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DYNAMIC INTERACTIONS OF BANK RISK, CAPITAL, LIQUIDITY, AND PROFITABILITY IN INDONESIA: EVIDENCE FROM VECM AND ARDL MODELS

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Abstract:

This study examines the dynamic relationships between banking prudential indicators, profitability, and macroeconomic variables in Indonesia using monthly data from 2010 to 2024. Given the presence of mixed integration orders identified through unit root tests, the analysis employs a combined Vector Error Correction Model (VECM) and Autoregressive Distributed Lag (ARDL) framework to capture both long-run equilibrium relationships and short-run dynamics. The findings indicate that internal banking factors play a more dominant role than macroeconomic variables in determining bank profitability. In particular, credit risk, measured by the non-performing loan (NPL) ratio, emerges as the most influential determinant, exerting a significant negative impact on profitability in the short run and remaining central in long-run dynamics. Liquidity and operational efficiency also affect profitability through time-varying mechanisms, reflecting a trade-off between risk and return. In contrast, capital adequacy and macroeconomic variables, including the policy interest rate and inflation, show limited short-run effects. The cointegration results should be interpreted with caution due to differences between the Trace and Max-Eigenvalue statistics; however, the consistency of ARDL results supports the robustness of the findings. Overall, the results highlight the critical importance of credit risk management and internal efficiency in sustaining banking performance.

Key words: *Banking Stability; Credit Risk; Capital Adequacy; Liquidity; Monetary Policy*

1. Introduction

The stability of the banking sector has become increasingly critical in the context of global financial uncertainty, monetary tightening, and post-pandemic economic adjustments. In emerging economies such as Indonesia, where financial intermediation remains predominantly bank-based, vulnerabilities in credit quality, capital adequacy, and liquidity conditions can rapidly propagate into broader systemic risks. Recent episodes of financial stress have demonstrated that disruptions within banking balance sheets do not remain isolated but instead interact dynamically with macroeconomic conditions, reinforcing the need for a system-wide perspective on financial stability (Bank Indonesia, 2024).

In Indonesia, the banking sector plays a central role in mobilizing savings, allocating credit, and transmitting monetary policy to the real economy. Over the past two decades, the industry has undergone substantial structural transformation, characterized by rapid credit expansion, regulatory strengthening, and deeper integration with global financial markets. While these developments have enhanced financial intermediation capacity, they have also increased the sensitivity of banks to fluctuations in asset quality, capital buffers, and macroeconomic policy shocks. Empirical evidence from Indonesia indicates that financial system stability is closely linked to macroeconomic conditions, including interest rates, exchange rates, and external shocks (Hastutik, 2023; Hudaya & Firmansyah, 2023). Additional evidence from Indonesian banking studies further confirms that bank-specific factors such as capital adequacy, efficiency, and risk management play a critical role in determining financial performance and stability (Peling & Sedana, 2021; Sufian & Habibullah, 2012).

A large body of empirical literature has examined the determinants of bank performance and stability, emphasizing the role of credit risk, capitalization, liquidity, and operational efficiency (Athanasoglou et al., 2008; Bonner & Eijffinger, 2016; Dietrich & Wanzenried, 2011). More recent studies highlight the importance of monetary policy transmission, showing that interest rate changes affect lending behavior, capital positions, and risk dynamics within the banking system (Gambacorta & Shin, 2018). However, much of this literature relies on static or partial-equilibrium approaches, which are limited in capturing feedback effects, dynamic adjustments, and shock propagation mechanisms among banking variables.

In the context of Indonesia, empirical research has largely focused on bank-level panel analyses examining profitability, efficiency, or credit risk, often using annual or quarterly data. Studies such as (Ramadhanti et al., 2019) highlight that capital adequacy and liquidity positively influence profitability, while credit risk negatively affects bank performance, emphasizing the importance of internal banking conditions. However, these approaches do not adequately capture system-wide interactions and short-run adjustment dynamics among prudential indicators and macroeconomic variables.

This study addresses these gaps by adopting a system-based dynamic approach to examine the interactions among credit risk, capital adequacy, liquidity exposure, operational efficiency, and macroeconomic variables in the Indonesian banking system. Using a Vector Error Correction Model (VECM) and monthly data from 2010 to 2024, the study captures

both long-run equilibrium relationships and short-run adjustment dynamics within a unified multivariate framework.

The contribution of this study is threefold. First, it utilizes high-frequency monthly banking data, enabling the identification of short-run dynamics that are often obscured in lower-frequency analyses. Second, it applies a system-based econometric framework that captures the endogenous interactions among banking variables and macroeconomic conditions, moving beyond conventional static approaches. Third, the study highlights the role of capital adequacy as a central adjustment mechanism linking credit risk, liquidity dynamics, and monetary policy transmission, offering important insights for macroprudential and monetary policy coordination in emerging banking systems.

2. Literature review

Empirical research on banking performance and stability has long emphasized the importance of prudential indicators and macroeconomic conditions in shaping bank behavior. A substantial body of literature identifies credit risk, capitalization, operational efficiency, and liquidity as key determinants of bank profitability and financial resilience. Early empirical contributions show that bank-specific characteristics play a central role in determining profitability and stability. For instance, credit risk, capital adequacy, and operational efficiency significantly influence bank profitability in European banking systems (Athanasoglou et al., 2008). Similarly, well-capitalized and cost-efficient banks exhibit stronger profitability, particularly during periods of financial stress (Dietrich & Wanzenried, 2011). These findings suggest that internal balance-sheet conditions remain critical drivers of banking performance across different institutional environments.

A second stream of literature focuses on the role of credit risk in shaping banking stability. Non-performing loans (NPL) represent a primary indicator of asset quality deterioration and are closely linked to both bank profitability and solvency. Empirical studies consistently document a negative relationship between NPL ratios and financial performance, as rising credit risk increases provisioning costs and weakens lending capacity. Examining emerging banking markets, it is found that credit risk exerts a strong negative impact on bank profitability, while macroeconomic conditions significantly influence banking outcomes (Sufian & Habibullah, 2012). A significant increase in NPL exacerbates banking risk and can become a source of systemic instability, particularly when combined with inadequate capital and macroeconomic pressures (Makri et al., 2014).

Capital adequacy represents another crucial dimension of banking stability. Regulatory capital requirements are designed to ensure that banks maintain sufficient buffers to absorb unexpected losses and sustain lending during economic downturns. Stronger capital positions enable banks to sustain credit supply even during periods of monetary tightening, thereby contributing to financial system stability (Gambacorta & Shin, 2018). Empirical evidence from both advanced and emerging economies indicates that well-capitalized banks tend to exhibit greater resilience to macroeconomic shocks and are better able to manage credit risk exposures. However, the relationship between capital adequacy and bank performance is often dynamic, as capital buffers may simultaneously respond to changes in risk conditions and regulatory pressures.

Liquidity management also plays a significant role in determining the stability of banking systems. Liquidity risk arises when banks face difficulties in meeting short-term funding obligations or converting assets into liquid resources. Regulatory liquidity requirements play a significant role in shaping banks' balance-sheet decisions and reserve demand, thereby influencing the stability of financial intermediation (Bonner & Eijffinger, 2016). Empirical studies further suggest that excessive lending relative to asset capacity can increase liquidity exposure and heighten vulnerability to funding shocks. In bank-dominated financial systems, where credit expansion plays a central role in economic activity, the interaction between liquidity conditions and lending behavior becomes particularly important for financial stability.

