, BNGA, BNII, BNLI, BTPN, BVIC, INPC, MAYA, MCOR, NISP, NOBU, and PNBN. The continuous-listing criterion improves comparability but limits applicability to newer listings, delisted banks, and distressed institutions that do not satisfy the screen. Of 135 potential bank-year records, BANK-2020 and BCIC-2020 were excluded from the regression sample because their retained market-capitalization values were zero, making the logarithmic transformation undefined; the resulting panel is therefore unbalanced with 133 observations. Data were collected from annual reports, financial statements, and retained company-level data records. ROA is the reported profit-before-tax-to-average-total-assets profitability ratio; NPL is the gross ratio of problem loans to total loans, with the corresponding gross problem financing measure used where that is the reported bank metric; CAR is year-end capital divided by risk-weighted assets; DPK is the year-end stock of current accounts, savings, and time deposits; LEV is total liabilities divided by total assets; BOPO is operating expenses divided by operating income; SIZE is year-end total assets; and MCAP is the year end market capitalization measure retained in the analytical workbook. Ratios are analyzed in decimal form. DPK, SIZE, and MCAP are log-transformed. BOPO, LEV, DPK, MCAP, SIZE, NPL, and ROA are winsorized at the 10th and 90th percentiles (W90), while CAR is left unwinsorized so that its unusually high reported values can be explicitly examined in sensitivity analysis.

The data combine cross-sectional and time-series dimensions and are analyzed as a panel using EViews. Common Effect, Fixed Effects, and Random Effects specifications are first compared, with the Chow Test and Hausman Test used as baseline model selection diagnostics. Because later tests identify heteroskedasticity and cross-sectional dependence,

the conventional Hausman decision is treated as a specification guide rather than as definitive robust inference. The heteroskedasticity diagnostic is the EViews Panel Cross-section Heteroskedasticity Likelihood Ratio Test, whose null hypothesis is homoskedastic residual variance across cross sections; the reported 27 degrees of freedom correspond to the cross-sectional variance terms evaluated by the unrestricted specification. Cross-sectional dependence is assessed using the Breusch Pagan Lagrange Multiplier, Pesaran scaled Lagrange Multiplier, and Pesaran cross section dependence statistics, while panel serial correlation is supplemented with a Wooldridge style first-order test (Fu & Zhu, 2023). Importantly, the final EViews 'Robust Statistics' output is not a fixed-effects covariance correction: it is Robust Least Squares using Mestimation with Bisquare weights, tuning constant 4.685, median absolute deviation scale, and Huber Type I standard errors and covariance. Accordingly, the cross-section Fixed Effects Model is retained as the baseline panel specification and the robust least-squares estimator is reported separately as an outlier-resistant sensitivity check. Reviewer-requested robustness checks additionally evaluate period fixed effects, loss-making versus profitable bank years, extreme CAR observations, alternative winsorization thresholds, variance-inflation factors and condition indices, models omitting either DPK or SIZE, and one year lagged regressors. These checks are used to assess stability and simultaneity concerns; because contemporaneous profitability can itself affect deposits and capital, all estimated relationships are interpreted as associations rather than causal effects (Colin Cameron & Miller, 2015; Fritsch et al., 2024).

Results and Discussion

Result

Table 1. Descriptive Statistics

	BOPO	CAR	LEV	DPK	MCAP	SIZE	NPL	ROA
Mean	0.865633	0.346535	0.824965	31.76342	30.51218	32.10370	0.029089	0.004765
Median	0.860000	0.253000	0.843784	32.03490	30.47934	32.26606	0.029500	0.007310
Maximum	1.121900	3.905000	0.905122	34.55503	33.63057	34.78522	0.047200	0.023807
Minimum	0.645000	0.105000	0.697356	29.38372	28.53709	29.84190	0.008900	-0.031801
Std. Dev.	0.144407	0.394698	0.065155	1.665272	1.535684	1.619840	0.012273	0.015601
Skewness	0.186247	6.421015	-0.681955	0.171580	0.650693	0.170921	-0.153476	-1.254373
Kurtosis	2.154875	53.46188	2.297807	1.875916	2.624682	1.801717	1.867347	3.913728
Jarque-Bera	4.726973	15025.23	13.04136	7.654833	10.16602	8.604761	7.631558	39.50488
Probability	0.094092	0.000000	0.001473	0.021766	0.006201	0.013536	0.022021	0.000000
Sum	115.1292	46.08910	109.7204	4224.535	4058.120	4269.792	3.868800	0.633732
Sum Sq. Dev.	2.752631	20.56379	0.560358	366.0531	311.2989	346.3522	0.019883	0.032128
Observations	133	133	133	133	133	133	133	133

Source: Authors' Data Processing, 2026.

