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THE IMPACT OF MACROECONOMIC SHOCKS ON CREDIT RISK IN INDONESIAN BANKING USING MACHINE LEARNING

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Abstract. This study analyzes how multivariate macroeconomic shocks transmit to credit risk in Indonesia's banking sector using a hybrid framework that combines a factor augmented vector autoregression with machine learning techniques. In contrast to conventional stress testing approaches that rely on linear assumptions, the model extracts latent macro financial factors through Principal Component Analysis and forecasts non performing loans using Elastic Net regression in order to address multicollinearity and enhance predictive stability across different phases of the business cycle. The empirical analysis employs monthly data covering the period from January 2010 to December 2024. Principal Component Analysis reduces the dimensionality of the macroeconomic dataset to six components that collectively explain 90.99 percent of total variance. The Elastic Net model is optimally tuned with an alpha value of 0.0668 and an L1 ratio of 0.1, placing greater emphasis on the ridge penalty to improve coefficient stability and out of sample reliability. The results indicate strong predictive performance, with an R squared of 61.91 percent and a root mean squared error of 0.0692. Liquidity related indicators, particularly money supply and loan growth, consistently emerge as the most influential determinants of non performing loans and exhibit a stable negative relationship throughout the sample period. A key empirical contribution of this study is the identification of parameter instability, as the BI Rate, exchange rate, and Industrial Production Index display reversals in their estimated effects when comparing the pre pandemic period with the full sample. Most notably, the BI Rate shifts from a positive to a negative association with non performing loans, providing empirical support for the Lucas Critique. This structural change is plausibly linked to regulatory forbearance under POJK 11/2020, which weakened the conventional transmission mechanism from higher interest rates to rising credit risk. Overall, the findings suggest that under conditions of extreme macroeconomic stress, policy interventions can fundamentally alter structural relationships and reduce the reliability of traditional linear forecasting models. The proposed framework therefore offers a robust alternative for regulatory stress testing by explicitly accommodating parameter instability and policy induced shifts in banking sector credit risk.

Keywords: *Credit Risk; Elastic Net; Sign Reversal; Lucas Critique; Liquidity; Indonesian Banking.*

I. INTRODUCTION

As a developing, bank-based economy, Indonesia is structurally exposed to macroeconomic uncertainty that can transmit rapidly into banking sector vulnerabilities. Indonesian banks therefore need to remain prepared for both external and domestic sources of uncertainty. External uncertainty has recently been shaped by geopolitical tensions in the Middle East and Eastern Europe, persistent trade frictions, and episodes of domestic political tension in several countries. Evidence from the World Uncertainty Index suggests that global uncertainty increased markedly during October 2024 to August 2025 (Ahir et al., 2025), as illustrated below.

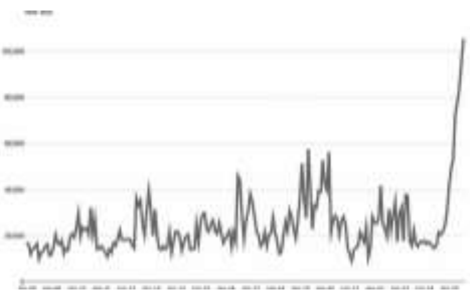

Figure 1. World Uncertainty Index
Source: World Uncertainty Index

Domestically, banks must also remain resilient to political and policy-related developments. At the end of August 2025, political escalation was accompanied by an adjustment in the government ministry. While such developments may generate short-term uncertainty, market confidence in the domestic economy remained relatively strong, as reflected in the Jakarta Composite Index (JCI), which recorded a 13% year-to-date increase with September 26, 2025 as the cut-off date for this study (IDX Composite Price, Real-Time Quote & News, 2025).

Figure 2. Jakarta Composite Index 2025 year to date
Source: Google Finance

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Indonesia's historical experience demonstrates the potential severity of macro-financial shocks for banking stability. During the 1997–1998 Asian Financial Crisis, macroeconomic stress evolved into a systemic banking disruption and a broader multidimensional crisis. The episode was catalyzed by Thailand's change in exchange rate regime amid foreign reserve shortages, which intensified uncertainty across ASEAN and triggered a shift of investor assets toward safer havens. Indonesia's banking system was severely affected, with more than 100 national banks closing operations and failing to perform their intermediation function. A key contributor was moral hazard and the accumulation of substantial foreign-currency liabilities, particularly denominated in U.S. dollars. Prior to the crisis, the rupiah traded around 2,000 per U.S. dollar, but depreciated sharply to approximately 16,900 per U.S. dollar (Katadata, 2018), leaving banks without adequate liquidity and capital to meet obligations. As the exchange rate shock amplified balance-sheet stress, liquidity constraints intensified and ultimately translated into solvency problems. During this period, macroeconomic conditions deteriorated sharply, output contracted, layoffs increased, and inflation remained elevated, prompting the government to liquidate numerous banks and consolidate viable institutions to restore capital adequacy.

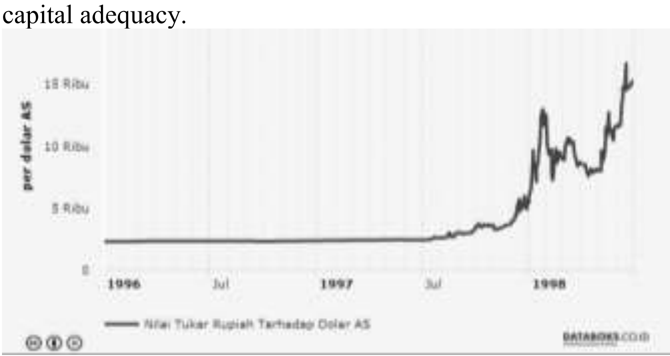

Figure 3. IDR to USD Exchange Rate (1997–1998)
Source: Katadata.co.id

Following the crisis, Indonesia implemented major financial-sector reforms aimed at improving resilience to macroeconomic shocks, most notably strengthening capital adequacy requirements to enhance loss-absorption capacity. Institutional reforms included establishing the Indonesia Deposit Insurance Corporation (LPS) to bolster depositor confidence and transferring banking supervision from the central bank to the Financial Services Authority (OJK), creating a supervisory framework separate from monetary policy and reducing potential conflicts of interest. In the decades that followed, the banking system generally demonstrated greater robustness during episodes of global turbulence. During the 2008 global financial crisis, only one mid-sized institution, Bank Century, experienced severe distress, while subsequent episodes such as the taper tantrum and European sovereign debt turbulence did not trigger major banking system disruptions. Even during the COVID-19 pandemic, the banking sector did not experience widespread liquidity or solvency failures (with rural banks excluded from this study's scope).