In addition to bank-specific indicators, macroeconomic conditions significantly influence banking performance and risk dynamics. Monetary policy represents a key transmission channel affecting bank lending behavior, funding costs, and asset quality. Changes in policy interest rates can alter credit demand, influence borrowing conditions, and affect borrowers' repayment capacity. Monetary policy transmission partly operates through the bank lending channel, whereby changes in interest rates affect banks' balance-sheet conditions and credit supply (Mishkin, 2014). When interest rates rise, funding costs increase and credit risk tends to expand, particularly for highly leveraged banks and in economies that heavily depend on bank-based intermediation (Dell'Ariccia et al., 2017).

Inflation also plays a complex role in shaping banking sector performance. Moderate inflation may support bank profitability when lending rates adjust faster than deposit rates, improving net interest margins. However, high or volatile inflation can increase macroeconomic uncertainty and deteriorate credit quality. Empirical findings on the relationship between inflation and banking stability remain mixed (Dell'Ariccia et al., 2017; Jordà et al., 2017).

Methodologically, a growing body of research has applied dynamic time-series models to capture the complex interactions among banking variables. Vector autoregression (VAR) and vector error correction models (VECM) allow researchers to examine both long-run equilibrium relationships and short-run adjustment dynamics among financial variables (Lütkepohl, 2005; Pedroni, 2013). For example, dynamic modeling approaches show that financial structure and macroeconomic volatility are closely linked through long-run equilibrium relationships (Bezooijen & Bikker, 2019). These approaches are particularly useful for identifying feedback effects and shock transmission mechanisms that cannot be captured by static regression models.

Despite these advances, empirical applications of dynamic multivariate models to emerging banking systems remain relatively limited, particularly when using high-frequency prudential indicators. Many studies continue to rely on annual or quarterly datasets, which may smooth cyclical fluctuations and obscure short-term adjustment dynamics. High-frequency banking data can provide valuable insights into the speed at which banking indicators respond to financial shocks and policy changes.

The literature on the Indonesian banking sector has largely focused on bank-level panel analyses examining determinants of profitability, efficiency, or credit risk. Studies on Indonesian banks frequently highlight the importance of capital adequacy, credit quality, and operational efficiency in shaping bank performance. However, most existing empirical

studies analyze these relationships using static regression approaches or focus on individual bank characteristics rather than system-wide interactions among banking indicators. As a result, relatively little empirical work has examined how prudential indicators and macroeconomic variables jointly evolve within a dynamic system.

Empirical studies focusing specifically on the Indonesian banking sector have generally examined the determinants of bank profitability, credit risk, and financial stability using bank-level panel data. For instance, the determinants of bank profitability in Indonesia include credit risk, capitalization, and operational efficiency, all of which significantly influence bank performance (Sufian & Habibullah, 2012). Similarly, bank-specific variables such as capital adequacy and liquidity conditions play an important role in determining profitability in emerging banking systems, including Indonesia (Alper et al., 2011).

Other studies focusing on the Indonesian banking sector emphasize the importance of credit quality and capital buffers for maintaining financial stability. Financial stability is a key determinant of economic sustainability, as instability may trigger broader financial crises. Using quarterly time-series data and an error correction model (ECM), this study examines the relationship between monetary policy variables money supply, interest rates, and exchange rates and financial stability in Indonesia (Hudaya & Firmansyah, 2023). Meanwhile, capital adequacy (CAR) and liquidity (LDR) are found to have positive and significant effects on profitability (ROA), whereas credit risk (NPL) has a negative and significant impact (Ramadhanti et al., 2019).

More recent research has also explored the relationship between macroeconomic conditions and banking stability in Indonesia, indicating that monetary policy variables particularly interest rates serve as key transmission channels affecting financial system resilience and adjustment dynamics (Hudaya & Firmansyah, 2023).

However, most existing studies on Indonesian banks rely on static panel regression models using annual or quarterly data, which limits their ability to capture dynamic interactions and short-run adjustment mechanisms among banking variables. Consequently, empirical evidence on the system-wide dynamic relationships between risk, capital, liquidity, efficiency, and macroeconomic policy in Indonesia remains relatively limited, particularly when using high-frequency banking statistics.

Given these limitations, there remains a need for empirical research that integrates prudential banking indicators with macroeconomic variables within a unified dynamic framework. Understanding the interactions between credit risk, capital adequacy, liquidity exposure, operational efficiency, and macroeconomic conditions is particularly important for emerging banking systems where financial intermediation remains highly bank-centered. By applying a Vector Error Correction Model (VECM) to monthly Indonesian banking data, this study seeks to provide a more comprehensive analysis of how banking stability evolves through both long-run equilibrium relationships and short-run adjustment mechanisms.

3. Methodology

3.1 Data Source and Sample Period

This study employs monthly secondary data obtained from the Indonesian Banking Statistics (SPI) published by the Financial Services Authority (Otoritas Jasa Keuangan, OJK). Macroeconomic variables, including the Bank Indonesia policy rate (BI Rate) and

inflation (measured using the Consumer Price Index, CPI), are sourced from Bank Indonesia and the Central Statistics Agency (Badan Pusat Statistik, BPS).

Monthly observations are used to capture short-run fluctuations and dynamic adjustment processes more effectively than quarterly or annual data, which may smooth cyclical movements and obscure early signals of financial vulnerability. The use of high-frequency data is particularly relevant in a VECM framework, as it allows for a more precise identification of short-run dynamics and adjustment speeds toward long-run equilibrium.

The dataset covers the period from January 2010 to December 2024, providing 180 observations suitable for time-series econometric analysis.

The variables included in the study represent key prudential banking indicators and macroeconomic conditions affecting the Indonesian banking system. Prudential indicators include credit risk measured by the non-performing loan ratio (NPL), capital adequacy (CAR), liquidity exposure proxied by the loan-to-asset ratio (LAR), operational efficiency measured by the cost-to-income ratio (CIR), and bank profitability proxied by return on assets (ROA). The macroeconomic variables include the BI Rate and inflation, reflecting monetary policy and price stability conditions.

3.2 Variable Definition and Measurement

This study employs several key variables, including bank risk, capital, liquidity, and profitability. Each variable is operationalized using well-established proxies in the banking and financial literature to ensure measurement validity and comparability. The definitions, proxies, and theoretical justifications of these variables are presented in Table 1.

Table 1. Variable Definition and Measurement

Variable	Description	Theoretical Link
Return on Assets (ROA)	Net income divided by total assets	Indicator of bank profitability and performance efficiency (Athanasoglou et al., 2008)
Non-performing Loan Ratio (NPL)	Non-performing loans divided by total loans	Proxy for credit risk reflecting asset quality deterioration and financial vulnerability (Gambacorta & Shin, 2018)
Capital Adequacy Ratio (CAR)	Capital divided by risk-weighted assets	Capital buffer ensuring solvency and loss-absorbing capacity (BIS, 2014)
Loan-to-Asset Ratio (LAR)	Total loans divided by total assets	Indicator of liquidity exposure and credit expansion intensity (Bonner & Eijffinger, 2016)
Cost-to-Income Ratio (CIR)	Operating expenses divided by operating income	Measure of operational efficiency and cost management performance (Dietrich & Wanzenried, 2011)
BI Rate	Central bank benchmark rate	Monetary policy instrument influencing funding costs and risk-taking behavior (Mishkin, 2014)
Inflation	Annual percentage change in consumer price index	Indicator of macroeconomic stability affecting purchasing power and credit risk (Dell'Ariccia et al., 2017)

All variables are tested for stationarity prior to estimation. Depending on the unit root test results, variables are transformed into first differences or maintained in levels as appropriate to ensure valid econometric inference.

