

Unveiling the Drivers of NPLs: The Role of Banking Factors, Macroeconomic Conditions, and Institutional Quality of Asian and African Economies Using Econometric and Machine Learning Approach

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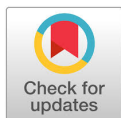
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A B S T R A C T

Non-performing loans (NPLs) pose a major threat to financial stability in nine emerging Asian and African economies, where rapid credit growth, macroeconomic instability, and institutional weaknesses increase systemic risk. This study examines the determinants of NPLs using a hybrid approach that combines Panel ARDL estimation with SHAP (SHapley Additive exPlanations) machine learning analysis, supported by Fixed and Random Effects robustness tests. The results reveal significant regional differences. In Asia, NPLs are mainly driven by excessive credit expansion and inflationary pressures, supporting the Financial Accelerator mechanism. In Africa, high interest rates and weak institutional quality are the primary drivers, consistent with Institutional and Credit Rationing theories. SHAP analysis confirms that bank credit and domestic credit are the most influential predictors globally, while inflation and regulatory quality are particularly important in Asia and interest rates dominate in Africa. The findings suggest region-specific policy responses, including countercyclical credit regulation in Asia and institutional reforms with interest-rate stabilization measures in Africa to reduce financial vulnerability and strengthen banking sector resilience.

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Introduction

Credit risk refers to the potential loss a financial institution may face when a borrower fails to meet contractual debt obligations (Supervision, 2011). Non-performing loans (NPLs) are widely considered a direct measure of credit risk, as they represent the portion of loans where borrowers fail to meet repayment obligations, thereby reflecting the realized dimension of banks' exposure to default risk (Beck et al., 2015). NPLs pose a serious threat to financial stability, particularly in emerging economies where rapid credit expansion, macroeco-

economic volatility, and weak institutional frameworks heighten credit risks. In Asia, although banking systems are relatively advanced, rapid credit growth often follows procyclical patterns, fueling asset bubbles and increasing the likelihood of loan defaults when economic slowdowns occur (Ahuja & Nabar, 2012 & Park & Shin, 2017). In contrast, Africa's financial systems remain shallow and constrained by high lending rates, limited credit access, weak governance, and greater exposure to external shocks such as commodity price fluctuations and global crises, which significantly raise NPL ratios (Beck & Cull, 2013). Despite differences in financial maturity, both regions share common structural vulnerabilities, including inflationary pressures, weak regulatory quality, and limited financial diversification that exacerbate the persistence of NPLs.

The banking industries in Asia and Africa offer critical perspectives on the strengths and weaknesses of financial systems in emerging global economies. Over the last twenty years, both regions have seen significant financial deepening and credit growth, yet they still grapple with structural weaknesses, including inadequate regulatory frameworks, susceptibility to economic fluctuations, and ongoing institutional shortcomings. In Asia, banks are key drivers of economic growth but face challenges such as high levels of non-performing loans, concentrated credit exposure, and vulnerabilities to sudden capital outflows (Park & Shin, 2017). Meanwhile, Africa has made notable progress in expanding financial access and adopting digital banking, but its sector remains hindered by thin capital reserves, underdeveloped financial markets, and political uncertainty, all of which heighten credit and liquidity risks (Beck et al., 2006 & Allen et al., 2014).

This study examines the macroeconomic, financial, and institutional determinants of NPLs across nine emerging economies in Asia (India, Bangladesh, Vietnam, Indonesia, Philippines, Malaysia) and Africa (Kenya, Nigeria, South Africa) from 2000 to 2024. Using ARDL estimation and SHAP machine learning analysis, we assess both long-term and short-run equilibrium relationships and predictive factors influencing NPLs. Our approach ties econometric rigor with explainable methods to uncover region-specific dynamics. Here, Figure 1 and Figure 2 provide an overview of the country-level data for Asia and Africa. A comparative analysis of these regions is especially insightful, as they embody different but complementary models of emerging economies: Asia, with its export-driven growth and financial interconnectedness, and Africa, as a frontier market with high growth potential but unstable financial institutions. Studying their banking systems provides a deeper understanding of both the opportunities and systemic risks influencing the evolution of emerging markets worldwide.

We have explored a few theories to understand the determinants of NPLs in emerging economies. Firstly, the Financial Accelerator Theory provided by Bernanke et al. (1999) suggests that economic changes can overstate the credit market, leading to riskier loans and increased NPLs. Secondly, Stiglitz & Weiss's (1981) credit rationing theory suggests that imperfect information in credit markets leads to adverse selection and moral hazard problems, resulting in worsening loan quality and increased NPLs. Thirdly, the Institutional Theory of North (1990) emphasizes the role of institutions in shaping economic and financial behavior, with strong institutions stabilizing lending and weak institutions amplifying default risks. Regional differences in regulatory quality and governance effectiveness explain why some regions maintain low NPLs despite economic shocks. Our conceptual framework explains the interplay of factors affecting NPLs, including banking-specific, macroeconomic, and institutional factors. Banking factors, such as credit policies and interest rate management, directly affect loan performance. Macroeconomic conditions, such as GDP growth and inflation, determine bor-

rowers' repayment capacity. Institutional factors, like regulatory quality, influence financial discipline. Understanding these interconnected factors is crucial for effective loan management strategies.