Despite these improvements, credit risk remains the central channel through which macroeconomic disturbances propagate into banks' balance sheets and, by extension, into the real economy. In bank-based systems such as Indonesia's, even moderate shifts in macro-financial conditions can translate into material changes in non-performing loans (NPLs), provisioning needs, and capital buffers, with downstream implications for credit supply, investment, and growth. Episodes of exchange-rate pressure, commodity price volatility, changes in domestic monetary policy, and fluctuations in global risk appetite have repeatedly demonstrated the sensitivity of Indonesian banks' loan portfolios to the macro environment. However, empirical analysis in this area faces two persistent challenges: condensing high-dimensional, co-moving macro-financial indicators into a compact representation of underlying conditions, and mapping those conditions into industry-level credit risk in a manner that is both predictively accurate and economically interpretable.

Existing research underscores the importance of macroeconomic factors for bank credit risk. For example, Abdolshah et al. (2021) show that inflation, economic growth, exchange rates, and unemployment significantly influence bank credit risk in Iran using VAR-based approaches and regression comparisons. Nevertheless, many stress-testing exercises remain rooted in univariate shock simulations, which are limited in scope because they do not reflect crisis realities in which multiple macroeconomic indicators deteriorate simultaneously, as observed during 1997–1998. This gap motivates the present study to examine the effects of multivariate macroeconomic shocks on Indonesian banking credit risk.

In addition, advances in data availability and machine learning provide an opportunity to enhance stress-testing methodology by capturing complex interdependencies that are often poorly represented by traditional linear frameworks. Indonesia's recent macro-financial environment offers a timely context for such analysis. After peaking in 2022–2023, headline inflation eased and remained benign through mid-2025 (Badan Pusat Statistik, 2025).

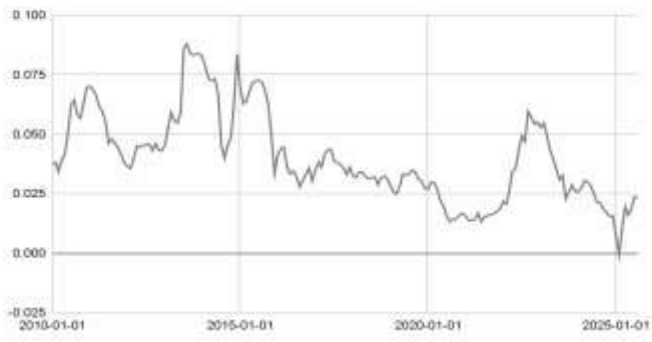

Figure 4. Inflation Rate (2010–2025)
Source: Badan Pusat Statistik

With inflation anchored and growth steady near 5%, Bank Indonesia entered an easing cycle, lowering the policy rate in August 2025 and again in September 2025, even as foreign exchange pressures persisted, with USD/IDR hovering in the mid-16,000s by October 2025 and having tested around 16,879 per U.S. dollar in April 2025 (Badan Pusat Statistik, 2025).

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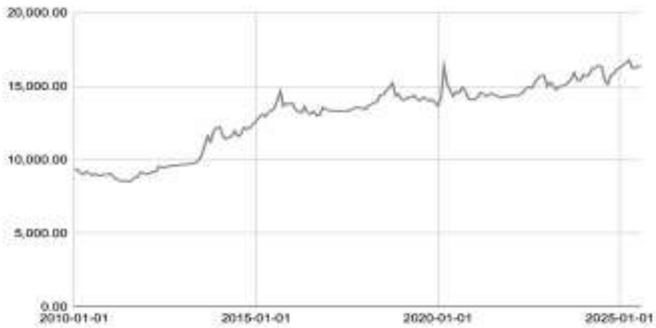

Figure 5. USD/IDR FX Rate (2010–2025)
Source: Badan Pusat Statistik

External buffers remained sizable. Bank Indonesia reported foreign exchange reserves of about USD 150.7 billion at end-August 2025, equivalent to around 6.3 months of imports, and preliminary September figures indicated reserves around USD 148.7 billion, reflecting debt service and rupiah stabilization measures amid elevated global uncertainty (Bank Indonesia, 2025). Liquidity conditions were supportive, with broad money (M2) rising around 6.5% year-on-year during June to July 2025 (Bank Indonesia, 2025).

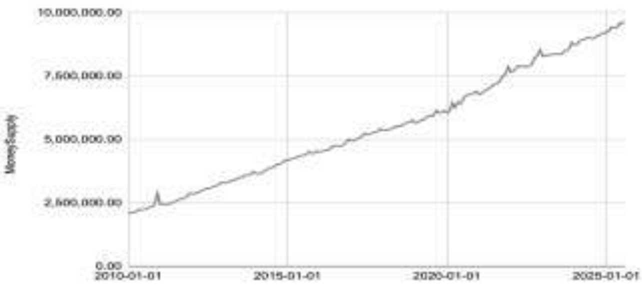

Figure 6. Money Supply (2010–2025)
Source: Badan Pusat Statistik

On the real activity side, the Industrial Production Index continued to recover after the COVID-19 shock but remained volatile, suggesting industrial momentum has not fully stabilized (Badan Pusat Statistik, 2025).

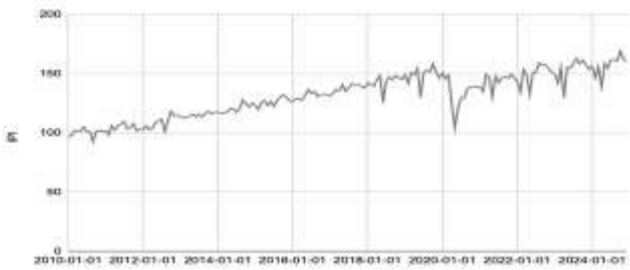

Figure 7. Industry Productivity Index (2010–2024)
Source: Badan Pusat Statistik

From the credit cycle perspective, OJK reported steady loan growth and still-contained banking credit risk, with loan growth around 7.0% year-on-year in July 2025, gross NPLs around 2.2–2.3% through mid-2025, net NPLs under 1%, and a high system capital adequacy ratio of around 25.8% (Otoritas Jasa Keuangan, 2025).

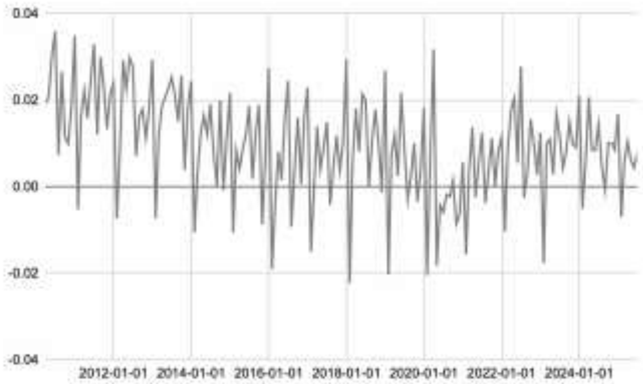

Figure 8. Loan Growth (%) (2010–2025)
Source: Otoritas Jasa Keuangan

At the same time, Indonesia's policy mix continues to evolve under the new administration, with fiscal efforts shifting toward growth acceleration, including liquidity support through state-owned banks and greater reliance on cash reserves. Taken together, Indonesia's 2024–2025 macro-financial configuration is characterized by disinflation and a domestic rate-cut cycle, supportive liquidity, ongoing exchange-rate vulnerability amid elevated global uncertainty, solid but uneven real momentum, healthy bank capital with moderate NPLs, and an active growth-oriented fiscal stance. This configuration provides a timely setting to measure how multivariate macro-financial shocks transmit into Indonesian banking credit risk and motivates the development of a stress-testing framework that integrates macroeconomic structure with machine learning methods to improve predictive performance and interpretability under potential parameter instability.