3.3 Econometric Strategy

Given that banking indicators and macroeconomic variables often exhibit non-stationary behavior and dynamic interdependence, this study employs a Vector Error Correction Model (VECM) to analyze both long-run equilibrium relationships and short-run adjustment dynamics among the variables.

The VECM framework is particularly suitable when variables are cointegrated, implying that although individual series may be non-stationary, a stable long-run equilibrium relationship exists among them (Johansen, 1988; Johansen & Juselius, 1990). In this context, VECM enables the decomposition of dynamics into long-run equilibrium components and short-run adjustment mechanisms.

However, the unit root test results indicate a mixed order of integration across variables. To address this methodological consideration, the VECM analysis is complemented with the Autoregressive Distributed Lag (ARDL) approach, which is specifically designed to accommodate a combination of I(0) and I(1) variables (Pesaran et al., 2001). This combined strategy ensures that the empirical findings are robust to different integration properties.

The multivariate system approach allows the model to capture feedback effects among banking indicators, the transmission of macroeconomic shocks, and the speed of adjustment toward long-run equilibrium. Compared with static regression models, VECM provides a richer representation of financial system dynamics by jointly modeling multiple endogenous variables and their intertemporal interactions.

3.4 Unit Root Testing

Before estimating the VECM, the stationarity properties of the variables are examined using the Augmented Dickey–Fuller (ADF) unit root test.

The results indicate a mixed order of integration. Banking variables such as NPL, CAR, CIR, LAR, and ROA are found to be stationary at levels (I(0)), while macroeconomic variables, namely inflation and the BI policy rate, become stationary after first differencing (I(1)).

The presence of mixed integration orders implies that the Johansen cointegration framework should be interpreted with caution, as it is theoretically designed for variables integrated of the same order, typically I(1). Therefore, the VECM results in this study are treated as indicative rather than definitive evidence of long-run relationships. To address this limitation, the analysis is complemented by the ARDL bounds testing approach, which is explicitly designed to accommodate mixed I(0)/I(1) variables (Pesaran et al., 2001). The consistency of results across both approaches strengthens the robustness of the empirical findings.

3.5 Lag Order Selection

The optimal lag length is determined using multiple information criteria, namely the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Hannan–Quinn Criterion (HQC).

The results indicate that the AIC suggests a lag length of two, while both the BIC and HQC select a more parsimonious lag of one. In the presence of such discrepancies, the selection is guided by both statistical and economic considerations.

Given the high-frequency nature of monthly banking data and the persistence commonly observed in financial time series, a lag length of two is selected to adequately capture short-run dynamic adjustments and propagation effects.

The selected lag structure is further validated using the Lagrange Multiplier (LM) test for serial correlation, which indicates that the residuals are free from autocorrelation. This confirms the adequacy of the chosen lag length for subsequent VECM estimation.

3.6 Johansen Cointegration Test

Long-run equilibrium relationships among the variables are examined using the Johansen cointegration test, which employs both the Trace statistic and the Maximum Eigenvalue statistic to determine the number of cointegrating vectors.

The Johansen procedure tests the null hypothesis of no cointegration against the alternative of at least one cointegrating relationship. Evidence of cointegration supports the use of the Vector Error Correction Model (VECM), where deviations from long-run equilibrium are captured through an error correction mechanism.

3.7 VECM Formulation

Let the vector of endogenous variables be defined as:

$$Y_t = [NPL_t, CAR_t, LAR_t, CIR_t, BI\ Rate_t, Inflation_t]$$

where NPL_t denotes credit risk, CAR_t capital adequacy, LAR_t liquidity exposure, CIR_t operational efficiency, BI $Rate_t$ the monetary policy rate, and $Inflation_t$ the inflation rate at time t.

The Vector Error Correction Model (VECM) is specified as:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta Y_{t-i} + \delta X_t + \varepsilon_t$$

where:

- Δ denotes the first-difference operator;
- $\beta' Y_{t-1}$ represents the cointegrating relationship capturing long-run equilibrium among the endogenous variables;
- α is the adjustment coefficient matrix measuring the speed of adjustment toward equilibrium;
- Γ_i captures short-run dynamic interactions among the variables;
- X_t is a vector of exogenous variables included in the short-run dynamics;
- δ is the associated coefficient vector;
- ε_t is a vector of white-noise error terms.

In this study, profitability (ROA) is treated as an exogenous variable in the short-run dynamics, such that:

$$X_t = [ROA_t]$$

The treatment of ROA as weakly exogenous is supported empirically by the statistical insignificance of its error correction term in the VECM estimation, indicating that profitability does not adjust to deviations from the long-run equilibrium.

Operational efficiency (CIR) is included as an endogenous variable, as cost dynamics are expected to interact with credit risk, capital adequacy, and liquidity conditions within the banking system.

3.8 Deterministic Components

A restricted constant specification (Case 2) is employed, allowing for an intercept in the cointegrating relationship while excluding deterministic trends from the system (Johansen, 1988).

This specification permits a non-zero mean in the long-run equilibrium relationship while maintaining stationarity of the error correction term. At the same time, it allows for intercept adjustments in the short-run dynamics without introducing deterministic trends that may bias the cointegration analysis.

The choice of this deterministic specification is consistent with the characteristics of macro-financial data, where variables may fluctuate around a stable mean without exhibiting a deterministic trend.

3.9 Impulse Response Function (IRF) & Variance Decomposition (FEVD)

Shock transmission within the banking system is analyzed using Impulse Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVD).

The IRFs trace the dynamic responses of key variables namely ROA, CAR, NPL, LAR, and CIR to one standard deviation orthogonalized shocks based on Cholesky decomposition. This approach allows the identification of the direction, magnitude, and persistence of shock propagation across the system.

To ensure statistical reliability, 95% confidence intervals are constructed using bootstrap simulations (Hall's percentile method) with 1,000 replications. This enables the distinction between statistically significant and insignificant responses.

Complementing the IRF analysis, FEVD quantifies the relative contribution of each variable to the forecast error variance of others over time, thereby identifying the dominant sources of fluctuations within the system.

Together, these methods provide a comprehensive characterization of dynamic interactions and shock transmission mechanisms within the banking system, consistent with established multivariate time series approaches (Lütkepohl, 2005).

3.10 Diagnostic and Stability Testing

Diagnostic tests are conducted to assess the adequacy, robustness, and stability of the estimated VECM model. These include tests for serial correlation, heteroskedasticity, normality, and parameter stability. The results are summarized in Table 2.

Table 2. Diagnostic and Stability Testing

Test	Purpose	Reference
LM Serial Correlation	Tests absence of autocorrelation in residuals	(Breusch, 1978)
ARCH / White Test	Tests for heteroskedasticity	(Engle et al., 2008)
Jarque–Bera Normality	Tests distributional assumption of residuals	(Jarque & Bera, 1987)
AR Roots Modulus	Assesses dynamic stability of the system	(Lütkepohl, 2005)

The Lagrange Multiplier (LM) test for serial correlation fails to reject the null hypothesis across all lag orders ($p > 0.05$), suggesting that the residuals are free from autocorrelation. This indicates that the dynamic specification of the model is adequate.

The stability condition is assessed using the AR Roots test. All characteristic roots lie strictly within the unit circle, confirming that the VECM is dynamically stable and suitable for impulse response analysis.

The Jarque–Bera test rejects the null hypothesis of normality. However, this result is not uncommon in financial time series, which often exhibit non-Gaussian and heavy-tailed distributions (Cont, 2001). Importantly, non-normality does not invalidate cointegration-based inference or the consistency of parameter estimates in large samples.

The model is considered adequate if residuals are free from serial correlation and the system satisfies stability conditions.