Descriptively, the 133 bank-year observations display substantial heterogeneity. The negative minimum ROA is not an isolated feature: 21 bank years are loss making and 112 are profitable. In the retained source data, loss making bank years have higher average NPL and BOPO than profitable bank years, indicating that credit-quality pressure and operating-cost intensity are concentrated more heavily among observations with negative profitability. DPK, MCAP, and SIZE are transformed using natural logarithms, while BOPO, LEV, DPK, MCAP, SIZE, NPL, and ROA are winsorized by clipping values below the 10th percentile and above the 90th percentile to those respective cut offs; CAR is not winsorized. The maximum CAR of 3.905 represents 390.5% and is associated with an exceptionally highly capitalized bank year, explaining much of the extreme skewness and kurtosis. Because such observations can exert disproportionate influence in a short panel, the main results are supplemented with loss making/profitable splits, alternative winsorization, and CAR exclusion sensitivity checks rather than relying on the distributional diagnostics alone (Cain et al., 2016; Chellai, 2025).

Model Selection Test

The model selection test was conducted to determine the panel data regression specification that best fits the characteristics of the research data. This stage compares the Common Effect Model (CEM), Fixed Effects Model (FEM), and Random Effects Model (REM) using the Chow Test and Hausman Test, ensuring that the model employed in the subsequent analysis is selected based on empirical test results.

Table 2. Chow Test

Effects Test	Statistic	d.f.	Prob.
Cross-section F	4.322399	(26, 99)	0.0000
Cross-section Chi-square	100.887004	26	0.0000

Source: Authors' Data Processing, 2026.

The Chow Test rejects the pooled Common Effect specification in favor of cross section fixed effects, indicating economically relevant time-invariant heterogeneity across banks. Because the 2020-2024 window also contains shocks shared by the banking system, this cross section result is supplemented by a period effect sensitivity specification rather than being interpreted as evidence that bank effects alone capture all unobserved heterogeneity (Mobonggi et al., 2022).

Table 3. Hausman Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	24.540369	7	0.0009

Source: Authors' Data Processing, 2026.

The conventional Hausman Test favors the Fixed Effects Model over the Random Effects Model. However, the subsequent evidence of heteroskedasticity and cross sectional dependence means that this conventional Hausman result is used as a baseline specification decision and interpreted cautiously. Reviewer requested sensitivity checks therefore add year effects and alternative covariance treatments to assess whether the substantive conclusions survive common shocks and non-standard residual behavior (Sani et al., 2024).

Table 4. Cross-Section Dependence Test

Residual Cross-Section Dependence Test			
Null hypothesis: No cross-section dependence (correlation) in residuals			
Equation: Untitled			
Periods included: 5			
Cross-sections included: 27			
Total panel (unbalanced) observations: 133			
Note: non-zero cross-section means detected in data			
Test employs centered correlations computed from pairwise samples			
Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	561.8877	351	0.0000
Pesaran scaled LM	7.959445		0.0000
Pesaran CD	4.063710		0.0000

Source: Authors' Data Processing, 2026.

The residual cross-section dependence tests jointly reject cross-sectional independence, showing that bank residuals share common variation over 2020-2024. This result is economically plausible in a banking system exposed to common pandemic, policy, funding, and recovery shocks. Ordinary bank-level clustering alone does not remove common time shocks; accordingly, the reviewer-requested two way fixed effects sensitivity specification adds year effects. In the retained analytical workbook, the residual Pesaran cross section dependence statistic falls from 2.366 (p=0.018) under bank fixed effects alone to 1.234 (p=0.217) after year effects are added, indicating that period controls absorb a material part of the common residual dependence. These sensitivity results support cautious inference and the explicit modeling of shared time shocks (Fu & Zhu, 2023).

Classical Assumptions

The Fixed Effects Model is retained as the baseline panel specification, after which residual diagnostics are used to assess whether conventional inference is adequate. The diagnostics cover residual distribution, cross section heteroskedasticity, multicollinearity, panel serial correlation, and cross sectional dependence. These tests are interpreted as diagnostics of estimator uncertainty rather than as a checklist that automatically validates or invalidates the model (Born & Breitung, 2016; Okolie et al., 2025).