The concept of credit risk in modern economics and finance is commonly attributed to Merton (1973) in "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." In this framework, credit risk is defined as the probability that a debtor fails to meet contractual obligations when the market value of assets falls below the market value of liabilities. This structural view emphasizes that default is fundamentally linked to the dynamics of asset values relative to debt burdens and highlights the importance of accurate valuation in assessing solvency risk. Merton's work was built on earlier foundational contributions. Altman (1968), in "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," developed an accounting-based approach to bankruptcy prediction using financial ratios and discriminant analysis, providing an empirical method to distinguish financially distressed firms from healthy ones. Black and Scholes (1973), in "The Pricing of Options and Corporate Liabilities," introduced an option-pricing perspective on corporate liabilities and offered a conceptual basis for default as an endogenous decision: if asset values fall below liabilities, shareholders may rationally choose to abandon the firm rather than continue servicing debt.

Banking credit risk operates within a closely related logic. In the basic intermediation model, deposits constitute bank liabilities, while loans represent earning assets. When

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borrowers fail to meet repayment obligations, loans deteriorate in quality and become non-performing loans (NPLs), reducing the value of bank assets relative to liabilities. Consequently, an increase in NPLs is widely interpreted as an increase in bank credit risk.

Macroeconomic conditions shape bank credit risk through multiple transmission channels. Within the Keynesian IS–LM framework, interest rates play a central role in determining equilibrium in goods and money markets. When central banks raise policy rates and lending rates increase, borrowers face higher debt-servicing costs, raising default probabilities and potentially increasing NPLs in the short run. Extending this logic, Bernanke and Blinder (1988) show that money supply shocks influence credit demand and credit availability, particularly when liquidity tightening constrains banks' lending capacity. Under such conditions, banks may ration credit, become more selective, and allocate lending to larger or safer borrowers, potentially restricting access for smaller firms, weakening production and employment, and amplifying default risk across the economy.

The macro-financial feedback loop is further emphasized in the financial accelerator framework of Bernanke et al. (1999), which explains how policy shocks affect output through balance-sheet conditions. Expansionary monetary policy, such as lowering benchmark interest rates, can stimulate investment and aggregate demand, thereby raising output and supporting repayment capacity. Expansionary fiscal policy can generate similar effects through higher government spending and stronger aggregate demand. However, prolonged accommodative policy may introduce risks by encouraging excessive risk-taking. Borio and Zhu (2012) argue that persistently low interest rates can induce a "search for yield," pushing banks toward riskier borrowers and looser lending standards. In such environments, a sudden adverse shock can produce rapid increases in default rates and heighten systemic vulnerability, particularly when interconnectedness is elevated.

Empirical studies provide additional support for the macro-credit risk nexus, although results vary across contexts. Awdeh et al. (2024) emphasize that higher inflation can undermine financial stability by increasing banks' exposure to credit risk and stress the importance of capital buffers to absorb losses when credit quality deteriorates. Similarly, Sharma et al. (2024) report a positive association between inflation and bank credit risk. Unemployment is also frequently linked to higher credit risk; Godfrey and Mutezo (2020) find that unemployment exerts a significant positive influence on bank credit risk, suggesting that labor market deterioration tends to raise default probabilities. However, evidence can be mixed: Pratama et al. (2025) report an opposing pattern in certain contexts, where rising unemployment correlates with lower measured credit risk. Beyond credit risk directly, Dan and Oanh (2024) find that the Manufacturing PMI negatively affects banking efficiency, which can indirectly pressure profitability indicators such as return on equity.

Methodologically, high-dimensional macro-financial datasets raise challenges due to co-movement, redundancy, and multicollinearity among indicators. Principal Component Analysis (PCA) is widely used to address these issues by transforming correlated variables into a smaller set of uncorrelated components that retain most of the information in the original dataset (Jolliffe, 2002). Mbaluka et al. (2022), for example, use PCA to construct factor groupings relevant to growth dynamics in Kenya, illustrating how dimensionality reduction can help summarize macroeconomic conditions into interpretable drivers. Meanwhile, the Vector Autoregression (VAR) framework remains a core tool for tracing dynamic shock transmission across macro-financial systems, given its flexibility in capturing interdependence without imposing strong structural restrictions. Mihaela et al. (2024), using a Bayesian VAR, show that monetary policy shocks propagate through production networks in G7 economies and that inter-sector linkages amplify transmission over time, highlighting the relevance of VAR-type frameworks for modern macro-financial analysis.

In parallel, machine learning offers alternative estimation strategies that relax strict parametric assumptions commonly used in linear regression. Hastie et al. (2009) discuss how machine learning models manage the bias–variance trade-off differently from traditional regression. Linear regression is typically stable and low-variance but can exhibit high bias when relationships are complex or non-linear. More flexible approaches such as k-nearest neighbors reduce bias by fitting directly to data structure but may suffer from high variance and overfitting. This motivates the use of regularization and robust validation. Breiman (2001), building on earlier work by Schapire and Singer (1999), shows that ensemble methods such as bagging and boosting can reduce prediction error by controlling both bias and variance. One widely used boosting implementation is Extreme Gradient Boosting (XGBoost), which has become prominent due to strong accuracy and computational efficiency.

The rise of complex machine learning models also raises interpretability concerns. Lundberg and Lee (2017) propose Shapley Additive Explanations (SHAP), an approach grounded in cooperative game theory that decomposes predictions into feature contributions in a consistent and transparent manner. In credit risk applications, Abdou et al. (2025) find that Random Forest models can deliver strong predictive performance in detecting credit risk in Egyptian banks, with bank-specific indicators such as asset size, efficiency, and institutional characteristics playing substantial roles. Similarly, Gafsi (2025) combines structural econometric measurement of market power, using stochastic frontier analysis to derive the Lerner index, with tree-based machine learning algorithms including CatBoost, XGBoost, LightGBM, and Random Forest to predict NPLs in UK participation and conventional banks. The study concludes that bank-specific financial indicators often outperform macroeconomic variables in predicting credit risk and highlights CatBoost as particularly strong when combined with SHAP-based explainability.