4. Results/findings

4.1 Diagnostic and Stability Tests

To evaluate the adequacy of the estimated model, a series of diagnostic and stability tests are conducted. The results are summarized in Table 3.

Table 3. Residual Diagnostics and Stability Tests

Test	Statistic	df	p-value	Conclusion
LM Serial Correlation (Lag 1)	38.402	49	0.862	No autocorrelation
LM Serial Correlation (Lag 2)	51.147	49	0.389	No autocorrelation
LM Serial Correlation (Lag 3)	58.186	49	0.173	No autocorrelation
Jarque–Bera Normality (Joint)	39143.51	14	0.000	Residuals not normally distributed
Heteroskedasticity (Joint Chi-square)	1231.89	840	0.000	Heteroskedasticity present
AR Roots (Stability Test)	All roots ≤ 1	–	–	Model is dynamically stable

Source: Processed data from 2010–2024, computed using EViews 13.

The results of the Lagrange Multiplier (LM) test indicate that the null hypothesis of no serial correlation cannot be rejected at all lag orders ($p > 0.05$). This finding suggests that the residuals are free from autocorrelation and that the dynamic specification of the model is appropriate. In other words, the selected lag structure is sufficient to capture the underlying temporal dependencies among the variables.

However, the Jarque–Bera normality test rejects the null hypothesis of multivariate normality ($p < 0.01$), indicating that the residuals are not normally distributed. Similarly, the heteroskedasticity test reveals the presence of time-varying variance in the residuals ($p < 0.01$). These findings are consistent with the stylized facts of financial and macroeconomic time series, which typically exhibit non-Gaussian distributions and volatility clustering (Cont, 2001).

Importantly, the presence of non-normality and heteroskedasticity does not invalidate the estimation of the VECM or the inference of long-run relationships. Under large sample

conditions, the estimators remain consistent and the cointegration framework is robust to such deviations from classical assumptions.

Furthermore, the stability of the model is confirmed by the roots of the characteristic polynomial. The results show that all roots lie within or on the unit circle, with unit roots corresponding to the cointegration structure imposed by the VECM. This indicates that the system is dynamically stable and suitable for impulse response function (IRF) and forecast error variance decomposition (FEVD) analysis.

Overall, the diagnostic results suggest that the VECM is well specified, dynamically stable, and appropriate for analyzing both short-run dynamics and long-run equilibrium relationships within the banking system.

4.2 Unit Root and Cointegration Results

To ensure the validity of the time-series analysis, stationarity and long-run relationships among the variables are examined using the Augmented Dickey–Fuller (ADF) unit root test and the Johansen cointegration test.

Table 4. Unit Root Test Results (Augmented Dickey–Fuller Test)

No.	Variable	ADF p-value	Order of Integration	Interpretation
1	NPL	0.0317	I(0)	Stationary at level
2	CAR	0.0000	I(0)	Stationary at level
3	CIR	0.0037	I(0)	Stationary at level
4	LAR	0.0181	I(0)	Stationary at level
5	Inflation	0.0000	I(1)	Stationary after first difference
6	BI Rate	0.0000	I(1)	Stationary after first difference
7	ROA	0.0232	I(0)	Stationary at level

Source: Processed data from 2010–2024, computed using EViews 13.

The ADF test results presented in Table 4 indicate that most banking variables, including non-performing loans (NPL), capital adequacy ratio (CAR), cost-to-income ratio (CIR), loan-to-asset ratio (LAR), and return on assets (ROA), are stationary at levels, implying that they are integrated of order zero, I(0). In contrast, macroeconomic variables, namely inflation and the BI policy rate, are found to be non-stationary at levels but become stationary after first differencing, indicating that they are integrated of order one, I(1).

These findings reveal the presence of mixed integration orders among the variables, which has important implications for model specification. Specifically, the combination of I(0) and I(1) variables justifies the use of complementary econometric approaches, where the Vector Error Correction Model (VECM) is supported by the Autoregressive Distributed Lag (ARDL) framework to ensure robustness under mixed integration conditions.

To investigate the existence of long-run equilibrium relationships, the Johansen cointegration test is employed. The results indicate that the Trace statistic supports the presence of at least one cointegrating relationship among the variables, while the Maximum Eigenvalue statistic provides weaker evidence.

The Trace statistic is given greater emphasis, as it evaluates the joint hypothesis of multiple cointegrating vectors and is generally considered more robust in empirical applications (Lütkepohl, 2005). Therefore, the results provide evidence supporting the existence of a long-run equilibrium relationship among the variables.

To further strengthen this conclusion, the cointegration results are cross-validated using the ARDL bounds testing approach. The ARDL results confirm the presence of a long-run relationship, thereby reinforcing the robustness of the findings despite the mixed integration properties of the data.

Overall, the results provide strong evidence that the variables are dynamically linked in the long run, justifying the application of the VECM framework to capture both equilibrium relationships and short-run adjustment dynamics within the banking system.

4.3 Johansen Cointegration Test Results

The Johansen cointegration test results presented in Table 5 provide evidence on the existence of long-run equilibrium relationships among the variables.

Table 5. Johansen Cointegration Test Results

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	p-value	Max-Eigen Statistic	5% Critical Value	p-value
None	0.2141	137.7639	125.6154	0.0073*	42.1661	46.2314	0.1280
At most 1	0.1783	95.5978	95.7537	0.0513	34.3608	40.0776	0.1914
At most 2	0.1353	61.2370	69.8189	0.1993	25.4398	33.8769	0.3559
At most 3	0.1155	35.7971	47.8561	0.4067	21.4771	27.5843	0.2484
At most 4	0.0443	14.3200	29.7971	0.8222	7.9295	21.1316	0.9080
At most 5	0.0291	6.3906	15.4947	0.6494	5.1617	14.2646	0.7213
At most 6	0.0070	1.2289	3.8415	0.2676	1.2289	3.8415	0.2676

Note:
* indicates rejection of the null hypothesis at the 5% significance level. The Trace test indicates one cointegrating relationship, while the Maximum Eigenvalue test does not provide supporting evidence.
Source: Processed data from 2010–2024, computed using EViews 13.

The Trace statistic indicates the presence of at least one cointegrating relationship at the 5% significance level, as the null hypothesis of no cointegration is rejected ($p = 0.0073$). This suggests that the variables share a stable long-run equilibrium relationship despite their potential non-stationary behavior.

However, the Maximum Eigenvalue statistic does not confirm this finding, as it fails to reject the null hypothesis of no cointegration ($p = 0.1280$). This discrepancy between the Trace and Max-Eigenvalue statistics is not uncommon in empirical applications.

The Trace statistic is given greater emphasis because it evaluates the joint hypothesis of multiple cointegrating vectors and is generally considered more robust in small and medium samples (Lütkepohl, 2005). Therefore, the results indicate the presence of one cointegrating relationship among the variables.

To further strengthen this conclusion, the cointegration findings are cross-validated using the ARDL bounds testing approach, which also confirms the presence of a long-run relationship. This complementary evidence reinforces the robustness of the long-run equilibrium relationship, particularly in the presence of mixed integration orders among the variables.

Overall, the results indicate that the banking and macroeconomic variables are linked through a stable long-run equilibrium, justifying the application of the VECM framework to capture both long-run relationships and short-run adjustment dynamics.

4.4 ARDL Results (Robustness Analysis)

To address the mixed integration properties identified in the unit root tests, the Autoregressive Distributed Lag (ARDL) model is employed as a robustness check. The ARDL framework is particularly appropriate in the presence of both I(0) and I(1) variables, as it allows consistent estimation without requiring uniform integration orders (Pesaran et al., 2001). The estimation results are presented in Table 6, while the model summary is reported in Table 7.