The residual distribution departs from normality, with negative skewness and excess kurtosis. Robust standard errors do not make residuals normal; rather, they may reduce the sensitivity of inference to some forms of variance misspecification. In a short panel with only five annual observations per bank, non-normal tails and influential bank-years remain relevant, so the distributional result is addressed through explicit influence and sensitivity checks, including the examination of the extreme CAR observation and alternative winsorization schemes, rather than being treated as resolved by the word 'robust' (Brooks, 2019; Cain et al., 2016).

Growth: Journal Management and Business
Volume 04 No 02 October 2026
E ISSN : 3031-7959

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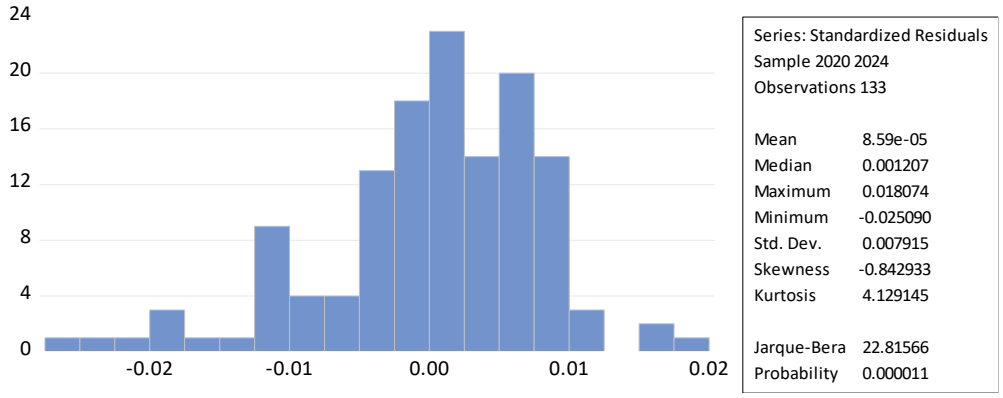

Source: Authors' Data Processing, 2026.
Figure 1. Residual Normality Test

Table 5. Panel Cross-Section Heteroskedasticity Likelihood Ratio Test

Test / Log-likelihood	Value	d.f.	Probability
Likelihood ratio	255.7410	27	0.0000
Restricted LogL	455.3552	126	—
Unrestricted LogL	583.2257	126	—

Source: Authors' Data Processing, 2026.

The EViews Panel Cross section Heteroskedasticity Likelihood Ratio Test rejects the null hypothesis that residual variance is homogeneous across the 27 bank cross sections. The reported 27 degrees of freedom arise from the cross-sectional variance components compared in the unrestricted specification, while the restricted model imposes a common residual variance. The significant likelihood-ratio result therefore indicates bank level heterogeneity in residual variance and cautions against conventional homoskedastic standard errors (Baltagi et al., 2010).

Multicollinearity Test

Table 6. Correlation and Multicollinearity Diagnostics

Variabel	BOPO	CAR	LEV	DPK	MCAP	SIZE	NPL
BOPO	1.000						
CAR	0.209	1.000					
LEV	-0.065	-0.570	1.000				
DPK	-0.591	-0.391	0.547	1.000			
MCAP	-0.518	0.064	-0.015	0.712	1.000		
SIZE	-0.588	-0.374	0.518	**0.998**	0.727	1.000	
NPL	0.322	-0.282	0.124	-0.143	-0.303	-0.160	1.000

Source: Authors' Data Processing, 2026.

The correlation matrix identifies a severe redundancy between DPK and SIZE, whose correlation is approximately 0.998. Reviewer-requested diagnostics confirm the problem: the

variance-inflation factors are approximately 357.24 for DPK and 328.99 for SIZE, and the maximum condition index is 48.57, well above conventional warning levels (Shrestha, 2020). The remaining variables show substantially lower variance-inflation factors. Sensitivity re-estimation also shows that the DPK coefficient loses significance when SIZE is removed, while the SIZE coefficient loses significance when DPK is removed. The coefficients of DPK and SIZE are therefore not interpreted as clean standalone effects; their signs and significance are explicitly treated as unstable because both variables capture closely related dimensions of bank scale.

Autocorrelation Test

Table 7. Panel Serial-Correlation Diagnostic

Test	Statistic	d.f.	Probability
Wooldridge-style first-order serial-correlation test	17.04	(1, 26)	0.0003
Durbin-Watson (descriptive only)	0.700651	—	—

Source: Authors' Data Processing, 2026.