Alongside tree-based approaches, regularization methods have also gained attention for high-dimensional economic and financial data. Sloboda et al. (2023) apply regularization to identify key drivers of poverty, illustrating the broader usefulness of shrinkage-based estimation for indicator selection. In macro-financial settings where multicollinearity is common, Elastic Net regression has become particularly relevant because it combines Lasso and Ridge penalties, enabling both variable selection and coefficient stabilization. Altebany (2021) reports that Elastic Net can outperform Lasso

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and Ridge in handling overfitting and multicollinearity in empirical applications. Al-Jawarneh et al. (2024) further demonstrate the robustness of Elastic Net with optimized tuning parameters in crude oil trade modeling, supporting its suitability for high-dimensional economic environments.

Framework

This study is grounded in the view that macroeconomic shocks influence banking credit risk through multiple channels, including monetary and fiscal policy transmission as well as external and domestic disturbances that shift equilibrium conditions in goods and money markets. Because macro-financial indicators tend to be highly correlated and jointly determined, the analytical challenge is to represent the underlying state of macro-financial conditions in a compact and information-rich form, while also estimating its relationship to credit risk in a way that is both stable and predictive. To address these challenges, the study adopts a hybrid framework that first uses PCA to construct a reduced set of latent macroeconomic factors, interpreted as a macro-financial index capturing common variation across indicators. These factors are then used within a VAR setting to model dynamic shock propagation and to represent multivariate macroeconomic shocks in a coherent time-series structure. Finally, the relationship between macro-financial conditions and banking credit risk is estimated using Elastic Net regression, which is designed to mitigate multicollinearity, reduce overfitting, and improve coefficient stability in high-dimensional environments. By combining factor extraction, shock transmission modeling, and regularized prediction, the framework aims to produce a stress-testing approach that is robust to complex interdependencies and better suited to periods of structural change.

The logical framework of this study follow this diagram:

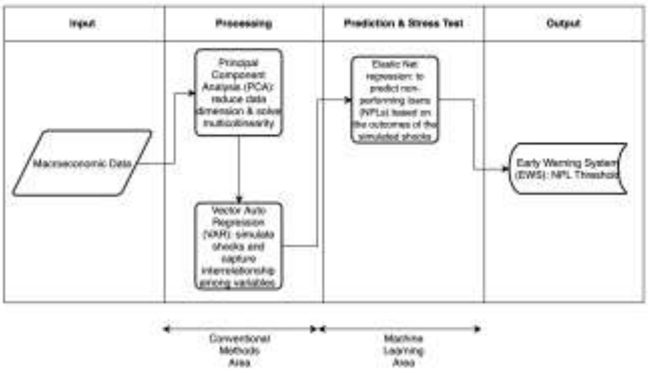

Figure 9. Logical Framework

Hypothesis

Based on the theoretical framework and standard macroeconomic transmission mechanisms, this study formulates the following hypotheses.

H1: Domestic Monetary Tightening and Credit Risk

A tightening of domestic monetary conditions, proxied by an increase in the BI Rate, is hypothesized to have a significant positive effect on non-performing loans (NPLs). Higher interest rates increase borrowers' debt-servicing burdens, thereby raising default probabilities and credit risk.

H2: Economic Output and Credit Risk

Positive shocks to economic activity, proxied by the Industrial Production Index (IPI) and the trade balance, are hypothesized to have a significant negative effect on NPLs. Improved economic conditions strengthen corporate and household cash flows, enhancing repayment capacity and lowering credit risk.

H3: External Stability and Exchange Rate Shocks

A depreciation of the Indonesian rupiah (IDR) against the U.S. dollar is hypothesized to have a significant positive impact on NPLs. This effect is expected to be stronger for borrowers with unhedged foreign-currency exposure and for firms that rely heavily on imported inputs.

H4: Capital Market Performance and Credit Risk

Negative shocks to the Indonesia Stock Exchange index (IHSG), used as a proxy for investor confidence and corporate wealth, are hypothesized to have a significant positive effect on credit risk. Declines in equity prices often signal weaker economic prospects and reduce collateral values, which can increase loan deterioration.

II. RESEARCH METHODS

This study employs a quantitative research design using secondary data and a simulation-based stress-testing approach. The methodology integrates conventional time-series econometrics to model the dynamic propagation of macroeconomic disturbances with machine learning to enhance predictive stability and robustness under multicollinearity and potential parameter instability. The primary objective is to estimate how multivariate macroeconomic shocks transmit into credit risk in Indonesia's banking sector, proxied by non-performing loans (NPLs), through an integrated PCA–VAR–Elastic Net framework implemented in Python.

The dataset consists of monthly time-series observations from January 2010 to December 2024, yielding 180 observations. Variables were selected to represent macroeconomic conditions, financial market dynamics, liquidity and credit supply, and external sector conditions. The indicators include exchange rate (FX; USD/IDR return), Jakarta Composite Index (JCI; equity return), BI Rate (monetary policy rate), CPI inflation (YoY), money supply (M2 growth), industrial production (IPI growth/level as specified), loan growth, trade balance change, and the target variable NPL. Data were obtained from publicly accessible, authoritative sources: Bank Indonesia for monetary and exchange-rate series, Otoritas Jasa Keuangan for NPL and loan statistics, and Badan Pusat Statistik for macroeconomic indicators. Monthly frequency is used to capture short-run macro-financial dynamics and credit risk adjustments, consistent with stress-testing practice in emerging markets.

Prior to model estimation, data preprocessing is conducted to ensure stationarity and to stabilize variance. Transformations are applied following standard time-series practice: NPL and BI Rate are first-differenced; exchange rate and JCI are log first-differenced; CPI is treated as YoY first difference; M2 is log second-differenced; IPI is retained in YoY level; loan growth is first-differenced; and trade balance is seasonally differenced and then first-differenced. Stationarity of transformed series is verified using the Augmented Dickey–

Fuller (ADF) test to reduce the risk of spurious regression and to ensure appropriate model specification for VAR estimation and subsequent supervised learning.

To construct a compact representation of macro-financial conditions, the study applies Principal Component Analysis (PCA) to the standardized macroeconomic dataset. Let $X_t$denote the standardized macroeconomic data matrix of dimension (K), where $T$is the number of observations and $K$is the number of macroeconomic variables. PCA seeks a linear transformation such that the principal component (PC) scores are given by $F = XW$, where Frepresents the extracted factors and $W$is the eigenvector (loading) matrix obtained from the eigen-decomposition of the covariance matrix of X. The k-th principal component is formed as a linear combination of the original standardized variables. Following the conventional information-retention criterion, only the first $m$components are retained such that the cumulative explained variance exceeds 90 percent, thereby preserving the majority of macroeconomic information while filtering noise and reducing dimensionality.