Table 6. ARDL Estimation Results (Dependent Variable: ROA)

Variable	Coefficient	Std. Error	t-Statistic	p-value
ROA(-1)	0.8209***	0.0497	16.5043	0.0000
NPL	-0.0982**	0.0462	-2.1256	0.0350
CAR	-0.0024	0.0040	-0.5883	0.5571
LAR	-0.0256***	0.0074	-3.4508	0.0007
LAR(-1)	0.0179**	0.0076	2.3607	0.0194
CIR	0.0067***	0.0019	3.4961	0.0006
CIR(-1)	-0.0046**	0.0019	-2.3444	0.0202
BI Rate	-0.0245	0.0179	-1.3695	0.1727
Inflation	0.0049	0.0116	0.4230	0.6728
Constant	0.8481***	0.2829	2.9984	0.0031

*** p < 0.01, ** p < 0.05, * p < 0.10

The selected model is ARDL(1,0,0,1,1,0,0) based on the Akaike Information Criterion (AIC).

Source: Processed data from 2010–2024, computed using EViews 13.

After presenting the estimation results, the ARDL model can be expressed as follows:

$$ROA_t = \alpha + \beta_1 ROA_{t-1} + \beta_2 NPL_t + \beta_3 CAR_t + \beta_4 LAR_t + \beta_5 LAR_{t-1} + \beta_6 CIR_t + \beta_7 CIR_{t-1} + \beta_8 BI\ RATE_t + \beta_9 INFLATION_t + \varepsilon_t$$

Substituting the estimated coefficients, the model becomes:

$$ROA_t = 0.8481 + 0.8209 ROA_{t-1} - 0.0982 NPL_t - 0.0024 CAR_t - 0.0256 LAR_t + 0.0179 LAR_{t-1} + 0.0067 CIR_t - 0.0046 CIR_{t-1} - 0.0245 BI\ RATE_t + 0.0049 INFLATION_t + \varepsilon_t$$

The estimation results indicate that the lagged dependent variable, ROA_{t-1}, is positive and highly significant ($p < 0.01$), confirming strong persistence in bank profitability. This suggests that profitability adjusts gradually over time and is influenced by its past performance, which is consistent with empirical evidence in the banking literature (Athanasoglou et al., 2008).

Credit risk, measured by the non-performing loan ratio (NPL), has a negative and statistically significant effect on profitability ($p < 0.05$). This finding implies that an increase in non-performing loans reduces bank profitability due to higher provisioning costs and deterioration in asset quality, in line with theoretical expectations (Gambacorta & Shin, 2018).

Liquidity, proxied by the loan-to-asset ratio (LAR), exhibits a significant negative contemporaneous effect ($p < 0.01$), while its lagged value shows a positive and significant impact ($p < 0.05$). This indicates a dynamic adjustment process, where aggressive lending may initially reduce profitability due to increased risk exposure but contributes positively over

time as loans generate returns. This result supports the risk–return trade-off in banking activities (Bonner & Eijffinger, 2016).

Operational efficiency, measured by the cost-to-income ratio (CIR), shows a positive and significant contemporaneous effect ($p < 0.01$), but a negative and significant lagged effect ($p < 0.05$). This suggests that cost management influences profitability in an intertemporal manner, reflecting immediate efficiency gains followed by adjustment costs, consistent with previous findings (Dietrich & Wanzenried, 2011).

In contrast, capital adequacy (CAR), the BI policy rate, and inflation do not show statistically significant effects on profitability in the short run. This may indicate that their influence operates through longer-term structural channels or indirect transmission mechanisms, particularly in the context of monetary policy and macro-financial stability (Dell'Ariccia et al., 2017; Mishkin, 2014).

Table 7. Model Summary

Statistic	Value
R-squared	0.8276
Adjusted R-squared	0.8184
F-statistic	90.1336 (p = 0.0000)
Durbin–Watson	2.1987
AIC	-0.6625

Source: Processed data from 2010–2024, computed using EViews 13.

From a model evaluation perspective, the ARDL specification demonstrates strong explanatory power, with an adjusted R-squared of 0.818, indicating that approximately 81.8% of the variation in profitability is explained by the model. The F-statistic is highly significant ($p < 0.01$), confirming the joint significance of the explanatory variables. Furthermore, the Durbin–Watson statistic (2.1987) suggests no evidence of residual autocorrelation, indicating that the model is well specified.

Overall, the ARDL results provide robust support for the findings obtained from the VECM framework. The consistency in the direction and significance of key variables particularly NPL, LAR, and CIR—across different econometric approaches strengthens the validity and reliability of the empirical results despite the presence of mixed integration orders.

4.5 Long-Run and Short-Run Dynamics: VECM Results

The long-run equilibrium relationship among the variables is presented in Table 8, which reports the normalized cointegrating equation based on the VECM estimation.

Table 8. Long-Run Cointegrating Equation (Normalized on ROA)

Variable	Coefficient	Std. Error	t-Statistic
ROA(-1)	1.0000	–	–
NPL(-1)	0.7747***	0.1678	4.6178
CAR(-1)	-0.0546**	0.0192	-2.8482
LAR(-1)	0.0521***	0.0137	3.8095
CIR(-1)	-0.0155***	0.0039	-3.9920
BI Rate(-1)	0.2709***	0.0732	3.7010

Inflation(-1)	-0.2815***	0.0507	-5.5485
Constant	-3.4314	–	–

Notes: *** p < 0.01, ** p < 0.05

Source: Processed data from 2010–2024, computed using EViews 13.

The cointegrating equation confirms the existence of a long-run equilibrium relationship among banking indicators and macroeconomic variables. Credit risk (NPL) shows a positive and significant long-run relationship with profitability, which may reflect risk-based pricing behavior, where banks compensate higher risk exposure with higher returns. This finding is consistent with studies highlighting the role of risk-taking in shaping bank performance (Claessens et al., 2018; Gambacorta & Shin, 2018).

Capital adequacy (CAR) exhibits a negative and significant effect, reflecting a trade-off between safety and profitability. Banks maintaining higher capital buffers tend to experience lower leverage and reduced returns on assets, consistent with prior empirical evidence (Berger, 2017; Demirgüç-Kunt & Huizinga, 1999).

Liquidity (LAR) positively affects profitability, suggesting that increased lending activity enhances long-run returns. This supports prior evidence that loan expansion remains a primary source of bank income (Bonner & Eijffinger, 2016; Borio et al., 2017).

Operational efficiency (CIR) has a negative effect, confirming that higher operational costs reduce profitability. This result aligns with the efficiency hypothesis in banking, where cost management is a key determinant of performance (Dietrich & Wanzenried, 2011; Maudos & Fernández de Guevara, 2004).

The BI policy rate exhibits a positive long-run relationship with profitability, indicating that higher interest rates may widen net interest margins (Mishkin, 2014; English et al., 2018). Conversely, inflation has a negative impact, suggesting that macroeconomic instability erodes real returns and increases uncertainty (Boyd et al., 2001; Dell'Ariccia et al., 2017).

The speed of adjustment toward long-run equilibrium is captured by the error correction term (ECT), as reported in Table 9.

Table 9. Error Correction Term (ECT)

Dependent Variable	ECT Coefficient	Std. Error	t-Statistic	Interpretation
D(ROA)	-0.0141	0.0407	-0.3469	Not significant
D(NPL)	-0.0870**	0.0314	-2.7760	Significant adjustment
D(CAR)	-0.2978	0.4413	-0.6750	Not significant
D(LAR)	0.8354	0.6260	1.3344	Not significant

Source: Processed data from 2010–2024, computed using EViews 13.