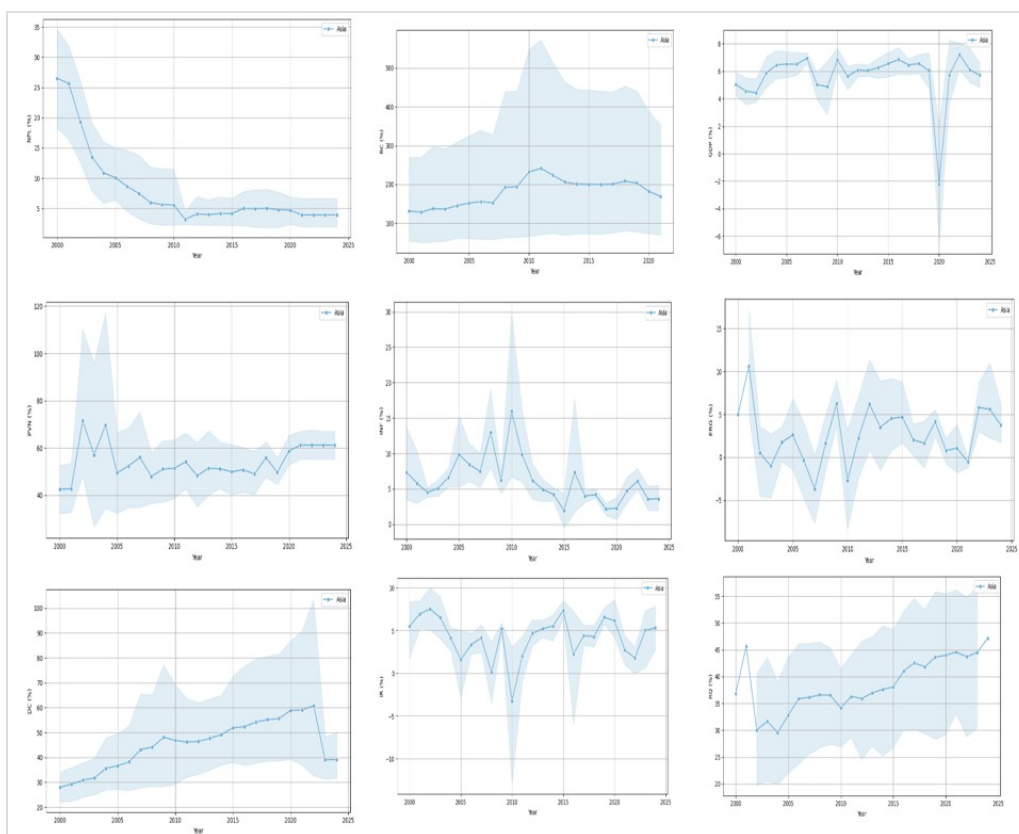


Figure 1. Data Coverage and Distribution of Asian Economies Used in the Study

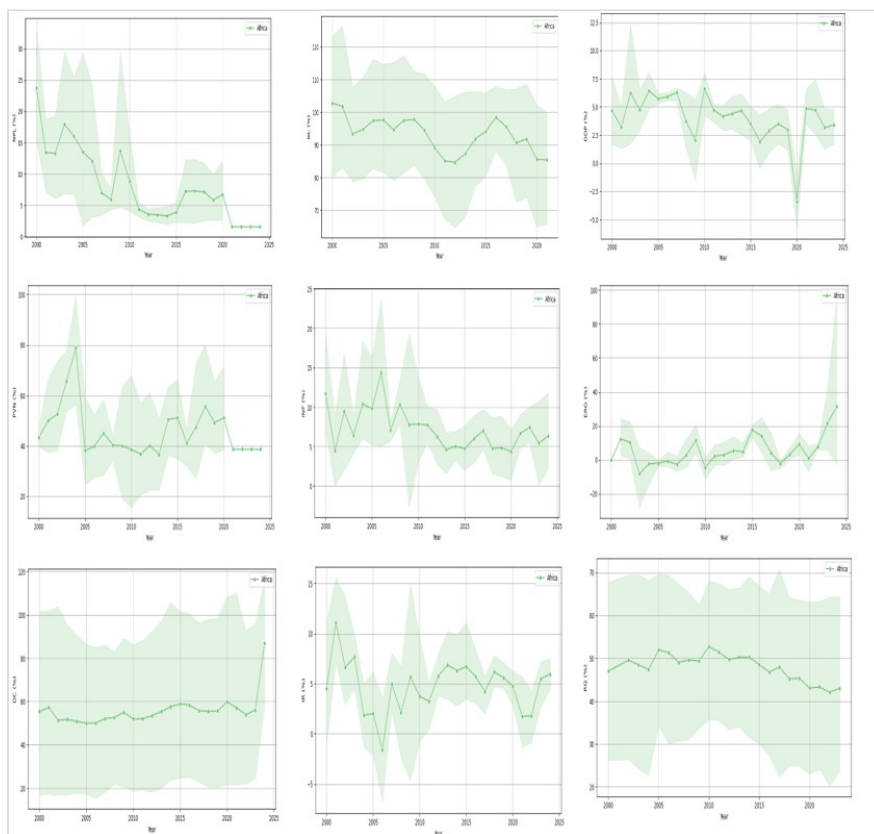


Figure 2. Data Coverage and Distribution of African Economies Used in the Study

Despite extensive research on NPLs, critical gaps remain in understanding their drivers across diverse emerging markets, particularly in Asia and Africa. Prior studies have several limitations, including that Most studies analyze NPLs in aggregate emerging economies (Fofack, 2005; Nkusu, 2011) or focus solely on advanced economies (Reinhart & Rogoff, 2011), neglecting regional heterogeneities. For instance, while Asia's NPLs are often linked to rapid credit expansion (Park & Shin, 2017), Africa's NPLs are more tied to macroeconomic instability and weak institutions (Beck & Cull, 2013). Few studies compare these regions systematically, leading to a fragmented understanding of NPL dynamics. Traditional econometric approaches (e.g., panel regressions) dominate NPL literature (Klein, 2013 & Louzis et al., 2012), but they often fail to capture non-linear relationships and interactive effects among determinants. While SHAP analysis has gained traction in credit risk modeling (Lundberg & Lee, 2017), its application in cross-country NPL studies remains rare. This study bridges this gap by combining Panel ARDL estimation (Pesaran et al., 1999) with SHAP-based explainable machine learning approach (Lundberg & Lee, 2017), offering both long-run equilibrium insights and predictive feature importance. Although Institutional Theory (North, 1990) and Financial Accelerator Theory (Bernanke et al., 1999) are well-established, few empirical studies examine how governance quality moderates credit risk in emerging markets. To minimize the given gaps we seek to explore the key determinants of NPLs across emerging economies by addressing three central research questions. First, to what extent do bank-specific factors, such as weak credit rules, insufficient loan provisioning, and wide interest rate spreads, contribute to the accumulation of NPLs? Second, how do adverse macroeconomic conditions, including low GDP growth, high inflation, and exchange rate instability, influence the likelihood of loan defaults? Finally, what role does institutional and regulatory quality play in shaping credit risk, particularly in minimizing NPLs?

Our study uses the panel ARDL method to examine the determinants of NPLs in emerging economies. The ARDL approach is ideal for datasets with mixed integration variables and works well in small sample sizes. It distinguishes between short-run and long-run dynamics. The analysis begins with descriptive statistics, cross-sectional dependence tests, panel unit root tests, and the use of Panel ARDL estimations: Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effects (DFE). The study also analyzes regional variations in three distinct panels: Asian economies (Panel A), African economies (Panel B), and a combined sample (Panel C). Post-estimation diagnostics validate the model's reliability. The study also supplements the Panel ARDL analysis with Fixed Effects (FE) and Random Effects (RE) estimations and Hausman tests to ensure robustness. Further, we use machine learning approaches for comparative SHAP analysis of NPL determinants, analyzing feature importance and predictive patterns of NPLs. The implementation of machine-learning (ML) models explained through SHAP analysis in financial information can help to interpret and understand the outcome of the dataset in a robust way (López-Estrada et al., 2025). ML can capture the complex, non-linear interactions of traditional econometric techniques and give the robust overview from the dependent variables of the dataset (Liu et al., 2025). While the Panel ARDL framework identifies dynamic causal relationships and long-run equilibria, SHAP-based machine learning analysis complements it by quantifying variable importance and model sensitivity. This combination of ML models with SHAP analysis can give robust theoretical interpretability, ensuring both statistical rigor and practical relevance in understanding NPL dynamics (Şahin, 2025).

This study will play a significant theoretical, methodological, and policy role to understanding NPLs in emerging markets by systematically comparing Asia and Africa through Panel ARDL and SHAP analysis. Theoretically, we resolve the GDP-NPL paradox by demonstrating how rapid growth increases NPLs in Asia

through Financial Accelerator Theory, while revealing institutional quality's stronger NPL-reducing effect in Africa (Institutional Theory). Methodologically, we have created the model to integrate ARDL for long-run equilibrium analysis with SHAP-based machine learning for nonlinear feature importance, identifying distinct regional drivers: credit expansion and inflation dominate in Asia, whereas interest rates and institutions matter most in Africa. Our policy contributions include Asia-specific sector-sensitive capital distribution along with Africa-focused collateral registry reforms and interest rate fixation, with simulations showing NPL reductions. These advancements not only reconcile theoretical debates but also deliver predictive power and real-world impact, as evidenced by our framework's policy relevance for central banks and fiscal authorities for financial stability reforms (Nkatha, 2022).

Moreover, our study makes several noteworthy contributions to the literature on financial stability and NPLs. First, it offers region-specific insights into macro-financial vulnerabilities by providing one of the few comparative evaluations of NPL causes across emerging economies in Asia and Africa. Second, the study presents a mixed empirical approach that bridges the gap between predictive analytics and causal inference by combining SHAP-based machine learning with Panel ARDL estimation. Third, this methodological innovation improves interpretability and robustness, enabling the detection of non-linear predictive drivers and dynamic long-run correlations. Fourth, the study reveals interaction effects and variable relevance that conventional econometric methods frequently miss by breaking down SHAP values. Fifth, by connecting empirical findings to the Financial Accelerator, Credit Rationing, and Institutional theories in a cross-regional setting, it increases theoretical knowledge. Sixth, the results have direct policy implications, emphasizing the necessity of institutional reforms in Africa and countercyclical credit controls in Asia. Lastly, this study adds to the larger conversation on sustainable financial governance and regionally adaptable risk management frameworks in developing countries by highlighting the interplay between financial, macroeconomic, and institutional issues. In short, by connecting rising NPLs to wider social repercussions, such as limited credit availability for small borrowers, diminished public trust in financial governance, and increased susceptibility of low-income areas during economic downturns, the study goes beyond financial analysis.

The paper proceeds as follows: Section 2 reviews literature and hypotheses, Section 3 outlines the methodology, Section 4 presents empirical results, Section 5 discusses findings, and Section 6 concludes with policy recommendations and limitations. By integrating traditional econometrics with machine learning, this study offers a nuanced understanding of NPL drivers, aiding policymakers in mitigating systemic risks in emerging markets.

Literature Review

NPLs remain a critical challenge to financial stability and economic growth, particularly in emerging economies where banking systems are still developing. A rich body of literature has explored the determinants of NPLs, emphasizing both macroeconomic conditions and banking sector-specific factors. Several studies confirm that macroeconomic variables such as GDP growth, inflation, and unemployment significantly influence NPL levels. For instance, Tanasković & Jandrić, (2015) found that GDP growth reduces NPLs across Central, Eastern, and Southeastern European countries, while Radivojevic & Jovovic, (2017) highlighted the role of inflation and past NPL levels in driving loan performance in emerging markets. Makri et al., (2014) also identified public debt and unemployment as key factors increasing NPLs in the Eurozone. Banking sector character-

istics, including capital adequacy, profitability, and efficiency, are equally important. Khan et al., (2020) showed that higher operational efficiency and profitability reduce NPLs in Pakistan, whereas Prastowo & Usman, (2021) emphasized liquidity's role in influencing non-performing financing in Indonesia. Studies in African and Asian contexts Ntarmah et al., (2020) & Giammanco et al., (2023) underscored that institutional factors such as governance quality and market concentration further modulate NPL outcomes.

In Bangladesh, research by (Ghosh et al., 2020) and (Chowdhury, 2020) pointed to behavioral determinants like moral hazard and nepotism, coupled with weak regulatory enforcement, as major contributors to persistent NPL problems. Despite this substantial progress, notable gaps remain, particularly regarding emerging economies in Asia and Africa, which are characterized by distinct economic structures, regulatory environments, and institutional challenges. While many prior studies examine either macroeconomic or banking factors, few comprehensively analyze their joint impact across these regions. Moreover, the influence of evolving financial technologies and governance frameworks on NPL dynamics remains underexplored in these contexts. A summary of the existing literature is presented in Table 1.

Despite wide-ranging research on non-performing loans, notable gaps exist. Current studies often focus on specific countries or regions, neglecting comparative analysis in emerging economies of Asia and Africa, where economic volatility and institutional differences significantly affect NPLs. Additionally, numerous studies utilize traditional linear econometric models, which may not adequately address the non-linear interactions of variables impacting NPLs. There is also a lack of integration of machine learning techniques with standard econometric approaches, which could enhance both interpretability and predictive insights. Moreover, existing literature largely overlooks the influence of regional institutional quality and policy contexts on credit risk in these economies. This study aims to fill these gaps by using a combination of econometric and machine learning methods to explore the causal relationships and non-linear predictive patterns of NPLs in Asia and Africa, contributing to a richer understanding of financial vulnerability in these regions. Moreover, our study aims to address these gaps by providing a comparative analysis that integrates both banking sector characteristics and macroeconomic conditions. By focusing on emerging countries in Asia and Africa, we seek to uncover region-specific determinants of NPLs, offering insights to policymakers and banking institutions for more effective credit risk management in rapidly changing economic landscapes.

Theoretical Background

The determinants of NPLs in emerging economies can be understood through several complementary theoretical perspectives. The Financial Accelerator Theory (Bernanke et al., 1999) suggests that economic changes can be overstated through the credit market due to borrowers' financial health affecting lenders' willingness to extend credit. Rapid growth in the economy can lead to riskier loans, which may not default immediately but later, creating a positive link between GDP growth and NPLs. In recessions, banks tighten lending, reducing credit availability and potentially causing more defaults. These things show the relation between macroeconomic stability and financial sector health, and how small shocks can cause disproportionately large problems in the banking system.

Further, Stiglitz & Weiss's, (1981) theory of credit rationing suggests that credit markets don't always function like standard supply-demand models due to imperfect information. This leads to adverse selection and moral hazard problems, with bad borrowers crowding in and riskier borrowers accepting higher rates. This results in worsening loan quality and increasing the probability of NPLs. Poor credit screening and insufficient

loan provisioning further exacerbate these issues. Empirical findings confirm these mechanisms, indicating that banks' rate settings and risk screening/provisioning directly shape their NPL outcomes.