After extracting latent macro-financial factors, a Vector Autoregression (VAR) model is estimated to capture dynamic interactions among these factors and to simulate shock propagation over time. Let $F_t$be the vector of mPCA factors. The VAR(p) model is specified as

$$F_t = c + A_1 F_{t-1} + \cdots + A_p F_{t-p} + u_t,$$

where $c$is a vector of intercepts, $A_i$are coefficient matrices capturing lag dynamics, and $u_t$is a vector of innovations representing shocks. Stress scenarios are introduced through a shock injection vector applied to the VAR innovation process to generate impulse paths consistent with predefined shocks. This step produces simulated trajectories of macro-financial factors under stress, capturing both contemporaneous impacts and dynamic persistence.

To map macro-financial conditions into credit risk, the study uses Elastic Net regression to forecast NPLs using factor-based predictors (including lagged factor paths from the VAR output). Elastic Net is selected because it is well-suited for high-dimensional predictors and multicollinearity, which are typical in macro-financial datasets and in lag-augmented specifications. The Elastic Net estimator solves the penalized optimization problem

$$min_{\beta} \left\{ \frac{1}{2T} \sum_{t=1}^{T} (y_t - X_t \beta)^2 + \alpha \left[(1-\rho) \frac{1}{2} \parallel \beta \parallel_2^2 + \rho \parallel \beta \parallel_1 \right] \right\},$$

where $y_t$denotes NPL (transformed), $X_t$denotes the predictor matrix, $\alpha$is the overall regularization strength, and ρ(L1 ratio) determines the balance between Ridge (L2) shrinkage and Lasso (L1) sparsity. The L1 penalty supports variable selection, while the L2 component improves coefficient stability. Hyperparameters $\alpha$and $\rho$are tuned using a validation procedure to obtain a model with strong generalization and minimal overfitting.

The stress-testing procedure is implemented in two linked steps. First, stress is defined in the original macroeconomic variables as scenario shocks, which are then projected into the factor space using PCA loadings. Conceptually, if ΔXrepresents the shock in macroeconomic variables, then the implied factor shock can be represented by $\Delta F = \Delta XW$. Second, the shocked factors are propagated forward through the VAR system to generate stressed factor paths. A decay mechanism can be applied to ensure scenario realism by allowing shock impacts to gradually dissipate over time through a decay parameter. The resulting stressed factor trajectories are then fed into the Elastic Net model to obtain stressed NPL forecasts. The stress impact is quantified by comparing stressed NPL predictions to baseline predictions, producing an estimate of incremental credit risk under each stress scenario.

Three primary stress scenario families are examined to represent key macro-financial vulnerabilities relevant to Indonesia: external shocks through rupiah depreciation (low, medium, severe), policy shocks through BI Rate increases (low, medium, severe), and market shocks through JCI declines (low, medium, severe). These scenarios are designed to reflect common stress-testing practice and to allow comparison of credit risk sensitivity across channels. Scenario magnitudes are calibrated to represent increasing severity while maintaining economic plausibility.

The overall research design therefore adopts a two-stage integrated framework. The VAR component functions as a scenario and shock-path generator by modeling interdependencies and producing dynamic responses consistent with impulse propagation. The Elastic Net component functions as the impact evaluator by translating baseline and stressed macro-financial factor paths into predicted NPL outcomes, with regularization ensuring stability under correlated predictors. This division of roles leverages the strengths of both approaches while mitigating the limitations of each when used in isolation, particularly the over-parameterization risk in VAR and the multicollinearity/overfitting risk in high-dimensional predictive models.

Model performance is evaluated using standard predictive metrics, including $R^2$and root mean squared error (RMSE). The tuned hyperparameters (optimal $\alpha$and L1 ratio) are also reported to document the regularization structure selected by the data. Validation is conducted using an out-of-sample or time-series-consistent split to avoid information leakage typical in time-series forecasting, ensuring that model assessment reflects real predictive conditions.

This research is conducted at the national banking-system level in Indonesia, using aggregated banking indicators. Data collection, processing, and model estimation were carried out between June and December 2025.

III. RESULTS AND DISCUSSION

Data Description

This study uses monthly macroeconomic and banking-industry indicators from January 2010 to December 2024, producing 180 observations. The dataset is constructed at the aggregate level, combining macroeconomic variables with industry-level banking indicators, rather than bank-specific panel data. All series were obtained from authoritative public institutions, namely the Financial Services Authority (OJK), Bank Indonesia, and the Central Statistics Agency (BPS). Table 1 reports descriptive statistics for the variables used in the empirical analysis.

Table 1. Descriptive Statistic

Variable	Unit	Mean	Std. Dev	Min	Max
NPL	%	2.654	0.409	1.770	3.540
BI Rate	%	5.690	1.240	3.500	7.750
Exchange Rate	IDR/USD	12887.483	2324.421	8508.000	16421.000
CPI	% (YoY)	0.041	0.018	0.013	0.088
M2	Billion IDR	5328838.011	2080836.971	2066480.990	9210815.720
IPI	Index	131.374	18.896	92.320	168.990
Loan Growth	% (YoY)	0.010	0.012	-0.022	0.036
Trade Balance	Million USD	1311.371	1819.848	-2331.000	7578.500
JCI	Index	5417.458	1229.243	2549.030	7670.730

To complement the descriptive statistics, Table 5 presents coefficients of variation to summarize relative volatility across variables. Variables closely tied to the business cycle, particularly loan growth and the trade balance, show the highest dispersion, with coefficients of variation of 126% and 138%, respectively. In contrast, variables that are more directly influenced by policy and institutional controls, such as the BI Rate and money supply, display comparatively more stable dynamics. The non-performing loan (NPL) ratio, which is the primary dependent variable, exhibits low volatility (15%), even lower than the BI Rate. This pattern is consistent with the interpretation that reported NPL levels are closely monitored and managed by regulators to avoid excessive fluctuations that could undermine banking stability. In addition, the Jakarta Composite Index (JCI) and the IDR/USD exchange rate show moderate volatility over the observation period.

Table 2. Coefficient of Variation

Variable	NPL	BI Rate	FX Rate	CPI	M2	IPI	Loan Growth	Trade Balance	JCI
Coef. of Variation (%)	15.3	21.7	18.04	44.67	39.05	14.4	126.26	138.77	22.7

Data Pre-Processing

Before applying Principal Component Analysis (PCA) and estimating the Vector Autoregression (VAR), the time series must satisfy stationarity conditions to reduce the risk of spurious inference. This study therefore applies the Augmented Dickey–Fuller (ADF) test after implementing transformations designed to stabilize variance, remove trends, and ensure stationary behavior. Table 6 summarizes the transformations applied to each variable.

Table 3. Data Transformation

Variable	Transformation Method
NPL	1st Difference
BI Rate	1st Difference
Exchange Rate	Log-1st Difference
CPI	YoY 1st Difference
M2	Log-2nd Difference
IPI	YoY level
Loan Growth	1st Difference
Trade Balance	Seasonal Difference + 1st Difference
JCI	Log-1st Difference

Table 3 reports the ADF test results for the transformed series. All variables reject the unit-root null hypothesis at conventional significance levels (p-value = 0.000), indicating that the transformed variables are stationary and appropriate for subsequent PCA, VAR, and supervised learning estimation.