The error correction results indicate that only the NPL equation has a negative and statistically significant adjustment coefficient, implying that credit risk plays a central role in restoring equilibrium within the banking system. This suggests that deviations from the long-run relationship are primarily corrected through adjustments in asset quality rather than profitability or other banking indicators.

The insignificant adjustment coefficient in the ROA equation suggests that profitability responds more slowly to disequilibrium conditions. This is consistent with financial intermediation theory, where profit adjustments are often subject to institutional rigidities and delayed transmission mechanisms (B. H. Baltagi, 2021; Lütkepohl, 2005). In particular, bank

profitability is typically influenced by accumulated balance sheet conditions and managerial decisions, which adjust gradually over time rather than instantaneously.

From an econometric perspective, the insignificance of the error correction term in the ROA equation indicates that profitability does not participate in the long-run adjustment process. This provides empirical support for treating ROA as weakly exogenous within the VECM framework. While a formal likelihood ratio (LR) test can be implemented, the use of the adjustment coefficient significance is widely accepted in applied VECM studies (Enders, 2010; Johansen, 1995).

Overall, these results confirm that credit risk serves as the primary adjustment channel in restoring long-run equilibrium, while profitability acts as a dependent outcome that reflects the cumulative effects of banking risk, liquidity, and efficiency conditions.

The short-run dynamics of bank profitability are summarized in Table 10, focusing on the ROA equation.

Table 10. Selected Short-Run Dynamics (D(ROA) Equation)

Variable	Coefficient	t-Statistic	Significance
D(ROA(-1))	-0.1842	-2.0934	**
D(NPL(-1))	-0.4252	-4.2385	***
D(NPL(-2))	0.0462	0.4239	Not significant
D(LAR(-1))	-0.0082	-1.0124	Not significant
D(CIR(-1))	0.0029	1.3692	Not significant
D(BI Rate(-1))	-0.0113	-0.1612	Not significant
D(Inflation(-1))	0.0097	0.3779	Not significant

Notes: *** $p < 0.01$, ** $p < 0.05$.

Source: Processed data from 2010–2024, computed using EViews 13.

The short-run results confirm that changes in credit risk (NPL) have a strong and negative effect on profitability, indicating that increases in non-performing loans immediately reduce bank earnings. This finding is consistent with empirical evidence highlighting the short-run burden of credit deterioration on bank performance (Louzis et al., 2012).

The persistence of profitability, reflected in significant lagged ROA terms, suggests dynamic adjustment behavior, which is common in banking systems characterized by inertia and gradual adjustment processes (Athanasoglou et al., 2008).

Macroeconomic variables, including interest rates and inflation, do not exhibit significant short-run effects, indicating that their influence is more pronounced in the long run. This supports the view that monetary policy transmission to bank performance occurs with lags (Bernanke & Gertler, 1995).

4.7 Impulse Response Analysis

The impulse response functions with 95% bootstrapped confidence intervals are presented in Figure 1.

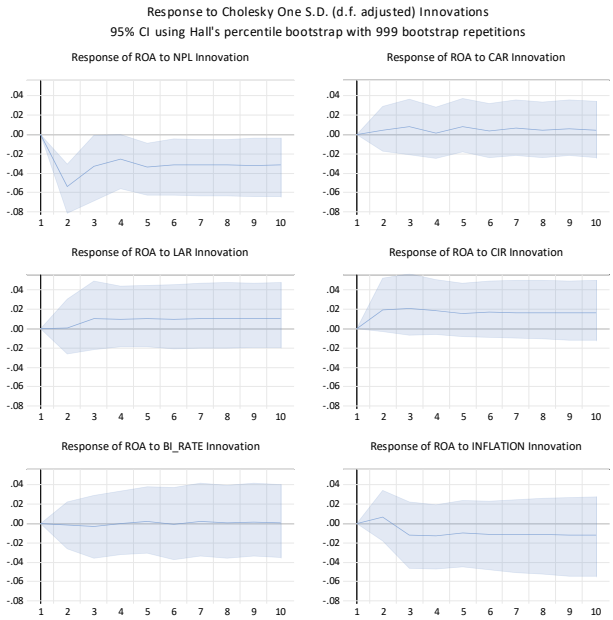

Figure 1. Impulse Response Functions of ROA to shocks in banking and macroeconomic variables with 95% bootstrapped confidence intervals

Figure 1 presents the impulse response functions (IRFs) of bank profitability (ROA) to one standard deviation shocks in banking and macroeconomic variables, accompanied by 95% bootstrapped confidence intervals based on Hall's percentile method. The shaded areas represent the confidence intervals, and responses are considered statistically significant when these bands do not include the zero line.

Overall, the impulse responses converge toward zero within approximately periods 6–8, indicating that shocks have transitory effects and that the system returns to its long-run equilibrium. This pattern confirms the dynamic stability of the estimated model, consistent with the theoretical framework of vector autoregressive systems (Lütkepohl, 2005).

A shock to credit risk (NPL) generates an immediate negative response in ROA, reaching its largest decline around period 2. The response is statistically significant during the early periods (approximately periods 1–3), as the confidence bands remain below zero. This indicates that deterioration in asset quality has a strong short-run impact on profitability. The magnitude of the response gradually diminishes over time, suggesting that banks adjust their risk exposure and absorb initial losses. This finding is consistent with the theoretical and empirical literature emphasizing the adverse effect of non-performing loans on bank profitability (Gambacorta & Shin, 2018; Makri et al., 2014). Similar evidence from the Indonesian context indicates that higher credit risk significantly reduces bank performance (Martini, 2022).

The response of ROA to capital adequacy (CAR) shocks is relatively small across all horizons and remains statistically insignificant, as the confidence intervals consistently include zero. This suggests that capital buffers do not exert a direct short-run effect on profitability but instead play a stabilizing role in maintaining financial resilience. This finding

aligns with the prudential regulation perspective that capital adequacy enhances stability rather than immediate profitability (Gambacorta & Shin, 2018).

Liquidity shocks (LAR) produce a positive response in ROA starting from period 2, with the effect peaking around periods 3–4. However, the response is not consistently statistically significant, as the confidence bands overlap with zero in several periods. This indicates that while increased lending activity may contribute to profitability, the effect is gradual and subject to uncertainty. This pattern reflects the risk–return trade-off in banking, where credit expansion can generate income but also introduces additional risk (Bonner & Eijffinger, 2016; Borio et al., 2017).

Operational efficiency (CIR) shows a positive and statistically significant response of ROA in the early periods (approximately periods 1–2), after which the effect declines and becomes statistically insignificant. This suggests that improvements in cost efficiency have an immediate but short-lived impact on profitability. This finding is consistent with the efficiency hypothesis, which posits that cost management enhances bank performance, particularly in the short run (Dietrich & Wanzenried, 2011). Empirical evidence from Indonesian banking studies highlights the importance of operational efficiency as a key determinant of profitability (Mawardi, 2017; Wetapo et al., 2023).

Shocks to macroeconomic variables, including BI Rate and Inflation, generate relatively small responses in ROA across all periods. The confidence intervals largely include zero, indicating that these effects are not statistically significant in the short run.

This suggests that monetary policy and inflation do not directly influence bank profitability but operate through indirect transmission channels and longer-term mechanisms (Dell'Ariccia et al., 2017; Mishkin, 2014). In the Indonesian context, monetary policy transmission to the banking sector is primarily mediated through credit channels and financial intermediation processes (Warjiyo, 2014).