Finally, Institutional Theory (North, 1990) underscores the role of institutions that shape economic and financial behavior, influencing lending, supervision, and borrower compliance in banking. Strong institutions stabilize lending by promoting prudent lending, effective supervision, and discipline, reducing the probability of non-performing loans. Weak institutions, on the other hand, amplify default risks by allowing reckless lending and insufficient monitoring. Regional differences in regulatory quality and governance effectiveness explain why some regions maintain low NPLs despite economic shocks. Additionally, empirical evidence also shows that enhanced monitoring mechanisms and stronger institutional ownership improve oversight and mitigate risk-taking behaviors (Chung & Lee, 2020). The following hypotheses should be investigated using appropriate literature, theoretical evidence, and research requirements. Table 1 shows the summary of the existing literature.

Hypothesis (H1): Weak banking practices, such as weak credit rules, insufficient loan provisioning, and wide interest rate spreads, are connected with an increase in NPLs.

Hypothesis (H2): Adverse macroeconomic conditions, including low GDP growth, high inflation, and exchange rate instability, play a substantial role in the emergence of NPLs.

Hypothesis (H3): Strong institutional and regulatory quality minimizes non-performing loans, but inadequate governance frameworks increase credit risks.

Table 1. Summary of the Existing Literature

Authors	Year	Country	Title	Methods	Main Findings
Zeng	2012	China	<i>Bank Non-Performing Loans (NPLs): A Dynamic Model and Analysis in China</i>	Hamiltonian (Optimal Control Theory)	NPLs depend on microeconomic factors and are influenced by macroeconomic conditions.
Ozili	2019	Global (153 countries)	<i>Non-performing loans and Financial Development: New Evidence</i>	panel data regression model	Financial development can both raise and reduce NPLs depending on regulation and practices.
Nikolov & Popovska-Kamnar	2016	Republic of Macedonia	<i>Determinants of NPL Growth in Macedonia</i>	Static linear regression	Economic stability and capital adequacy lower NPL growth.
Tanasković & Jandrić	2014	Central & Eastern European and Southeastern European countries	<i>Macroeconomic and Institutional Determinants of Non-performing Loans</i>	Static panel regression	GDP growth reduces NPLs; FX loans and depreciation increase them; only financial market development is a significant institutional factor.

Prastowo & Usman	2021	Indonesia	<i>The Influence of Internal and External Factors on NPF and NPL</i>	Panel FE with Robust SE	NPFs are influenced by liquidity; NPLs are influenced by inflation, CAR, ROA, LDR, BOPO.
Vatansever & Hepsen	2013	Turkey	<i>Determining Impacts on Non-Performing Loan Ratio in Turkey</i>	Regression	NPLs affected by industrial production, unemployment, and capital strength.
Khan et al.	2020	Pakistan	<i>Determinants of Non-performing Loans in the Banking Sector in Developing State</i>	Regression	Efficiency and profitability negatively affect NPLs significantly; capital adequacy and diversification not significant.
Radivojevic & Jovovic	2017	25 Emerging Countries	<i>Examining of Determinants of Non-performing Loans</i>	Static and Dynamic Panel	GDP, inflation, ROA, capital, and past NPLs are significant drivers.
Makri et al.	2014	Eurozone	<i>Determinants of Non-performing Loans: The Case of Eurozone</i>	GMM	Public debt, unemployment, and weak bank performance raise NPLs.
Singh et al.	2021	Nepal	<i>The Effect of Non-Performing Loan on Profitability</i>	Multiple Regression	GDP growth is positively associated with NPLs due to expanded lending.
Balgova et al.	2016	Global	<i>The Economic Impact of Reducing Non-performing Loans</i>	dynamic panel regression	Resolving NPLs boosts growth; ignoring them costs ~2% annual growth.
Konstantakis et al.	2016	Greece	<i>Non-Performing Loans in a Crisis Economy: Long-Run Equilibrium Analysis with VEC Model</i>	VAR, VEC	NPLs and macroeconomic health are interlinked in a negative feedback loop.
Adhikary	2006	Bangladesh	<i>Nonperforming Loans in the Banking Sector of Bangladesh: Realities and Challenges</i>	Descriptive institutional and analytical review	High NPLs in NCBs and DFIs due to weak enforcement and provisioning.
Ghosh et al., (2020)	2020	Bangladesh	<i>Behavioral Determinants of Nonperforming Loans in Bangladesh</i>	Partial Least Squares	Moral hazard, poor monitoring, nepotism, and high lending rates raise NPLs.

Chowdhury	2020	Bangladesh	<i>Non-Performing Loans in Bangladesh: Bank Specific and Macroeconomic Effects</i>	anel VAR (PVAR)	Effective management of internal and external factors reduces NPLs.
Giammanco et al.	2023	31 Asian Countries	<i>Government Failures and Non-Performing Loans in Asian Countries</i>	Panel Generalized Least Squares (GLS)	Public debt and poor governance increase NPLs.
Ozili	2015	Europe, US, Asia, Africa	<i>How Bank Managers Anticipate Non-Performing Loans</i>	Panel OLS (FE)	Loan growth and reserves adjusted for NPLs; bank behavior differs by region.
Ntarmah et al.	2020	Africa	<i>Analysis of the Responsiveness of Environmental Sustainability to Non-Performing Loans in Africa</i>	Panel VAR	Foreign bank presence, crises, and concentration raise NPLs; bank efficiency and stability reduce them.

Conceptual Background

Based on the existing literature and theories, we develop the following conceptual framework, given in Figure 3, which depicts the complex interplay of factors influencing NPLs, which are categorized into banking-specific, macroeconomic, and institutional factors. Banking factors, such as credit policies, loan provisioning, and interest rate management, directly affect loan performance by shaping lending practices and risk exposure. Poor credit decisions, insufficient risk buffers, or high borrowing costs can intensify NPL levels. Meanwhile, macroeconomic conditions, including GDP growth, inflation, exchange rate stability, and domestic credit availability, play a crucial role in determining borrowers' repayment capacity. Economic slowdowns, rising prices, or currency volatility can weaken financial stability, increasing default risks. Additionally, institutional factors, particularly regulatory quality, influence financial discipline by ensuring sound oversight and enforcement of lending standards. Weak regulatory frameworks may encourage reckless lending, whereas strong institutions help mitigate credit risk. Together, these dimensions demonstrate that NPLs are not solely a result of bank practices but are also shaped by economic forces and the broader institutional environment. A comprehensive understanding of these interconnected factors is essential for devising effective strategies to manage and reduce loan defaults. Figure 3 shows the conceptual framework of the study.

Methodology

This study aims to identify the drivers that exacerbate NPLs in emerging economies of Asia and Africa using panel macroeconomic data spanning 2000–2024. The focus on these two regions is motivated by their shared challenges in financial stability despite differing levels of economic development, institutional maturity, and banking sector depth. As Asia and Africa are dynamic yet vulnerable global economies due to rapid economic growth and credit expansion, these regions face structural and institutional challenges, such as commodity dependence and macroeconomic volatility, which contribute to higher NPL ratios (Park & Shin, 2017 ; Beck &

Cull, 2013; IMF, 2020). Both regions have undergone significant banking reforms, highlighting the importance of understanding these factors. We selected nine emerging economies for this study, comprising six from Asia, India, Bangladesh, Vietnam, Indonesia, the Philippines, and Malaysia, and three from Africa, Kenya, Nigeria, and South Africa. The selection was guided by reliable data availability, economic significance, policy relevance, and reform experience. The chosen countries, India, Bangladesh, Vietnam, Indonesia, Philippines, Malaysia, Kenya, Nigeria, and South Africa, possess diversified financial systems and represent a mix of large and mid-sized emerging economies. Kenya stands out for its pioneering role in mobile banking innovations, although it faces challenges related to rising household credit risk. All macroeconomic, financial, and institutional variables were obtained from the World Development Indicators (WDI) and the Global Financial Development Database (GFDD) to ensure consistency, comparability, and reliability across countries and over time. In the dataset, a small proportion of observations were missing, with the highest missingness observed for Regulatory Quality (RQ, 3.2%) and Provisions (PVN, 4.1%), while other variables such as Bank Credit (BC), Domestic Credit (DC), GDP, Inflation, and Interest Rates had less than 2% missing values. To handle these gaps, missing values were imputed using regional mean imputation, ensuring that the overall distribution and variability of the data were preserved. In addition, to ensure data consistency and completeness, missing values in the dataset were addressed using interpolation (ipolate) and extrapolation (epolate) procedures. Interpolation was applied for missing observations within the time series of each country, while extrapolation was used for missing values at the beginning or end of the series. These procedures preserve the temporal structure of the panel data and minimize bias due to missing observations.