Table 4. Augmented Dickey–Fuller Test

Variable	ADF Stat	p-value
BI Rate	-5.9255	0.000
Exchange Rate	-10.4009	0.000
CPI	-5.8635	0.000
M2	-9.5088	0.000
IPI	-6.4481	0.000
Loan Growth	-10.2978	0.000
Trade Balance	-4.9979	0.000
JCI	-5.6352	0.000

To evaluate potential instability in macro-credit relationships following the pandemic, Elastic Net models are estimated on two samples: a pre–COVID-19 subsample (January 2010 to December 2019) and the full sample (January 2010 to December 2024). This split is motivated by the scale of policy interventions during the COVID-19 period, which may have altered the data-generating process and weakened the stability of pre-pandemic structural relationships. This concern aligns with the Lucas Critique (Lucas, 1976), which argues that policy regime shifts can change behavioral relationships and render historical coefficients unreliable for forecasting under new policy environments.

Stress Scenario Construction

Because this study adopts a simulation-based "what-if" framework, scenario magnitudes are calibrated based on explicit assumptions to represent low, medium, and severe tail-risk conditions. The stress test applies three shocks simultaneously within each severity class. The low-shock scenario assumes a 0.5% increase in the BI Rate, a 3% rupiah depreciation against the U.S. dollar, and a 4% instantaneous decline in the JCI. The medium (normal) scenario assumes a 1% BI Rate increase, a 5% rupiah depreciation, and an 8% instantaneous JCI decline. The severe scenario assumes a 500 basis-point BI Rate increase, a 30% rupiah depreciation, and a 30% instantaneous decline in the JCI, interpreted as a market crash. These shocks are imposed concurrently to represent crisis environments in which multiple macro-financial stressors materialize at the same time.

The calibration of the severe scenario, particularly the 500 basis-point policy rate increase, is intended to capture extreme tail-risk events comparable to the 1997/98 Asian Financial Crisis, when interest rates were increased aggressively in attempts to stabilize exchange-rate collapse. As a reference point, the 2013 taper tantrum episode involved a sizeable tightening cycle and was associated with significant currency depreciation and a sharp decline in the equity index, illustrating that combined stress across rates, FX, and equity markets can occur in practice (Bank Indonesia, 2013; Enoch et al., 2001). By incorporating a 30% depreciation and a 30% market crash alongside a large policy rate shock, the severe scenario evaluates banking credit risk under conditions that exceed

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standard cyclical volatility and approximates systemic macro-financial turbulence (Sahminan et al., 2017).

Table 5. Shock Scenario

Scenario	Description
External Shock	Rupiah depreciates (low, medium, severe)
Policy Shock	BI Rate increases (low, medium, severe)
Market Shock	JCI declines/crashes (low, medium, severe)

Model Robustness

To mitigate multicollinearity and reduce dimensionality, the study applies PCA and incorporates the extracted components into a VAR framework following the Factor-Augmented VAR (FAVAR) approach as developed by Bernanke (2004). Figure 9 presents the PCA scree plot. In this study, the first six principal components are retained because they cumulatively explain 90.99% of the total variance, meeting the pre-specified information-retention threshold.

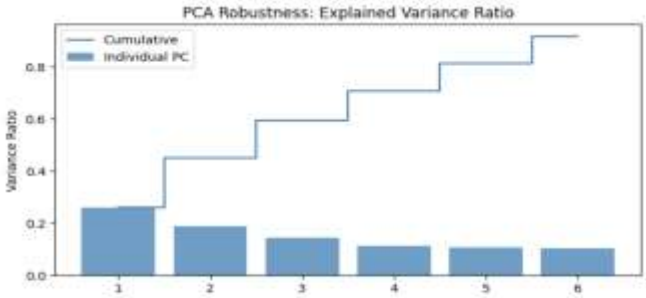

Figure 10. Scree Plot PCA

Model robustness is then evaluated based on the predictive performance of the Elastic Net model. The results indicate an RMSE of 0.0692 and an R-squared of 0.6191, with an optimal alpha of 0.0668833579 and an optimal L1 ratio of 0.1. Consistent with forecasting interpretation in Hyndman et al. (2006), the RMSE value suggests a relatively small average prediction error relative to the dependent variable's scale, implying good predictive accuracy, especially given that the dependent variable is expressed as a ratio.

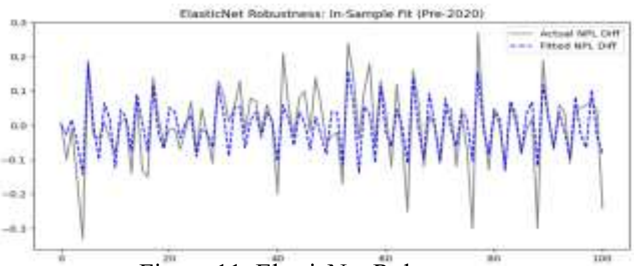

Figure 11. ElasticNet Robustness

An R-squared of 0.6191 indicates that approximately 61.9% of the variation in NPLs is explained by the predictors selected through Elastic Net. The relatively low alpha implies moderate regularization, indicating that the model avoids excessive coefficient shrinkage. The L1 ratio of 0.1 indicates a stronger Ridge component, which favors coefficient stability and the retention of correlated predictors, consistent with the rationale for Elastic Net in multicollinear environments (Zou et al., 2005).

NPL Projection Under Stress

Figures 12 to 14 summarize the projected NPL responses under the defined stress scenarios. When the model is estimated using pre–COVID-19 data (January 2010 to December 2019), NPLs are projected to increase under stress, reaching a peak of 4.13% in 2025 under the severe shock scenario. In contrast, when the model is estimated using the full sample (January 2010 to December 2024), including the COVID-19 period, the projected NPL path remains stable and, under the same stress magnitude, tends to decline.