Overall, the impulse response analysis indicates that internal banking factors particularly credit risk and operational efficiency play a more dominant role in shaping short-run profitability dynamics than macroeconomic variables. The temporary nature of the responses further confirms that the banking system exhibits a stable adjustment path and efficiently absorbs shocks over time.

4.8 Forecast Error Variance Decomposition

To complement the impulse response analysis, the forecast error variance decomposition (FEVD) is used to quantify the relative contribution of each variable in explaining variations in bank profitability. This method provides additional insights into the importance of internal banking factors and macroeconomic variables across different time horizons. The results are presented in Table 11.

Table 11. Forecast Error Variance Decomposition (FEVD) of ROA (%)

Period	S.E.	ROA (%)	NPL (%)	CAR (%)	LAR (%)	CIR (%)	BI Rate (%)	Inflation (%)
1	0.1692	100.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.2254	93.3849	5.7478	0.0324	0.0005	0.7476	0.0051	0.0817
3	0.2582	92.2520	5.9799	0.1241	0.1513	1.1953	0.0198	0.2777

4	0.2906	92.3860	5.4968	0.1008	0.2329	1.3626	0.0156	0.4054
5	0.3207	92.1546	5.6271	0.1448	0.2889	1.3467	0.0185	0.4194
6	0.3476	92.0639	5.6195	0.1345	0.3262	1.3847	0.0160	0.4553
7	0.3728	91.9788	5.6039	0.1487	0.3597	1.4013	0.0172	0.4904
8	0.3965	91.9357	5.5896	0.1431	0.3836	1.4149	0.0154	0.5177
9	0.4189	91.8851	5.5874	0.1484	0.4046	1.4162	0.0155	0.5428
10	0.4402	91.8624	5.5703	0.1455	0.4212	1.4209	0.0144	0.5653

Note: The table reports the percentage contribution of each variable to the forecast error variance of ROA over a 10-period horizon. The decomposition is based on Cholesky one standard deviation innovations with the ordering: ROA, NPL, CAR, LAR, CIR, BI Rate, and Inflation.
Source: Processed data from 2010–2024, computed using EViews 13.

Table 11 presents the forecast error variance decomposition (FEVD) of bank profitability (ROA) over a 10-period horizon, providing insights into the relative contribution of each variable in explaining fluctuations in profitability.

In the short run (period 1), variations in ROA are entirely explained by its own shocks (100%), indicating a high degree of persistence in bank profitability. This dominance gradually declines over time, reaching approximately 91.86% in period 10. Despite this decline, ROA remains the primary source of its own variability, suggesting strong inertia and gradual adjustment dynamics. This finding is consistent with the empirical evidence of profitability persistence in banking systems, as documented by Athanasoglou et al. (2008), who highlight the role of internal adjustment processes and structural rigidities in shaping bank performance.

Among the explanatory variables, credit risk (NPL) emerges as the most influential determinant after ROA itself. Its contribution increases from 5.75% in period 2 to approximately 5.57% in period 10, indicating a relatively stable and persistent effect over time. This result confirms that asset quality plays a central role in driving profitability dynamics. The importance of credit risk is consistent with theoretical and empirical studies showing that higher non-performing loans increase provisioning costs and reduce bank earnings (Gambacorta & Shin, 2018; Makri et al., 2014). In the Indonesian context, empirical evidence consistently shows that credit risk is a dominant determinant of bank profitability (Martini, 2022; Nuhadilah & Laila, 2021).

Operational efficiency (CIR) exhibits a gradually increasing contribution, rising from 0.75% in period 2 to approximately 1.42% in period 10. This pattern suggests that cost efficiency becomes more relevant in explaining profitability variations over the medium to long term. The increasing contribution of CIR highlights the importance of internal cost management in sustaining bank performance, in line with the efficiency hypothesis (Dietrich & Wanzenried, 2011). This is further supported by empirical evidence from Indonesian banking studies, which indicates that inefficiencies in operational costs significantly reduce profitability (Mawardi, 2017; Wetapo et al., 2023).

Liquidity (LAR) contributes modestly but shows a clear upward trend, increasing from near zero in the early periods to approximately 0.42% in period 10. This indicates that lending activity has a delayed but growing influence on profitability dynamics. The relatively small magnitude suggests that while credit expansion contributes to income generation, its impact is gradual and subject to risk considerations. This finding aligns with the risk–return

trade-off in banking activities, where increased lending may enhance profitability over time but also introduces higher risk exposure (Bonner & Eijffinger, 2016; Borio et al., 2017).

In contrast, capital adequacy (CAR) exhibits a minimal contribution throughout the forecast horizon, remaining below 0.15% even in later periods. This suggests that capital buffers do not directly influence short-run profitability fluctuations but instead play a stabilizing role within the banking system. This finding is consistent with the prudential perspective that capital adequacy primarily enhances resilience rather than short-term performance (Gambacorta & Shin, 2018). Empirical evidence from Indonesian studies also emphasizes the role of capital in maintaining financial stability (Andriansyah et al., 2025; Margaretha & Letty, 2017).

Macroeconomic variables, including the BI policy rate and inflation, contribute negligibly to the variance of ROA. The contribution of BI Rate remains below 0.02% across all periods, while Inflation increases slightly but remains below 0.57% in period 10. These findings indicate that macroeconomic shocks have limited direct influence on short-to medium-term profitability dynamics. This result supports the view that monetary policy transmission to bank performance operates indirectly and with lags (Dell'Ariccia et al., 2017; Mishkin, 2014). In the Indonesian context, empirical evidence suggests that macroeconomic effects on banking performance are transmitted through broader financial system channels rather than through immediate direct impacts (Hudaya & Firmansyah, 2023; Warjiyo, 2014).

Overall, the FEVD results confirm that internal banking factors particularly credit risk and operational efficiency play a more dominant role in explaining profitability dynamics compared to external macroeconomic variables. The persistence of ROA and the relatively small contribution of other variables further emphasize the importance of bank-specific characteristics in shaping profitability outcomes. These findings are consistent with the impulse response analysis, which also indicates that profitability responds more strongly to internal banking shocks than to macroeconomic disturbances.

5. Discussions

5.1 Discussion of Empirical Findings

This study examines the dynamic interactions between banking prudential indicators, profitability, and macroeconomic variables in Indonesia using a combination of Vector Error Correction Model (VECM) and Autoregressive Distributed Lag (ARDL) approaches. The findings are interpreted by distinguishing between short-run dynamics and long-run equilibrium relationships to provide a clearer understanding of banking system behavior.

Given the presence of mixed integration orders identified in the unit root tests, the ARDL model is employed as a robustness approach alongside the VECM specification. The ARDL framework is well suited for situations involving mixed integration orders, as it allows for consistent estimation under such conditions (Pesaran et al., 2001). The consistency of results across both approaches enhances the robustness and reliability of the findings.

Credit Risk as the Primary Driver

Credit risk (NPL) emerges as the most influential determinant of bank profitability. In the short run, the ARDL results and impulse response analysis indicate that increases in NPL immediately reduce profitability, reflecting the direct impact of deteriorating asset quality

on bank performance. The variance decomposition results further confirm that NPL provides the largest contribution among explanatory variables in explaining short- to medium-term fluctuations in ROA.

In the long run, the VECM results suggest that credit risk remains a key determinant of equilibrium dynamics within the banking system. Although the error correction term in the ROA equation is not statistically significant, indicating that profitability does not adjust directly toward long-run equilibrium, the adjustment process appears to be driven by changes in other variables, particularly credit risk.