The pooled Durbin Watson statistic is retained only as a descriptive indicator and is not used as the primary serial-correlation test because it does not adequately diagnose within-bank dependence in a fixed effects panel. A reviewer-requested Wooldridge-style first-order serial-correlation test rejects the null of no within-bank serial correlation ($F \approx 17.04$, $p < 0.001$). This result reinforces the need for panel-aware inference and sensitivity analysis rather than relying on the pooled Durbin Watson statistic alone (Kalifa & Bektaş, 2018).

Hypothesis Testing

Hypothesis assessment distinguishes the selected panel specification from the separate outlier-resistant estimator. The cross-section Fixed Effects Model is the baseline panel model selected by the Chow and Hausman procedures. Because the residual diagnostics reveal heteroskedasticity, serial correlation, and cross-sectional dependence, its conventional p-values are not treated as the sole basis for inference. The EViews Robust Least Squares M-estimation output is therefore reported separately as a sensitivity check. Agreement across these specifications is interpreted as stronger evidence; disagreement is treated as specification uncertainty rather than resolved by labeling the M-estimator as 'FEM robust'.

Table 8. Baseline Cross-Section Fixed Effects Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.017793	0.126454	-0.140705	0.8884
NPL	-0.295552	0.101727	-2.905361	0.0045
CAR	-0.002416	0.002207	-1.094359	0.2765
DPK	0.037624	0.011503	3.270827	0.0015
SIZE	0.041485	0.012563	3.302199	0.0013
LEV	0.011525	0.036320	0.317320	0.7517
MCAP	-0.001734	0.001247	-1.390943	0.1674

BOPO	-0.090724	0.011297	-8.030659	0.0000
R-squared	0.895949	Adjusted R-squared	0.861266	
F-statistic	25.83213	Prob(F-statistic)	0.000000	

Source: Authors' Data Processing, 2026.

Table 9. Robust Least Squares Sensitivity Check (M-estimation)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.058126	0.008006	7.260539	0.0000
NPL	-0.038288	0.022950	-1.668304	0.0953
CAR	0.007847	0.000831	9.441832	0.0000
DPK	-0.004313	0.002660	-1.621336	0.1049
SIZE	0.004577	0.002613	1.751521	0.0799
LEV	-0.015182	0.007310	-2.076897	0.0378
MCAP	0.000222	0.000322	0.689101	0.4908
BOPO	-0.058724	0.002484	-23.63679	0.0000
	Robust Statistics			
R-squared	0.585944	Adjusted R-squared		0.562757
Rw-squared	0.940126	Adjust Rw-squared		0.940126
Akaike info criterion	245.1311	Schwarz criterion		273.6480
Deviance	0.001508	Scale		0.002536
Rn-squared statistic	1727.580	Prob(Rn-squared stat.)		0.000000
	Non-robust Statistics			
Mean dependent var	0.004765	S.D. dependent var		0.015601
S.E. of regression	0.009377	Sum squared resid		0.010992

Source: Authors' Data Processing, 2026.

The baseline Fixed Effects Model and the robust M-estimation do not yield identical coefficient-level conclusions. In the baseline fixed-effects specification, NPL is negatively associated with ROA, DPK and SIZE are positively associated with ROA, and BOPO is negatively associated with ROA, while CAR, LEV, and MCAP are not statistically significant. In the separate M-estimation sensitivity check, NPL and DPK become statistically insignificant, CAR becomes positive and significant, LEV becomes negative and significant, SIZE is only marginal at the 10% level, MCAP remains insignificant, and BOPO remains negative and highly significant. The robust table's R-squared of 0.585944 is the unweighted R-squared reported by the EViews M-estimator and should not be conflated with the baseline fixed-effects R-squared or the robust weighted Rw-squared. Thus, H1 and H3 receive support in the baseline fixed-effects model but weaken under M-estimation, while H2 is supported only by the M-estimation check. This divergence is substantive evidence of specification sensitivity rather than a reason to privilege one estimator without qualification.

Discussion

The combined results point to substantial specification sensitivity. The baseline fixed-effects model captures bank-specific time-invariant heterogeneity, whereas the separate M-estimation reduces the influence of extreme observations but does not preserve fixed effects or directly solve cross-sectional dependence. The reviewer-requested period-effect check further shows that common time shocks matter for residual dependence. Consequently, the discussion emphasizes associations that are stable across specifications and treats sign or significance changes as evidence of uncertainty rather than as proof that one estimator reveals the 'true' effect.