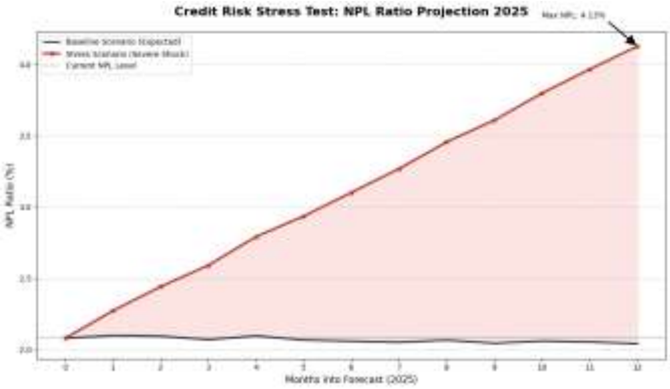

Figure 12. Stress-test Result (Severe Shocks)

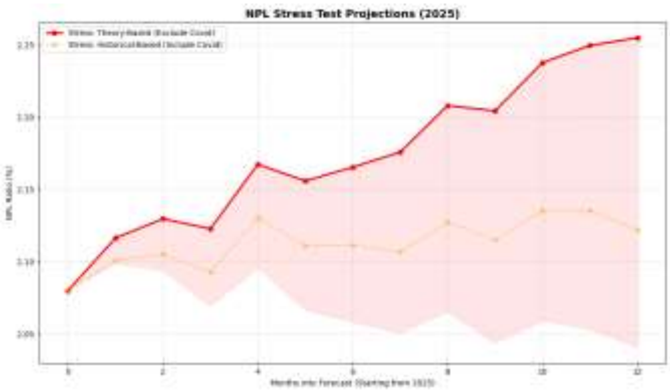

Figure 13. Stress-test Result (Low Shocks)

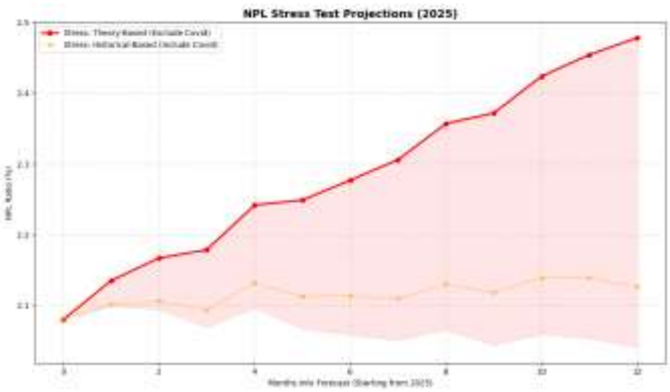

Figure 14. Stress-test Result (Medium Shocks)

This divergence is consistent with the Lucas Critique, indicating that large policy interventions can alter structural relationships and invalidate pre-crisis parameters when applied to post-intervention environments. During the pandemic, Indonesia implemented extensive stabilization measures affecting the banking sector. A key intervention was POJK 11/2020, which provided regulatory forbearance by allowing more flexible asset-quality assessment and reporting. As a result, the measured NPL ratio could remain contained despite macroeconomic weakening, because recognition of repayment impairment and reclassification could be delayed or treated differently under restructuring programs. The inclusion of the COVID-19 period thus introduces a “policy-induced stability” channel, in which reported NPL dynamics reflect not only market-driven credit conditions but also regulatory and accounting frameworks. This interpretation aligns with evidence that forbearance during systemic shocks can weaken the observed link between macroeconomic stress and reported credit risk (Baudino, 2020), while potentially masking latent vulnerabilities under restructuring programs (Ari et al., 2021).

Impact Coefficients and Structural Change

Table 8 compares the estimated direction of influence (sign) for each variable across the pre–COVID-19 sample and the full sample that includes COVID-19 observations. Three variables exhibit sign reversals after COVID-19 is included, namely the BI Rate, the exchange rate, and the industrial production index (IPI). Other variables retain consistent signs across the two samples, suggesting more stable structural relationships with NPLs.

Table 6. Impact Coefficient to NPL

Variable	Before COVID-19	Include COVID-19	Status
BI Rate	0.007392 (Positive)	-0.00330 (Negative)	Sign Flip
Exchange Rate	-0.001544 (Negative)	0.00015 (Positive)	Sign Flip
CPI	-0.000371 (Negative)	-0.00014 (Negative)	Constant
M2	-0.026910 (Negative)	-0.03150 (Negative)	Constant
IPI	0.004535 (Positive)	-0.00110 (Negative)	Sign Flip
Loan Growth	-0.026640 (Negative)	-0.02780 (Negative)	Constant
Trade Balance	-0.000040 (Negative)	-0.00370 (Negative)	Constant
JCI	-0.001718 (Negative)	-0.00970 (Negative)	Constant

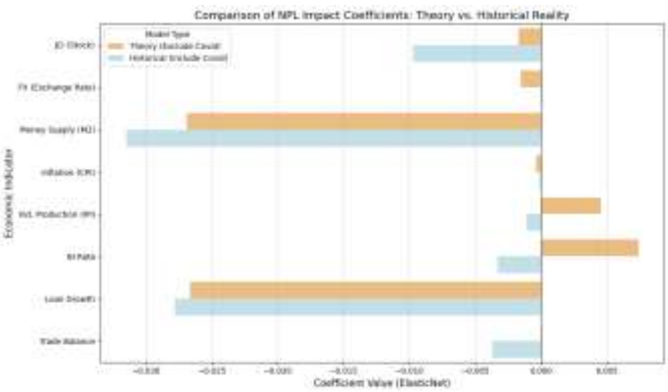

Figure 15. Comparison of Variables Impact to NPL

The sign flips are indicative of a structural break in the macro-credit risk transmission mechanism associated with the pandemic and subsequent policy responses. The BI Rate coefficient shifts from positive to negative, suggesting that in the post-pandemic regime, interest rate movements may have operated more as signals of normalization or policy credibility, while the direct cost-of-borrowing channel was muted by extensive restructuring and forbearance under POJK 11/2020. This interpretation is consistent with the view that monetary transmission can change across regimes and can be shaped by policy complementarities and crisis interventions (Hofmann & Peersman, 2017). The exchange-rate coefficient reverses from negative to positive, consistent with a shift from a commodity-linked revenue channel in the pre-pandemic period toward a stronger cost-push and valuation channel post-pandemic, where depreciation increases input costs and foreign-currency liabilities, thereby worsening solvency conditions (Calvo & Reinhart, 2002). In contrast, the stability of negative coefficients for M2, JCI, and loan growth emphasizes that liquidity and market confidence remain central determinants of credit quality across regimes.

Liquidity as the Dominant Predictor

Across both samples, money supply (M2) and loan growth have the largest magnitude coefficients and display consistent negative signs, indicating that tighter liquidity and slower credit expansion are associated with higher NPLs. Economically, these variables reflect banking system liquidity and the strength of credit intermediation. Liquidity contraction limits financing availability for firms and households, weakens economic activity, and reduces income and cash flows, thereby increasing default risk and NPL formation. In addition, tight liquidity conditions can raise interbank rates and banks’ funding costs, which may be passed through to borrowers via higher lending rates, further increasing debt-servicing burdens. Liquidity contraction is also closely related to weaker household consumption, which is particularly important in Indonesia given the consumption-driven structure of the economy. A reduction in consumption signals a broader slowdown that weakens repayment capacity across retail and MSME segments.