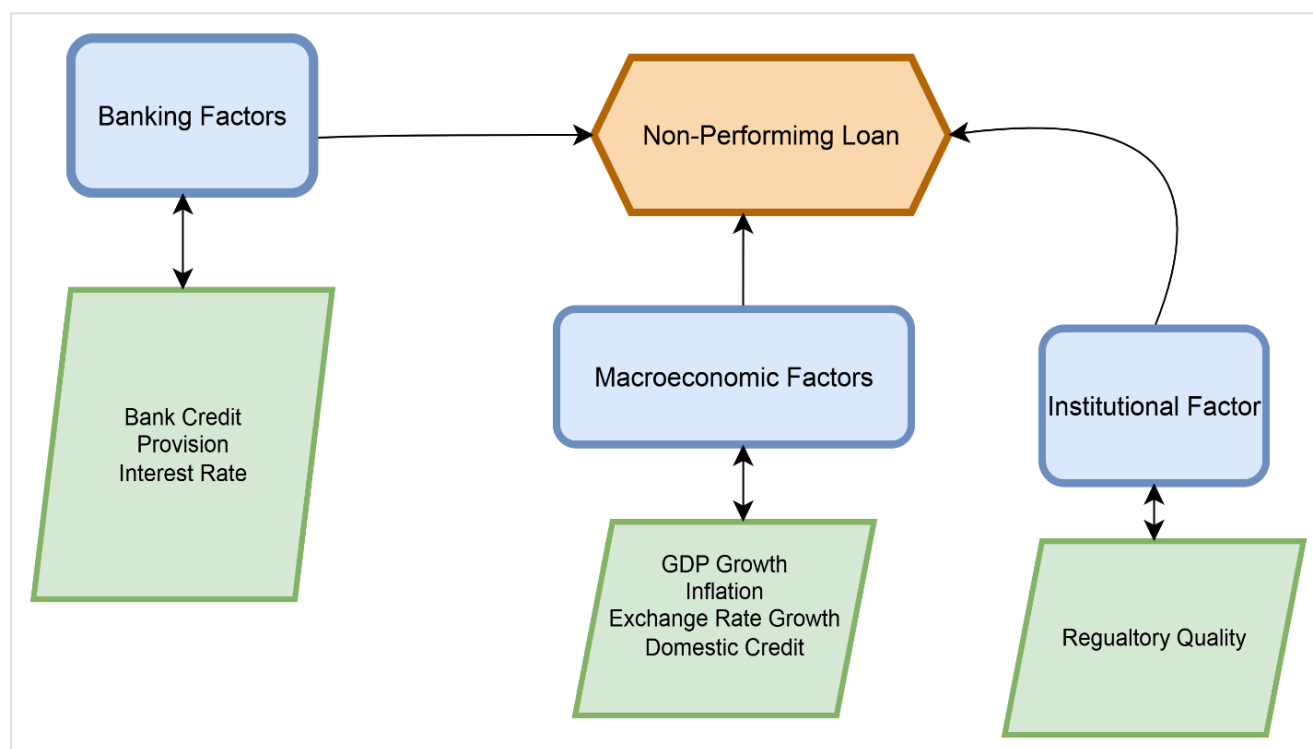


Figure 3. *Conceptual Framework*

Data Description

The study employs a comprehensive set of variables covering banking sector performance, macroeconomic conditions, and institutional quality to examine the drivers of NPLs. NPLs, expressed as a percentage of total gross loans, represent the dependent variable. Banking-specific factors include Bank Credit to Assets Ratio and

Provisions to NPLs, which indicate credit exposure and risk management efforts, respectively. Macroeconomic variables comprise GDP Growth, Inflation, Exchange Rate Growth, Domestic Credit to the Private Sector, and Real Interest Rate, capturing economic growth, price stability, currency dynamics, credit availability, and borrowing costs. Institutional quality is measured by Regulatory Quality, an index reflecting government effectiveness in policy formulation and enforcement. Data for banking variables are obtained from the GFDD, while macroeconomic and institutional indicators are sourced from the World Bank's WDI; both are considered authentic and reliable sources. Table 2 represents the variable specification and description that are used in our study.

Table 2. Variable Specification and Description

Variable	Sign	Description	Definition	Sources
Non-Performing Loans	NPL	Non-Performing Loans (as % of total gross loans)	The share of loans in default or close to being in default, expressed as a percentage of total gross loans.	GFDD
Bank Credit	BC	Bank Credit to Assets Ratio (%)	The ratio of a bank's total credit to its total assets, reflecting the extent of loan financing in asset composition.	GFDD
Provision	PVN	Provisions to Non-Performing Loans (%)	Loan loss provisions set aside to cover potential losses from non-performing loans, expressed as a percentage of total NPLs.	GFDD
GDP Growth	GDP	Gross Domestic Product Growth	Annual percentage growth rate of GDP at market prices based on constant local currency.	WDI
Inflation	INF	Inflation, Consumer Prices (annual %)	Annual percentage change in the cost to the average consumer of acquiring a basket of goods and services.	WDI
Exchange Rate Growth	ERG	Growth in Real Effective Exchange Rate	Annual percentage change in a country's real effective exchange rate, adjusted for inflation differentials.	WDI
Domestic Credit	DC	Domestic Credit to Private Sector (% of GDP)	Financial resources provided to the private sector, expressed as a percentage of GDP.	WDI
Interest Rate	IR	Real Interest Rate (%)	Lending interest rate adjusted for inflation as measured by the GDP deflator.	WDI
Regulatory Quality	RQ	Regulatory Quality	An index measuring the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.	WDI

Model Specification

After evaluating the literature, the study uses the panel data estimate strategy, notably the panel ARDL method, to achieve its main goal. The ARDL approach examines a series of mixed I (0) and I (1) to provide accurate and relevant estimates. The study recommends it over other strategies (Nkoro & Uko, 2016). The ARDL bound test requires stationarity rank to determine degrees for lower and higher orders (Ozturk & Acaravci, 2010).

We use the panel ARDL model because of its advantages over other econometric methodologies. ARDL is ideal for datasets with mixed integration variables, avoiding the constraints of approaches that require all variables to be integrated at order 1. ARDL's capabilities make it an ideal candidate for our research objectives. The baseline equation of our study has been given in equation 1.

$$NPL_{it} = \alpha_i + \tau_t + \sum_{j=1}^p \theta_j NPL_{i,t-j} + \sum_{j=0}^q \beta_j X_{i,t-j} + \varepsilon_{it} \quad (1)$$

Here, Let $i=1, \dots, N$, of index countries and $t=1, \dots, T$ of years

To examine the determinants of non-performing loans (NPLs) in emerging economies, we employ a Panel ARDL approach, which accommodates variables with different orders of integration while capturing both short-run dynamics and long-run equilibrium relationships. Our analysis begins with descriptive statistics to summarize the data distribution, followed by cross-sectional dependence tests to account for potential correlations across countries. We then conduct panel unit root tests to verify that the dependent variable is stationary at first difference $[I(1)]$ while allowing independent variables to be stationary at level $[I(0)]$, first difference $[I(1)]$, or a mix. The Panel ARDL model is estimated using three estimators, PMG, and DFE. To assess regional variations, we analyze three distinct panels: Asian economies (Panel A), African economies (Panel B), and a combined sample (Panel C). Finally, we perform post-estimation diagnostics, including cointegration tests and stability checks, to validate the model's reliability. This comprehensive methodology allows us to rigorously evaluate the macroeconomic, financial, and institutional drivers of NPLs across different emerging market contexts. The parameterized panel ARDL model is shown in equation 2.

$$\begin{aligned} \Delta NPL_t = & \varphi_0 + \sum_{i=0}^n \varphi_{1i} \Delta NPL_{t-i} + \sum_{i=0}^n \varphi_{2i} \Delta BC_{t-i} + \sum_{i=0}^n \varphi_{3i} \Delta PVN_{t-i} \\ & + \sum_{i=0}^n \varphi_{4i} \Delta GDP_{t-i} + \sum_{i=0}^n \varphi_{5i} \Delta INF_{t-i} + \sum_{i=0}^n \varphi_{6i} \Delta ERG_{t-i} \\ & + \sum_{i=0}^n \varphi_{7i} \Delta DC_{t-i} + \sum_{i=0}^n \varphi_{8i} \Delta IR_{t-i} + \sum_{i=0}^n \varphi_{9i} \Delta RQ_{t-i} \\ & + \beta_1 NPL_{t-1} + \beta_2 BC_{t-1} + \beta_3 PVN_{t-1} + \beta_4 GDP_{t-1} \\ & + \beta_5 INF_{t-1} + \beta_6 ERG_{t-1} + \beta_7 DC_{t-1} + \beta_8 IR_{t-1} + \beta_9 RQ_{t-1} + \mu_t \end{aligned} \quad (2)$$

Here, t is the time trend; the Δ is the first difference operator; μ_t is a white noise; the are the short-run parameters, while denote the long-run multipliers.

Robustness Check

To ensure the robustness of our findings, we supplement our Panel ARDL analysis with FE and RE estimations across all three models, Panel A (Asian economies), Panel B (African economies), and Panel C (combined sample). The FE model controls for unobserved time-invariant country-specific heterogeneity, while the RE model assumes that individual-specific effects are uncorrelated with the regressors, providing efficiency gains if this assumption holds (Wooldridge, 2010). We conduct Hausman tests to determine whether FE or RE is more appropriate for each panel, ensuring that our results are not driven by model specification biases. By comparing the consistency and significance of coefficients across ARDL, FE, and RE frameworks, we validate the reliability

of our key findings on the determinants of non-performing loans (NPLs). This multi-model approach strengthens the credibility of our conclusions, confirming whether the observed relationships persist under different estimation techniques and across distinct regional groupings. The equations of fixed effect and random effect are shown in equation 3.

$$NPL_{it} = \alpha_i + \tau_t + \beta X_{it} + u_{it} \quad (3)$$

Here, with capturing unobserved, time-invariant country heterogeneity, are common time shocks.

$$NPL_{it} = \alpha_i + \tau_t + \beta X_{it} + c_i + u_{it} \quad (4)$$

Here, where is the country-specific random effect assumed to be uncorrelated with regressors.

Machine Learning Models and SHAP-Based Feature Importance Analysis

Random Forest Regression

To decrease variance and improve generalization, Random Forest Regression, a popular ensemble learning technique, builds a set of decision trees and combines their predictions (Breiman, 2001). To provide variety and avoid overfitting, each tree is trained on a bootstrapped sample using randomly chosen feature subsets. The approach is resilient to noise and non-linearity in the data since the final forecast is calculated as the average of the outputs of individual trees. The equation for Random Forest regression is given in equation 5.

$$\hat{Y} = \frac{1}{T} \sum_{t=1}^T h_t(x) \quad (5)$$

where is the prediction of the t^{th} tree, and T is the number of trees.

CatBoost Regression

A gradient boosting method called CatBoost was developed primarily to handle categorical data effectively (Dorogush et al., 2018). It constructs decision trees one after the other, fixing the residual mistakes of the prior ensemble. CatBoost handles categorical data without requiring a lot of preprocessing by using target statistics encoding and ordered boosting to prevent prediction shift. Faster training and inference are also made possible by its symmetric tree structure, which preserves good accuracy. The equation for CatBoost regression is given in equation 6

$$\hat{Y} = \sum_{m=1}^M \eta f_m(x_i) \quad (6)$$

where represents the prediction of the m^{th} tree, M is the number of boosting rounds, and η is the learning rate.