This finding supports the argument that asset quality is a key determinant of bank performance (Athanasoglou et al., 2008; Gambacorta & Shin, 2018). In the Indonesian context, empirical evidence also shows that non-performing loans represent a dominant factor influencing bank profitability (Andriansyah et al., 2025; Margaretha & Letty, 2017; Widarjono, 2012).

Liquidity and Dynamic Lending Effects

Liquidity (LAR) exhibits both short-run and long-run effects on profitability. In the short run, the results indicate that increases in lending may initially reduce profitability, as reflected in the impulse response analysis, due to higher risk exposure. However, over time, profitability gradually recovers, indicating a dynamic adjustment process.

In the long run, liquidity contributes to equilibrium relationships by supporting income generation through lending activities. This reflects the risk–return trade-off inherent in banking operations.

This finding supports the argument that lending activities affect profitability differently across time horizons, reflecting dynamic adjustments in banking operations (Bonner & Eijffinger, 2016; Dendawijaya, 2009; Sudiyatno & Suroso, 2010).

Operational Efficiency and Cost Dynamics

Operational efficiency (CIR) also demonstrates both short-run and long-run effects. In the short run, the ARDL and IRF results indicate that cost adjustments may have temporary effects on profitability. In the long run, however, higher operational costs are associated with lower profitability, reflecting the importance of cost efficiency in sustaining bank performance.

This finding is consistent with the efficiency hypothesis, which highlights the role of cost management in enhancing bank performance (Dietrich & Wanzenried, 2011). In the Indonesian context, empirical studies also show that inefficiencies in operational costs significantly reduce bank profitability (Andriansyah et al., 2025; Junaidi, 2021; Mawardi, 2017).

Capital Adequacy and Stability Trade-off

Capital adequacy (CAR) does not show a statistically significant effect on profitability in the short run, as indicated by the ARDL results. This suggests that capital buffers are not directly linked to short-term performance.

In the long run, CAR functions primarily as a stabilizing mechanism rather than a direct driver of profitability. This finding aligns with the prudential framework and is supported by

empirical evidence emphasizing the role of capital in maintaining financial stability (Margaretha & Letty, 2017; Settlements, 2011; Yuliani et al., 2023).

Macroeconomic Variables and Transmission Mechanism

Macroeconomic variables, including the BI policy rate and inflation, exhibit relatively weak and statistically insignificant effects on profitability in the short run. The impulse response and variance decomposition results further confirm their limited contribution to profitability fluctuations.

In the long run, macroeconomic variables may influence banking performance indirectly through broader economic conditions, although this relationship is not strongly captured in the short-run dynamics.

This finding supports the argument that monetary policy transmission operates with time lags and does not immediately affect banking performance (Dell'Ariccia et al., 2017; Mishkin, 2014). In the Indonesian context, empirical evidence further indicates that macroeconomic effects are transmitted indirectly through financial system conditions (Boediono, 2001; Warjiyo, 2014).

5.2 Interpretation of Cointegration Evidence

The Johansen cointegration test results indicate a discrepancy between the Trace statistic and the Maximum Eigenvalue statistic. While the Trace test suggests the presence of a long-run relationship, the Max-Eigenvalue test does not fully confirm this finding. Therefore, the evidence of cointegration should be interpreted with caution.

To address this limitation, the study employs ARDL estimation, which is better suited for mixed integration orders. The consistency of findings across both approaches enhances confidence in the existence of long-run relationships (Lütkepohl, 2005).

5.3 Role of Profitability within the System

The results indicate that profitability (ROA) does not act as the primary adjustment variable in restoring long-run equilibrium. In the short run, profitability responds to shocks in other banking indicators, while in the long run, it reflects the cumulative effects of credit risk, liquidity, and efficiency conditions.

This suggests that profitability should be interpreted as an outcome variable rather than a driving force within the system. Similar conclusions are found in Indonesian banking studies, which emphasize the role of internal performance factors in determining profitability.

5.4 Policy Implications

The findings of this study provide several important policy implications. In the short run, managing credit risk is crucial to prevent immediate declines in profitability. In the long run, strengthening risk management frameworks and maintaining asset quality are essential for sustaining banking stability.

Improving operational efficiency is also critical, as cost management affects both short-run performance and long-run profitability. In addition, lending policies should be carefully managed to balance risk and return over time.

Finally, the limited short-run impact of macroeconomic variables suggests that policymakers need to enhance monetary transmission mechanisms to ensure that macroeconomic policies effectively influence banking sector performance.

6. Conclusions

This study examines the dynamic interactions between banking prudential indicators, profitability, and macroeconomic variables in Indonesia by employing a combined Vector Error Correction Model (VECM) and Autoregressive Distributed Lag (ARDL) framework. By integrating these approaches, the study is able to capture both long-run equilibrium relationships and short-run adjustment dynamics within the banking system, while also addressing the presence of mixed integration orders identified in the unit root tests.

The empirical findings consistently demonstrate that internal banking factors play a more dominant role than macroeconomic variables in determining bank profitability. In particular, credit risk, as measured by the non-performing loan ratio (NPL), emerges as the most influential determinant. The results show that increases in NPL significantly reduce profitability, a finding that is supported across ARDL estimation, impulse response analysis, and variance decomposition. This underscores the critical importance of asset quality in shaping bank performance and highlights the central role of credit risk as a key transmission mechanism within the banking system.

Liquidity and operational efficiency are also found to influence profitability, although their effects exhibit dynamic and time-varying characteristics. Liquidity, proxied by the loan-to-asset ratio (LAR), reflects a trade-off between risk and return, where lending expansion may initially reduce profitability but contributes positively over time. Similarly, operational efficiency, as measured by the cost-to-income ratio (CIR), plays an important role in determining performance, indicating that effective cost management remains essential for sustaining profitability. In contrast, capital adequacy (CAR) does not show a significant direct effect on profitability, suggesting that its primary function lies in enhancing financial stability rather than driving short-run performance.

The analysis further reveals that macroeconomic variables, including the BI policy rate and inflation, have relatively weak and statistically insignificant effects on profitability in the short run. This suggests that the transmission of macroeconomic shocks to the banking sector operates through indirect and lagged mechanisms, with internal bank conditions exerting a more immediate influence on performance outcomes. In addition, the error correction mechanism indicates that profitability does not act as the primary adjustment variable in restoring long-run equilibrium, as reflected by the insignificant adjustment coefficient in the ROA equation. Instead, the adjustment process appears to be driven by changes in other banking indicators, particularly credit risk.

From a methodological perspective, the study contributes by addressing the issue of mixed integration orders through the use of the ARDL model as a robustness approach alongside the VECM specification. While the Johansen cointegration test provides partial evidence of a long-run relationship, the divergence between the Trace and Maximum Eigenvalue statistics suggests that the results should be interpreted with caution. Nevertheless, the consistency of findings across different econometric approaches strengthens the robustness and credibility of the conclusions.

Overall, the findings suggest that bank profitability in Indonesia is primarily driven by internal risk and efficiency factors rather than external macroeconomic conditions, and that adjustments within the banking system are largely facilitated through changes in credit risk rather than profitability itself. These results imply that strengthening credit risk management, improving operational efficiency, and maintaining prudent lending practices are essential for sustaining bank performance and ensuring financial stability. At the same time, the limited short-run impact of macroeconomic variables indicates the need for policymakers to enhance the effectiveness of monetary transmission mechanisms within the banking sector.

Despite its contributions, this study is subject to several limitations. The use of aggregate banking data may obscure heterogeneity across individual banks, and the analysis is limited to a specific set of macroeconomic variables. Future research may extend this study by employing bank-level data, incorporating additional macroeconomic indicators, or exploring nonlinear modeling approaches to better capture structural changes in banking dynamics.

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