Refinancing dynamics represent an additional mechanism: many firms depend on rolling working capital and refinancing existing obligations. When banks restrict lending in a liquidity-tight environment, refinancing channels are disrupted, increasing the probability of default and consequently raising NPLs. The dominance and stability of liquidity variables are consistent with the financial accelerator mechanism proposed by Bernanke et al. (1999), where tighter liquidity conditions weaken borrower balance sheets and raise external finance premiums. The findings also align with the bank lending channel argument that credit supply contraction can amplify real-sector stress, particularly in economies with high bank dependence such as Indonesia, where MSMEs are strongly reliant on banking credit (Kashyap & Stein, 2000). The persistence of these relationships across both samples implies that liquidity remains a fundamental structural determinant of credit quality, even when price-based channels such as interest rates exhibit regime-dependent behavior (Acharya et al., 2011).

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Sign Flip Phenomenon

Three variables show sign reversals when the sample is extended to include the COVID-19 period: the BI Rate, the exchange rate, and the IPI. Figure 13 illustrates the co-movement between the BI Rate and NPLs. Under conventional transmission, higher policy rates raise lending rates, increase debt-servicing burdens, and tend to elevate NPLs. However, during the pandemic, the introduction of POJK 11/2020 allowed regulatory forbearance and expanded restructuring capacity, which could dampen measured NPL responses even when interest rates later increased as part of broader stabilization efforts. The empirical pattern, in which NPLs decline during periods of policy rate increases after 2023, provides quantitative evidence consistent with a sign reversal in the BI Rate–NPL relationship within the post-pandemic regulatory regime.

Figure 16. BI Rate and NPLs Movement

For the exchange rate, the pre–COVID-19 coefficient is negative, implying that rupiah depreciation coincided with lower NPLs. One plausible explanation is a commodity windfall channel: depreciation episodes may have overlapped with periods of rising commodity prices that improved revenues and repayment capacity for commodity-linked borrowers, reducing NPL pressures. Figure 14 illustrates the relationship between the exchange rate and palm oil prices. In the post–COVID-19 period, the coefficient turns positive, indicating a shift toward a cost-push and valuation mechanism, where depreciation increases imported input costs and raises the local-currency burden of foreign-currency debt, thereby worsening borrower solvency and increasing NPL risk.

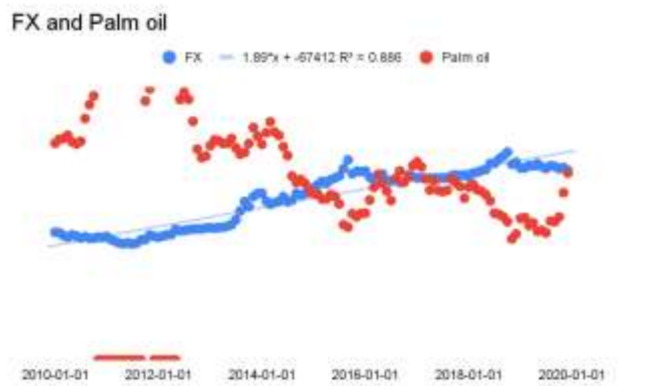

Figure 17. Exchange Rate and Palm Oil Price

The IPI coefficient also reverses from positive in the pre–COVID-19 sample to negative in the full sample. The pre-pandemic positive sign may reflect sectoral leverage dynamics in production-intensive industries, where expansions could coincide with aggressive borrowing and risk accumulation. In the post-pandemic period, the relationship becomes consistent with standard theory: stronger industrial activity improves cash flows and repayment capacity, thereby reducing NPLs. Overall, the sign flip phenomenon suggests that the pandemic acted as a structural break that changed the mapping between macro conditions and measured credit risk, reinforcing the need for stress-testing models that can accommodate regime shifts and policy-induced parameter instability.

Variables with Consistently Negative Relationships

Several variables retain consistent negative coefficients across both samples, including the Jakarta Composite Index (JCI), trade balance, and CPI. The persistent negative relationship between JCI and NPLs is consistent with the idea that stronger equity valuations reflect improved corporate balance sheets and higher distance-to-default, thereby lowering credit risk in a structural sense. The trade balance also operates as a macro-financial buffer; stronger external performance provides foreign exchange liquidity and supports corporate revenues, strengthening repayment capacity during periods of domestic volatility. The CPI's negative coefficient suggests that, within the sample period, inflation dynamics may often reflect demand-side strength rather than purely adverse supply shocks. In this interpretation, higher inflation coincides with stronger household income and consumption, sustaining repayment capacity in retail and MSME segments and reducing NPL pressures. Taken together, these stable relationships underscore the importance of liquidity conditions, market confidence, and external stability in safeguarding Indonesia's banking asset quality across different macroeconomic regimes.

IV. CONCLUSIONS

This study examines the impact of multivariate macroeconomic shocks on credit risk in the Indonesian banking sector using a hybrid framework that combines Factor-Augmented Vector Autoregression and Elastic Net regression. The results indicate that banking credit risk in Indonesia is sensitive to the interaction of multiple macro-financial pressures rather than to isolated shocks. When monetary tightening, exchange rate depreciation, and equity market corrections occur concurrently, the simulated stress tends to increase non-performing loans, reinforcing the view that credit risk transmission intensifies under compounded macroeconomic disturbances. The stress-test projections also suggest that asset quality can deteriorate under adverse scenarios relative to normal conditions, underscoring the importance of evaluating banking resilience using multivariate stress environments that more closely resemble crisis dynamics. From a methodological perspective, the Elastic Net model performs well in a high-dimensional macro-financial setting. By addressing multicollinearity and stabilizing coefficient estimates through regularization, the model demonstrates strong predictive accuracy and explains a substantial share of variation in non-performing loans. The

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comparison between the pre-pandemic model and the model that incorporates the pandemic period reveals a clear divergence in estimated relationships. This pattern is consistent with the idea that large-scale policy interventions during the pandemic, including restructuring programs and regulatory forbearance, altered the observed transmission of macroeconomic shocks into reported credit risk. Consequently, reported non-performing loans during periods of strong regulatory support may reflect a combination of underlying credit conditions and policy-driven reporting dynamics, implying that conventional relationships may become less reliable under regime changes. The findings carry several implications for policymakers, banks, and future research. For regulators, the results support strengthening stress-testing frameworks by incorporating machine learning approaches that can capture interaction effects, non-linearities, and parameter instability that traditional linear models may not adequately represent. The prominence of liquidity-related indicators in the analysis highlights the importance of maintaining adequate liquidity conditions and closely monitoring credit expansion as part of macroprudential surveillance. For the banking industry, the evidence emphasizes proactive capital and provisioning strategies to enhance loss-absorption capacity ahead of downturn risks, as well as portfolio diversification to reduce concentration in sectors that are highly sensitive to macroeconomic fluctuations. For future research, using bank-level micro data would enable a more granular assessment of heterogeneity across institutions and clarify how bank characteristics shape resilience to shocks. Further studies may also compare the present approach with alternative machine learning methods, including ensemble and deep learning models, to evaluate whether additional predictive gains can be achieved while preserving interpretability for regulatory stress-testing purposes.

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