XGBoost Regression

Extreme Gradient Boosting, or XGBoost, is a sophisticated boosting technique renowned for its regularisation processes and scalability (Chen & Guestrin, 2016). It provides quicker and more accurate convergence by optimising a differentiable loss function using both first- and second-order derivatives. XGBoost utilizes column subsampling, shrinkage, and L1 and L2 regularization to prevent overfitting. Because of its exceptional

accuracy and efficiency, the model is frequently used in regression tasks. The equation for XGBoost regression is given in equation 7.

$$\tau(\theta) = \sum_{i=1}^n l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \quad (7)$$

where l is the loss function, f_t is the new tree, and Ω represents the regularization term.

SHAP

SHAP is a model-agnostic interpretability technique that allocates feature significance using Shapley values from cooperative game theory (Lundberg & Lee, 2017). It ensures additivity, consistency, and fairness in explanations by calculating the marginal contribution of each feature, considering all potential feature subsets. SHAP values are a typical tool for transparent AI and explainable machine learning because they offer both global insights (feature priority ranking) and local interpretability (per-instance explanations). In this experiment, we used Random Forest, CatBoost and XGBoost regression models with all the data and continent-wise data and integrated with SHAP analysis to identify the feature importance of feature variables for NPL outcome.

To empirically investigate the determinants of NPLs across emerging economies, this study employs a mixed methodological framework that integrates econometric and machine learning approaches. Here, the Panel ARDL model is chosen for its ability to handle mixed integration orders in macro-financial datasets, allowing for both short-run adjustments and long-run equilibrium relationships, which is crucial for analyzing NPLs affected by macroeconomic shocks (Pesaran et al., 1999). FE and RE models provide robust validation, capturing country-specific heterogeneity and testing for specification errors using the Hausman test (Wooldridge, 2010). Additionally, integrating machine learning models like Random Forest, CatBoost, and XGBoost addresses non-linear relationships and enhances predictive analytics, while SHAP facilitates interpretability, effectively combining causal inference with practical policy considerations (Lundberg & Lee, 2017). Hence, we use the mixed approach following (Aich et al., 2025).to approach ensures methodological coherence and strengthens the reliability of findings. The econometric and machine learning components are applied sequentially with complementary goals to provide methodological coherence. To provide causal and policy-relevant inference, the Panel ARDL framework is first used to discover theoretically supported short-run dynamics and long-run equilibrium linkages among NPLs and their determinants under mixed orders of integration (Pesaran et al., 1999). By capturing non-linear effects, interaction patterns, and predictive significance that conventional econometric models might miss, the machine learning analysis that follows, interpreted through SHAP values, enriches inference without compromising theoretical structure (Lundberg & Lee, 2017).

Results

Description

The descriptive statistics in Table 3 reveal important insights into the distribution and variability of key variables related to NPLs and their determinants. On average, NPLs stand at 8.057%, indicating moderate credit risk, and range (1.1% to 37.3%) highlight significant disparities, with some institutions facing severe loan quality issues while others maintain very low NPL levels. Banking-specific factors such as bank credit and provi-

sioning show considerable variation, with credit expansion ranging dramatically from 39.316 to 898.048, suggesting that aggressive lending practices in some cases may contribute to higher NPLs. Provisioning levels average 50.695% but vary widely (9.863 to 137.4), reflecting differing risk management approaches across institutions. Interest rates also exhibit notable fluctuations, with a mean of 4.375% but extreme values, including negative rates as low as -20.497%, likely due to unconventional monetary policies in certain economies.

Macroeconomic conditions further influence NPL dynamics, with GDP growth averaging 4.958% but dipping as low as -9.518% in some cases, underscoring the impact of economic downturns on loan performance. Inflation averages 6.663%, yet reaches alarming highs (42.303%) in certain observations, potentially eroding borrowers' repayment capacity. Exchange rate growth displays extreme volatility (-28.233% to 129.228%), indicating currency instability that could heighten default risks, particularly for foreign currency-denominated loans. Domestic credit expansion varies widely (8.07% to 133.786%), reflecting differing levels of financial deepening across economies. Finally, regulatory quality scores range from weak (8.458) to strong (76.442), suggesting that governance effectiveness plays a critical role in shaping NPL outcomes. Generally, the data emphasizes the multifaceted nature of NPL determinants, with significant heterogeneity across banking practices, macroeconomic conditions, and institutional frameworks.

Table 3. Descriptive statistics

Statistic	NPL	BC	PVN	GDP	INF	ERG	DC	IR	RQ
mean	8.057	140.565	50.695	4.958	6.663	3.978	49.479	4.375	42.362
std	7.848	167.426	17.646	2.787	5.696	11.589	32.131	4.491	17.752
min	1.100	39.316	9.863	-9.518	-5.992	-28.233	8.070	-20.497	8.458
25%	2.751	73.439	41.200	3.838	3.658	-0.209	27.639	2.634	27.027
50%	5.050	86.332	47.618	5.332	5.619	2.372	38.959	4.761	42.381
75%	9.949	101.834	59.400	6.569	8.129	6.340	60.506	6.502	55.714
max	37.300	898.048	137.400	15.329	42.303	129.228	133.786	18.180	76.442

Correlation

Table 4 represents the correlation matrix that reveals several key relationships between NPLs and their determinants. NPLs show a moderate negative correlation with bank credit (-0.257) and domestic credit (-0.384), suggesting that higher credit availability is associated with lower NPLs, possibly due to better financial intermediation. However, NPLs have a weak positive correlation with inflation (0.167) and interest rates (0.198), indicating that rising prices and borrowing costs may strain borrowers, increasing defaults. Regulatory quality exhibits a moderate negative correlation with NPLs (-0.362), reinforcing that stronger governance helps reduce loan defaults. Interestingly, GDP growth shows almost no correlation with NPLs (0.043), contradicting conventional expectations, while exchange rate growth also has minimal impact (0.039). Among macroeconomic factors, inflation and interest rates are strongly negatively correlated (-0.696), likely reflecting monetary policy responses to price stability. Domestic credit and regulatory quality display a moderate positive correlation (0.559), implying that well-regulated economies tend to have deeper financial systems. Thus, the findings highlight that banking factors (credit policies, interest rates) and institutional quality play a more significant role in NPLs than macroeconomic fluctuations, though inflation remains a notable risk factor. **Figure 4** presents the correlation graphically.

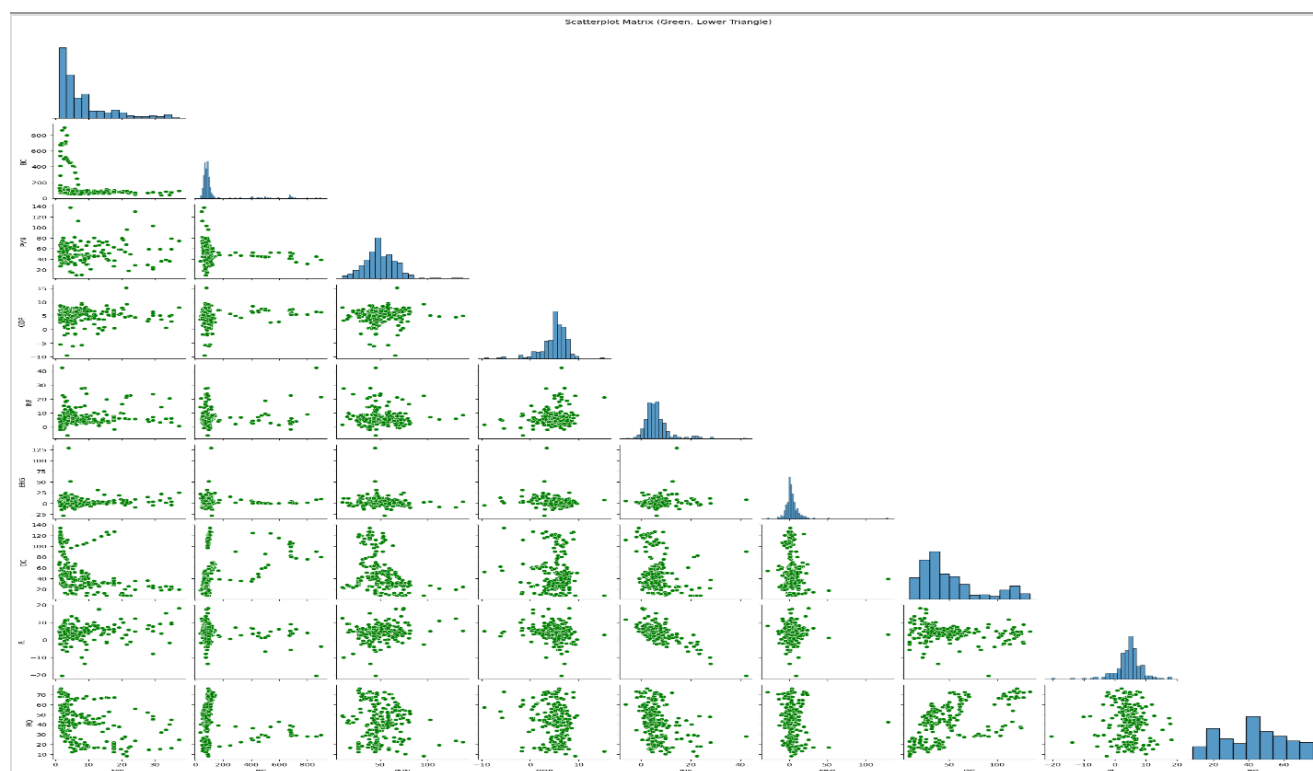


Figure 4. Correlation Matrix

Table 4. Correlation Matrix

	NPL	BC	PVN	GDP	INF	ERG	DC	IR	RQ
NPL	1								
BC	-0.257	1							
PVN	0.049	-0.146	1						
GDP	0.043	0.141	0.073	1					
INF	0.167	0.147	-0.076	0.160	1				
ERG	0.039	-0.013	-0.098	-0.148	0.129	1			
DC	-0.384	0.407	-0.325	-0.054	-0.275	-0.089	1		
IR	0.198	-0.223	0.202	-0.173	-0.696	0.007	-0.225	1	
RQ	-0.362	-0.176	-0.101	-0.212	-0.328	-0.096	0.559	-0.080	1

Unit Root Test

The Augmented Dickey-Fuller (ADF) test shows that most variables are non-stationary at level but become stationary after first differencing, indicating they are integrated of order one, $I(1)$. However, BC, GDP, DC, and RQ are non-stationary but achieve stationarity after differencing and the result is given in Table 5. The Kao and Pedroni cointegration tests confirm a significant long-run equilibrium relationship among variables in a model, rejecting the null hypothesis of no cointegrations (see Table 6).