Non-Performing Loans show a negative association with profitability in the baseline fixed-effects model, but the relationship becomes statistically insignificant under the M-estimation sensitivity check and also weakens when alternative timing is considered. The negative direction is consistent with the economic mechanism through which problem loans reduce interest realization and increase provisioning and recovery costs, and it aligns with evidence reported by Masdjojo et al., (2023) and Priharta and Gani, (2025). At the same time, the instability across specifications is consistent with Junaeni et al., (2023), who report a negative but insignificant relationship. The evidence therefore supports credit risk as a plausible profitability pressure but does not establish a stable or causal NPL effect over this short period.

Capital adequacy is the clearest example of estimator dependence. CAR is not statistically significant in the baseline fixed-effects model but becomes positive and significant under robust M-estimation. Additional checks that remove the extreme high-CAR bank-year or exclude observations with CAR above one do not produce a stable significant CAR effect in the two-way fixed-effects sensitivity specification. Prior studies are likewise mixed: Butola et al., (2022) and Junaeni et al., (2023) and Wang et al., (2022) emphasize a supportive role for capitalization, whereas Priharta and Gani, (2025) and Puspitasari et al., (2021) report different directions or levels of significance. The present evidence therefore suggests that capital adequacy may support profitability under some specifications, but it does not justify ranking capital as unambiguously more important than credit risk or funding.

Third-Party Funds also display unstable coefficient behavior. DPK is positively associated with ROA in the baseline fixed-effects model but becomes negative and statistically insignificant under M-estimation. More importantly, DPK is almost perfectly correlated with SIZE, and reviewer-requested variance-inflation diagnostics indicate severe redundancy; the significance of DPK or SIZE changes when the other is removed. Economically, this is plausible because larger banks generally carry larger deposit bases. The conceptual distinction between funding capacity and funding productivity remains useful deposits contribute to profitability only when they are transformed into earning assets at margins that cover funding costs and risk but the present data do not support a clean standalone DPK effect. This cautious interpretation is compatible with the mixed evidence reported by Amimakmur et al., (2024) and Nurkhin et al., (2023).

Among the controls, BOPO shows the most stable negative association with ROA across the examined specifications, while leverage is significant only in the M-estimation check and SIZE and MCAP are not consistently significant. The BOPO coefficient must nevertheless be interpreted carefully because BOPO and ROA share closely related income statement components: higher operating expenses relative to operating income mechanically compress earnings that also enter profitability. Its negative coefficient therefore reflects both

an economically meaningful efficiency channel and a degree of accounting overlap, rather than a fully independent managerial mechanism. Leverage also requires banking specific interpretation because deposits and other liabilities are integral to intermediation; a higher liability to asset ratio is not directly comparable with leverage in non-financial firms. The lack of stable SIZE and MCAP effects further indicates that greater scale or market valuation does not automatically translate into higher asset based profitability.

Overall, the evidence supports a more qualified conclusion than a simple ranking of determinants. Credit risk, capital adequacy, and third-party funding are economically relevant banking dimensions, but their estimated coefficients vary across the baseline fixed-effects model, M-estimation, period effect checks, tail treatments, and collinearity-sensitive specifications. BOPO is the most stable negative correlate, although part of this stability may reflect its mechanical link with earnings. The study's contribution is therefore to show that profitability evidence during the 2020-2024 disruption to recovery cycle is conditional on model choice, common shocks, and the joint structure of bank balance-sheet variables. This makes transparent robustness assessment and cautious associative interpretation central to the empirical contribution.

Conclusion

This study examines profitability associations for 27 selected banking issuers listed on the Indonesia Stock Exchange during 2020-2024 and should not be generalized to the entire Indonesian banking system. The baseline fixed-effects model and the separate robust M-estimation do not yield identical conclusions for NPL, CAR, DPK, SIZE, or leverage, indicating meaningful specification uncertainty. BOPO exhibits the most stable negative association with ROA, but its interpretation is tempered by mechanical overlap between operating income components and profitability. The results therefore do not establish that capital management is economically more important than credit risk or funding, nor do statistically insignificant coefficients imply that NPL or DPK is irrelevant. Rather, the evidence is consistent with the practical importance of maintaining adequate capital, controlling operating costs, and deploying funding productively while recognizing that these relationships are associative rather than causal. The study is limited by the short five-year window, pandemic and recovery shocks, two excluded bank-year records, severe DPK SIZE collinearity, influential high CAR observations, contemporaneous simultaneity, and time varying bank specific factors that fixed effects cannot eliminate. Future work should use longer panels, clearer exogenous timing or instrumental strategies, and richer common shock controls to test whether these associations persist beyond the present sample and period.

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