ARDL Estimation

The PMG estimation results given in Table 7 reveal several key long-run relationships between NPLs and their determinants across different regions. The PMG results for Asia reveal several important long-run relation-

ships between banking sector variables, macroeconomic conditions, and non-performing loans. The positive coefficient of 0.188 for bank credit indicates that credit expansion is associated with deteriorating loan quality, suggesting that periods of increased lending may lead to relaxed underwriting standards or excessive risk-taking by banks. This finding aligns with theoretical expectations that credit booms often sow the seeds for future loan quality problems. The surprisingly positive coefficient of 0.806 for GDP growth suggests that periods of economic expansion in Asia may paradoxically coincide with rising NPLs. Inflation shows an exceptionally strong positive relationship with NPLs (coefficient of 4.866), indicating that macroeconomic instability significantly impairs borrowers' repayment capacity. The substantial coefficient of 4.198 for interest rates demonstrates how monetary policy conditions affect loan performance, as higher rates increase debt servicing burdens for both households and corporations. On the positive side, the negative coefficient of -0.134 for provisioning indicates that stronger loan loss reserves are associated with better loan performance. This likely reflects both a direct effect (as provisions cover existing bad loans) and an indirect effect (as higher provisions may indicate more prudent risk management practices).

Table 5. Unit Root Test

Variables	ADF	
	At Level	First Difference
NPL	-4.709***	-9.837***
BC	-1.777	-3.927***
PVN	-11.260***	-7.300***
GDP	-2.938**	-10.786***
INF	-5.278***	-6.715***
ERG	-9.088***	-5.985***
DC	-1.917	-12.444***
IR	-9.347***	-8.227***
RQ	-1.547	-12.629***

Note: *, ** & *** indicate significant levels of 10%, 5%, and 1% respectively.

Table 6. Residual cointegration test

Test Type	ADF Statistic	p-value	Cointegration (at 1%)
Kao Residual Cointegration Test	-5.12059	0.000	Cointegrated
Pedroni Residual Cointegration Test	-5.059187	0.000	

In African economies, the strong negative coefficient (-0.657) for regulatory quality demonstrates that improving governance standards, strengthening oversight, and enhancing institutional frameworks can substantially decrease NPLs, likely by promoting more responsible lending practices and better risk management in the banking sector. When examining all regions together, three consistent patterns emerge. First, economic growth surprisingly correlates with higher NPLs (0.848), suggesting that rapid expansions may encourage riskier lending that later turns problematic. Second, inflation maintains its damaging effect (1.099), as rising prices erode borrowers' repayment capacity. Third, the persistent negative coefficient for regulatory quality (-0.548) confirms that better governance helps reduce NPLs across all markets. Most strikingly, interest rates

show the most universally strong impact (1.260), with higher rates consistently leading to more loan defaults regardless of region, emphasizing how monetary policy directly affects financial stability through the NPL channel. The PMG results showed in Table 7 that temporary credit tightening measures can effectively reduce NPLs across all markets, suggesting that banks can improve loan portfolio quality by selective lending or reducing credit expansion. Africa's faster adjustment speed to NPL imbalances suggests greater efficiency or volatility in its financial systems, possibly due to shallower markets or immediate policy transmission mechanisms.

The results reveal a significant difference between short-run and long-run dynamics of NPLs, with inflation and interest rates influencing long-term trends, while credit policies have immediate effects. African markets exhibit heightened short-term sensitivity. The negative error correction terms across all models suggest that NPL levels naturally gravitate towards equilibrium over time, with the journey back to equilibrium varying significantly by region.

Table 7. Long-run Effect

Variable	Panel A			Panel B			Panel C		
	PMG	MG	DFE	PMG	MG	DFE	PMG	MG	DFE
BC	0.188***	0.114	-0.004	0.171**	-1.721	0.403	0.106**	-0.498	0.021
PVN	-0.134***	-0.106	-0.271***	0.144	0.041	0.189	-0.213***	-0.057	0.026
GDP	0.806***	0.077	-0.221	0.231	-0.838	-0.518	0.848***	-0.228	-0.056
INF	4.866***	0.367	-0.143	0.679	0.909	-0.597	1.099***	0.548	0.249
ERG	0.101**	0.501**	0.433**	0.104	0.030	-0.008	0.065	0.345**	0.105
DC	0.388***	-0.126	-0.022	0.693	3.842*	-0.437	0.411***	1.197	-0.067
IR	4.198***	0.992	-0.322	0.798*	0.848	0.286	1.260***	0.944	0.986**
RQ	-0.181	-0.147	0.067	-0.657***	-0.074	-0.192	-0.548***	-0.123	-0.069

Note: *, ** & *** indicate significant levels of 10%, 5%, and 1% respectively.

From our above findings, the ARDL results demonstrate that NPL dynamics in emerging economies are shaped by a combination of procyclical credit behavior, macroeconomic instability, and institutional strength. While Asia's NPLs are primarily driven by growth-led credit expansion and inflationary pressures, Africa's experience underscores the critical role of interest rate stability and regulatory quality. These cross-regional patterns emphasize that effective NPL management requires region-specific policy responses anchored in sound credit governance and macro-financial coordination.

Robustness Check

Table 9 shows the findings of the robustness check. We have conducted both fixed effect and random effect analyses, and based on the Hausman test, we concluded that the random effect model is more appropriate for these analyses. The random effects model for Asia reveals several significant relationships with NPLs. Bank credit shows a strong negative coefficient (-0.017), indicating that increased lending is associated with lower NPLs in the region. Inflation (1.128) and interest rates (1.500*) demonstrate substantial positive effects, confirming that macroeconomic instability drives loan defaults. Regulatory quality (-0.079) appears as an impor-

tant mitigating factor, while provisioning (-0.060) also helps reduce NPLs. The positive coefficient for domestic credit (0.056) suggests potential risks during financial sector expansion.

Table 8. Short-Run

Variable	Panel A			Panel B			Panel C		
	PMG	MG	DFE	PMG	MG	DFE	PMG	MG	DFE
D.BC	-0.184*	0.037	-0.007	-0.202**	0.370	-0.096	-0.166**	0.148	-0.012
D.PVN	-0.012	-0.034	-0.007	-0.094*	-0.065	-0.048	-0.013	-0.045	-0.012
D.GDP	0.0626	-0.110	0.011	0.071	0.485*	0.277	-0.109	0.088	0.011
D.INF	-0.1253	-0.509	0.200	-0.208	-1.274***	1.026**	0.074	-0.763*	0.412
D.ERG	0.0327	-0.099*	-0.031	-0.187	-0.086	0.039	-0.040	-0.095	0.011
D.DC	0.3234	0.318	0.007	-0.086	-2.229*	-0.064	0.036	-0.531	-0.012
D.IR	-0.119	-0.680*	0.251	-0.292	-1.092***	0.875	-0.035	-0.817***	0.312
D.RQ	0.0346	0.067	-0.004	0.071	0.191	-0.137	0.076	0.108*	-0.012
cons	-10.497***	2.437	3.587	-9.490	4.504	-3.686	-0.731	3.126	0.712
ect	-0.173***	-0.368***	-0.192	-0.494	-0.874***	-0.430***	-0.252**	-0.537***	-0.012

Note: *, ** & *** indicate significant levels of 10%, 5%, and 1% respectively.

These results highlight Asia's particular sensitivity to both macroeconomic conditions and banking sector variables. Africa's random effects estimation shows similar patterns to Asia but with some distinct differences. Like Asia, inflation (1.128) and interest rates (1.500) significantly increase NPLs, while regulatory quality (-0.079) reduces them. However, the bank credit coefficient (-0.016*) is slightly less negative than in Asia, possibly reflecting different credit market structures. Domestic credit again shows a positive relationship (0.055), and provisioning (-0.060) remains significant. The results emphasize how Africa's NPLs are similarly affected by macroeconomic factors but may respond differently to banking sector variables compared to Asia. The combined sample analysis reinforces key findings while showing some integration effects. Regulatory quality's impact strengthens (-0.106), and inflation (0.924) and interest rates (1.116*) remain significant drivers of NPLs, though with slightly reduced coefficients. Bank credit (-0.016*) maintains its negative relationship, while domestic credit (0.054**) continues to show a positive link. Notably, provisioning becomes insignificant in the combined model, suggesting its effects may be region-specific. These results confirm the robustness of core relationships while revealing how regional aggregation can alter the perceived importance of certain variables.

In short, the study investigates the dynamics between macroeconomic variables and NPLs, highlighting the risk of endogeneity due to reverse causality. We employ the Panel ARDL model to tackle this, which uses lagged variables to mitigate endogeneity and captures the influence of loan quality on macroeconomic outcomes. Additionally, cointegration tests confirm long-run equilibrium relationships, ensuring robust estimates. Fixed Effects and Random Effects models address unobserved heterogeneity, with the Hausman test supporting the RE specification.

Machine Learning Approaches: Comparative SHAP Analysis of NPL Determinants

The SHAP analysis in **Figure 5** reveals critical insights into non-performing loan prediction across Asia and Africa, while also providing a global perspective. In Asia, banking stability indicators - particularly Bank Credit and Domestic Credit consistently rank as top predictors across all machine learning models, complemented by Regulatory Quality and Provisions. The CatBoost model uniquely highlights Inflation as a significant factor in this region. Africa presents an even more pronounced dominance of credit-related variables, with BC and DC showing exceptionally high importance in XGBoost (BC reaching a SHAP value of +2.96), while Interest Rates emerge as a distinctive predictor absent in Asia's key variables. Both regions demonstrate that financial sector metrics substantially outweigh macroeconomic indicators in predictive power.

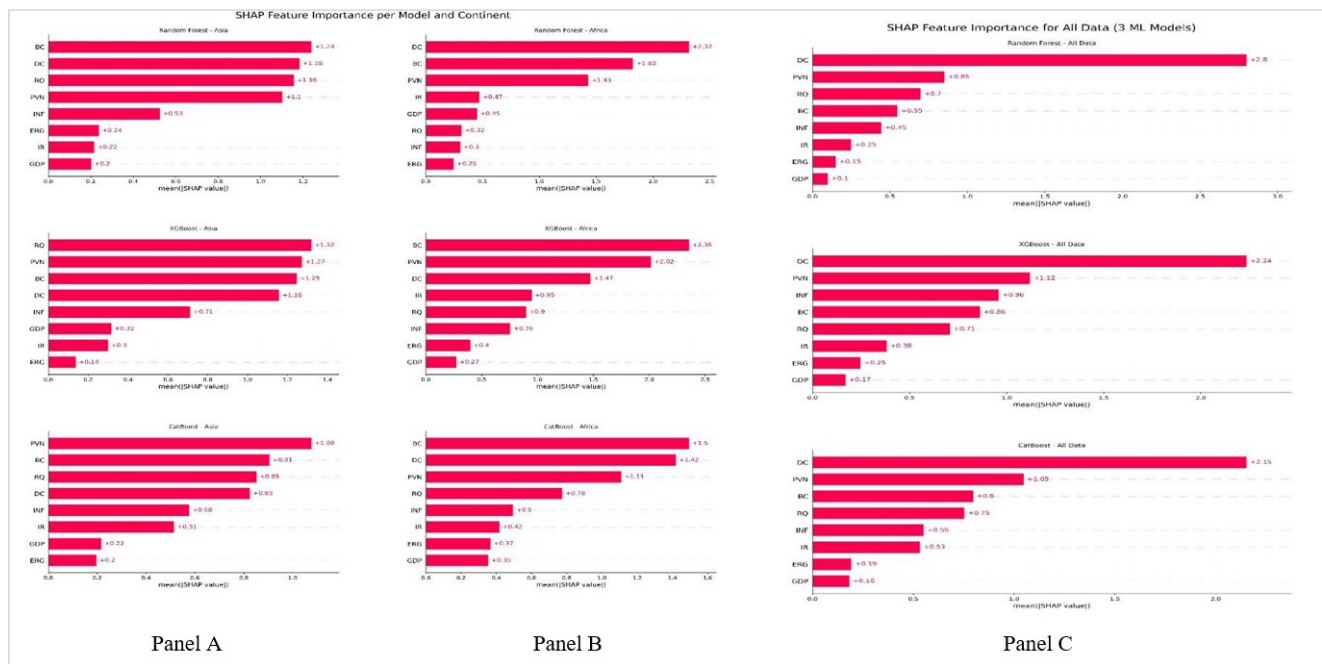


Figure 5. Relative Contribution of Variables in Prediction

Table 9. Robustness Check with Alternative Method

	Panel A		Panel B		Panel C	
Variable	FE	RE	FE	RE	FE	RE
BC	-0.012**	-0.017***	-0.012***	-0.016***	-0.010	-0.016***
DC	-0.052	0.056**	-0.051	0.055**	-0.067	0.054**
ERG	0.152*	0.125	0.152*	0.125	0.023	-0.020
GDP	-0.026	0.082	-0.026	0.082	-0.012	0.167
INF	1.461***	1.128***	1.461***	1.128***	0.988***	0.924***
IR	1.910***	1.500***	1.910***	1.500***	1.166***	1.116***
PVN	-0.042	-0.060**	-0.042	-0.060**	0.020	0.004
RQ	-0.002	-0.079**	-0.001	-0.079**	-0.112*	-0.106***
const	-1.509		-1.509		4.837	

Note: *, ** & *** indicate significant levels of 10%, 5%, and 1% respectively.

The global analysis incorporating all data reinforces these findings, with BC and DC maintaining their position as the most influential variables across Random Forest, XGBoost, and CatBoost models. Random Forest assigns particularly high SHAP values to these credit indicators, while XGBoost and CatBoost show relatively greater emphasis on Provision and Inflation. This consistent pattern across continents and models underscores the universal importance of banking sector health in NPL prediction, while macroeconomic factors consistently demonstrate limited predictive value. These results strongly suggest that risk management frameworks should prioritize financial sector variables, with region-specific adaptations: incorporating regulatory and inflation metrics for Asian markets, while placing additional emphasis on credit conditions and interest rate effects in African contexts. The findings provide robust evidence for developing tailored, data-driven approaches to credit risk assessment in different geographical markets.

To assess robustness, SHAP value rankings were compared across Random Forest, XGBoost, and CatBoost models with cross-validated tuning. The consistent ordering of key predictors, particularly Bank Credit, Domestic Credit, Inflation, Interest Rates, and Regulatory Quality, indicates that the results are stable and not driven by a specific model specification.

Feature Importance and Predictive Patterns of NPLs

In Figure 6, the variables non-performing loans, bank credit to assets ratio, loan loss provisions, GDP growth, inflation, exchange rate growth, domestic credit, interest rate, and regulatory quality can be interpreted as features in a predictive modeling framework, where NPL is the target variable. Panel A indicates a feature-target relationship with more stable and consistent signal patterns, suggesting that features like bank credit, GDP, and regulatory quality have higher predictive power and stronger feature importance for NPL variance in the Asian region. Negative correlations between regulatory, GDP, and NPL suggest that well-governed, high-growth economies tend to have lower predicted default risks. Panel B reveals a mixed feature-target mapping, where macroeconomic variables such as inflation and exchange rate growth introduce higher variance, leading to weaker predictive accuracy in the African Region. Panel C shows that regulatory quality generally has a negative relationship with Non-Performing Loans NPL, suggesting that stronger governance reduces credit default risk. Inflation and Exchange Rate Growth show a positive association with NPL, while bank credit and domestic credit have mixed relationships.

Discussion

This study combines PMG estimation and SHAP-based machine learning analysis to examine the determinants of NPLs across emerging economies in Asia and Africa. The empirical results consistently indicate that credit expansion, macroeconomic instability, institutional quality, and monetary policy play central roles in shaping NPL dynamics, though their relative importance differs across regions. These findings are broadly consistent with established theoretical frameworks in financial economics, including the Financial Accelerator Theory (Bernanke et al., 1999), Credit Rationing Theory (Stiglitz & Weiss, 1981), and Institutional Theory (North, 1990).

Empirical interpretation of growth and monetary conditions

The results reveal a positive association between GDP growth and NPLs in Asia and in the full sample, a finding that appears counterintuitive at first glance. However, this pattern can be explained by procyclical

lending behavior, whereby periods of strong economic growth encourage rapid credit expansion and relaxed lending standards. Such dynamics increase borrower risk exposure, leading to higher default rates once economic conditions normalize (Bernanke et al., 1999; Ahuja & Nabar, 2012).

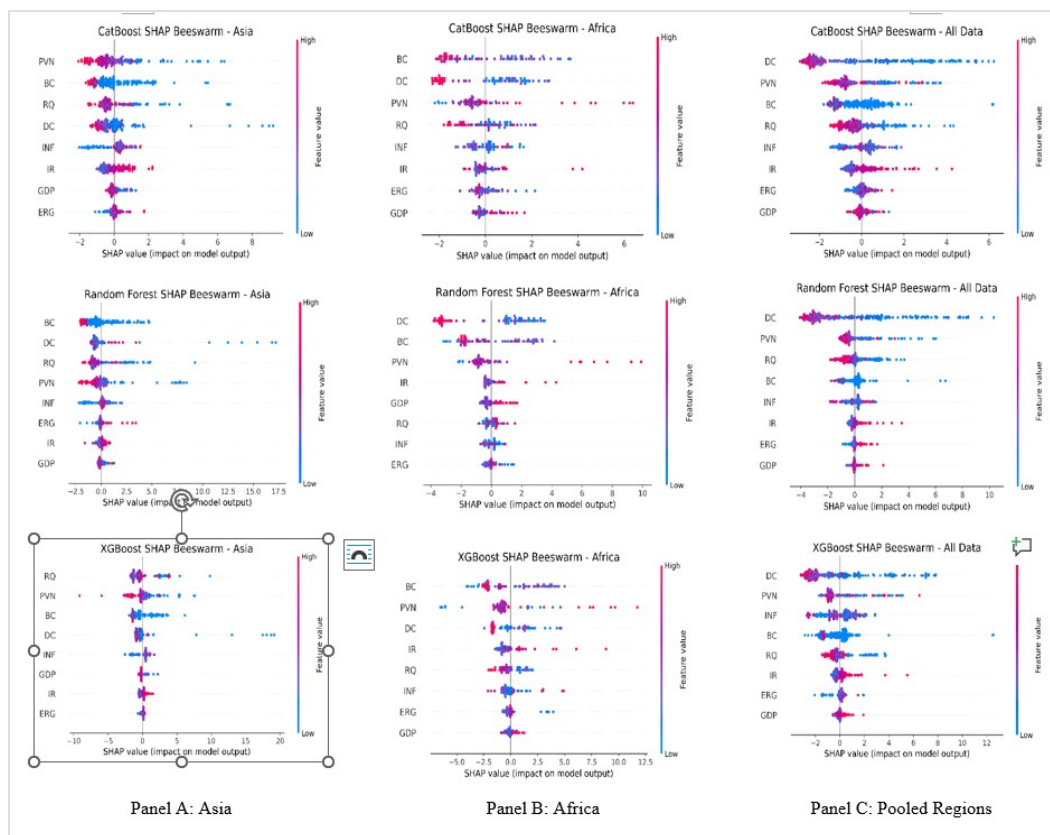


Figure 6. Comparative Panel Results for Asia, Africa, and Pooled Regions

Theoretical linkage to the Financial Accelerator mechanism

This empirical outcome aligns closely with the Financial Accelerator Theory, which posits that economic upturns amplify credit cycles and risk-taking through balance-sheet effects (Bernanke et al., 1999). During booms, banks tend to extend credit to marginal borrowers, increasing vulnerability to future shocks (Aikman et al., 2015). The positive and significant effect of interest rates on NPLs further supports this mechanism, as higher borrowing costs raise debt servicing burdens and intensify default risks, an effect that is particularly pronounced in African economies, where interest rates emerge as a key predictor in the SHAP analysis.

Credit expansion and information asymmetry

Both PMG estimates and SHAP feature importance rankings strongly support the positive relationship between bank credit expansion and NPLs. Credit-related variables, including bank credit and domestic credit, dominate NPL prediction across regions, consistent with empirical evidence that rapid credit growth and financial deepening tend to be associated with higher non-performing loans in emerging markets (Alihodžić & Ekşi, 2018). This finding reflects the central role of credit market imperfections in driving loan performance and aligns with prior studies showing that excessive credit expansion can erode underwriting standards and increase default risk.

Theoretical interpretation through Credit Rationing Theory

These results are consistent with Stiglitz & Weiss's (1981) Credit Rationing Theory, which emphasizes adverse selection and moral hazard under asymmetric information. Rapid credit growth may attract riskier borrowers or encourage excessive risk-taking, ultimately increasing default probabilities (Berger & Udell, 2004). The negative association between loan loss provisions and NPLs further supports this interpretation, as higher provisions indicate stronger risk screening and forward-looking credit management (Bouvatier et al., 2014).

Institutional quality and regulatory effectiveness

Institutional variables also play a crucial role in shaping NPL dynamics (Klein, 2013). The PMG results show a strong negative relationship between regulatory quality and NPLs, particularly in African economies. This suggests that stronger governance frameworks and supervisory effectiveness can substantially reduce credit risk.

Theoretical and regional interpretation of institutional effects

These findings align with institutional theory (North, 1990), which argues that robust institutional frameworks reduce financial fragility by promoting prudent lending and effective oversight (Čihák et al., 2013). In Africa, where institutional weaknesses are more pronounced, improvements in regulatory quality significantly lower NPLs (Beck et al., 2006). The SHAP analysis further validates these results, identifying regulatory quality as a key predictor in Asia, while macroeconomic volatility, especially inflation, introduces greater predictive variance in Africa.

Macroeconomic instability and inflation dynamics

Inflation emerges as a particularly influential determinant of NPLs in Asian economies, with large coefficients in the PMG estimates and high SHAP importance scores in CatBoost models. High inflation erodes real incomes and weakens borrowers' repayment capacity, thereby increasing default risk. This result is consistent with previous empirical findings (Nkusu, 2011; Fofack, 2005). Thus, the findings corroborate earlier evidence linking credit growth, macroeconomic instability, and NPL accumulation (Louzis et al., 2012; Nkusu, 2011; Berger & Udell, 2004), while reinforcing the critical role of institutional quality in mitigating financial fragility (Čihák et al., 2013; (Beck & Cull, 2013). Importantly, the results underscore the need for region-specific policy responses: countercyclical credit regulation, inflation management, and regulatory strengthening in Asia, alongside interest rate stabilization, institutional reform, and enhanced credit risk monitoring in Africa.

Policy Implications

The empirical findings underscore that NPLs are shaped by an interplay of financial, macroeconomic, and institutional factors, necessitating region-specific policy approaches to mitigate credit risk effectively. For Asia, where NPL dynamics are largely driven by rapid GDP growth, inflation, and credit expansion, policy measures should focus on curbing procyclical credit risks through coordinated financial and monetary reforms. Policymakers should adopt countercyclical credit regulations, such as dynamic provisioning that builds buffers during credit explosions and the enforcement of loan-to-value and debt-to-income ratio caps to limit excessive risk-taking in sectors like real estate and consumer lending. At the same time, macro prudential oversight needs strengthening through the use of sectoral risk weights to discourage concentrated exposures in high-risk industries and the integration of AI-driven early warning systems, leveraging SHAP-based models, to identify emerging NPL risks in real time. Finally, refining inflation-targeting frameworks is essential, ensuring

that monetary policy tightens when credit growth outpaces GDP growth, while central banks and financial regulators coordinate to align inflation management with broader financial stability objectives.

For Africa, where NPL challenges are rooted in macroeconomic instability, high interest rates, and weak institutional frameworks, policy actions should focus on stabilizing fragile financial systems through monetary, institutional, and regulatory reforms. Monetary policy reforms should aim to gradually lower lending costs by reducing policy interest rates where feasible and introducing liquidity support mechanisms to prevent abrupt credit contractions during shocks. At the same time, institutional strengthening is critical, including enhancing contract enforcement, improving collateral recovery processes, and establishing credit bureaus and secured transaction registries to reduce information asymmetry in lending. Broader macroeconomic stabilization measures are also essential, such as maintaining fiscal discipline to contain inflation and exchange rate volatility, while diversifying economies away from commodity dependence to reduce exposure to external shocks. Finally, supervisory and regulatory capacity building must be prioritized through risk-based training for banking supervisors and the gradual adoption of Basel III liquidity and capital standards to enhance resilience within the banking sector.

The cross-regional evidence underscores that NPLs are not merely a banking sector problem but a macro-institutional challenge, requiring integrated policy frameworks that link financial stability, macroeconomic management, and institutional governance. Policymakers must closely monitor financial, real economy linkages, recognizing how monetary policy, credit cycles, and GDP growth interact to shape NPL trajectories, while ensuring that credit expansion does not outpace real economic capacity. Equally important is institutional governance, as stronger regulatory quality enhances repayment incentives and reduces opportunistic defaults, thereby lowering systemic risk. Finally, data-driven risk management should be mainstream into regulatory practice, with advanced analytics, such as SHAP-based machine learning models, used for stress testing, predictive monitoring, and timely interventions, enabling authorities to detect vulnerabilities early and respond proactively to emerging credit risks.

Finally, it is important to consider the underlying regulatory and institutional contexts to further interpret these regional variations. Categorizing countries into regional groups for analysis, it highlights significant regulatory differences within Asia affecting NPL behavior and banking stability. Further, advanced economies like Malaysia, South Korea, and Singapore follow Basel III standards, promoting strong capital adequacy and effective supervision, which help manage NPLs. Conversely, South Asian countries like Bangladesh, India, and Pakistan struggle with regulatory implementation, leading to higher NPL accumulation. Hence, the findings suggest that institutional strength and regulatory quality play crucial roles in credit risk mitigation, reflecting varying NPL determinants across the region. Policymakers are advised to enhance supervisory measures and align regulations with international standards for improved NPL management.

Conclusion and Limitations

This study presents a thorough empirical investigation into the determinants of non-performing loans in emerging economies of Asia and Africa, applying ARDL estimation to capture long-run relationships and short-run effects and SHAP analysis to provide predictive insights and model interpretability. The findings demonstrate that credit expansion, macroeconomic instability, institutional quality, and monetary policy are central drivers of NPLs, though their impacts vary significantly across regions. Using a hybrid methodology

that combines SHAP-based explainable machine learning with Panel ARDL statistical methods, this study adds to the body of literature by offering a unique cross-regional assessment of NPL factors in Asia and Africa. The analysis demonstrates region-specific processes by which credit expansion, macroeconomic instability, and institutional quality influence NPL dynamics by jointly identifying long-run causal linkages and non-linear feature importance factors.

Basically, NPL dynamics are largely shaped by credit booms that emerge during rapid GDP growth and loose lending standards in Asia, leading to higher default rates in subsequent periods, an outcome consistent with the Financial Accelerator Theory. Additionally, high inflation and interest rates erode borrowers' repayment capacity, while strong regulatory quality and adequate loan-loss provisioning help mitigate credit risks. In Africa, however, the key determinants of NPLs are rooted in macroeconomic instability, particularly inflation and exchange rate volatility, which raise uncertainty in debt servicing, aligning with Credit Rationing Theory. Elevated interest rates further exacerbate repayment burdens, while weak institutional structures amplify financial vulnerabilities; conversely, improvements in governance, credit bureau systems, and contract enforcement significantly reduce NPLs, highlighting the role of Institutional Theory.

In addition, the machine learning analysis provides complementary insights by identifying bank credit and domestic credit as the most powerful global predictors of NPLs, while also uncovering regional asymmetries: in Asia, inflation and regulatory quality exert a stronger influence, whereas in Africa, interest rates dominate and macroeconomic shocks generate higher variance, indicating weaker capacity for financial shock absorption. These insights carry important policy implications. For Asia, effective measures include countercyclical credit regulations such as dynamic provisioning, strengthening oversight through sector-specific risk weights, and pursuing tighter inflation-targeting frameworks to prevent overheating. For Africa, priorities lie in monetary policy reforms to reduce lending costs and stabilize interest rates, institutional strengthening through better governance and enforcement mechanisms, and macroeconomic stabilization strategies such as fiscal discipline and diversification away from commodity dependence.

Nonetheless, the study has limitations, including data constraints, methodological assumptions, and external validity. It may not fully reflect structural heterogeneity across countries and may not extend to advanced economies or emerging regions. Future research should conduct sectoral-level disaggregation, incorporate political and governance-related risk factors, and use advanced approaches like Dynamic Stochastic General Equilibrium modeling. However, by framing NPL mitigation as both an economic and social priority, the study emphasizes that strengthening financial governance is integral to achieving inclusive development and social resilience in emerging markets.

Therefore, this study emphasizes that NPLs are not merely a banking sector concern but a broader macro-institutional challenge that demands region-specific, multidimensional strategies. Addressing NPLs requires integrating financial regulation, monetary stability, and institutional reforms, tailored to the distinct economic and governance contexts of Asia and Africa. By offering robust empirical evidence and highlighting future research avenues, the study contributes to both theoretical understanding and practical policymaking, equipping regulators and researchers with insights to better navigate the evolving landscape of credit risk in emerging markets.

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Author contributions

Bithe Rani Aich: Conceptualization, Data curation, Writing – original draft, Writing – review & editing.

Muhammad Tanveer Islam: Data curation, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing.

Sanjay Bhattacharjee: Conceptualization, Investigation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare no conflicts of interest.

Ethics statement

Not applicable.

Data availability

Data available on request from the corresponding author.

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