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-RESEARCH ARTICLE-

LOAN DEFAULTS AND BANK PERFORMANCE, A PARDL ANALYSIS: IS IT A CRITICAL CONDITION FOR BANKS' FINANCIAL HEALTH?

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—Abstract—

The research investigates how non-performing loans influence banking sector outcomes in South Africa, using a quantitative framework and a three-stage panel data approach. Loan default remains a widely discussed issue both within South Africa and internationally. The analysis is based on data from 10 commercial banks covering the period 2012–2023. The Panel Autoregressive Distributed Lag (PARDL) method was employed to examine both long-run and short-run associations between loan default levels and bank performance. Empirical results indicate that, over the long term, loan defaults exert a statistically significant adverse effect on the performance of South African banks. In addition, the findings confirm a one-way causal relationship running

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from loan defaults to bank performance. The study recommends that banks strengthen governance and risk control mechanisms to mitigate default risk. Suggested measures include implementing asset-backed recovery frameworks, increasing loan loss provisioning, diversifying credit portfolios, and reinforcing compliance with regulatory standards.

Keywords: Loan Defaults, Commercial Banks, South Africa, Return on Assets, Return on Equity, Growth, Panel Autoregressive Distribution Lag.

INTRODUCTION

Despite repeated episodes of financial distress, recessions, and banking-sector crises across different economies over recent decades, the banking system remains a central pillar of economic activity. It performs a critical intermediary function by managing financial resources of households, firms, and governments, thereby sustaining liquidity circulation, which is essential for macroeconomic stability and growth (Mkele, 2024).

Examining the nexus between loan defaults and bank performance is therefore crucial, as increasing credit risk can undermine profitability, weaken financial resilience, and threaten overall systemic stability, especially in emerging markets. In South Africa, the banking structure is oligopolistic, well-developed, and highly competitive, with dominance concentrated in five major institutions (SARB, 2024). These include Amalgamated Banks of South Africa Limited (ABSA), First National Bank (FNB), Standard Bank, Capitec, and Nedbank. Collectively, including Investec Bank, these institutions control nearly 90% of total banking sector assets (Statista, 2022). Commercial banks also serve as the core of economic activity, forming an essential link between savers and borrowers, as well as between trade and industry, while ensuring adequate liquidity flow within the economy (Meylievich, 2022).

Globally, loan default has remained a long-standing concern due to its severe implications for banking-sector profitability and overall financial system stability (Gjeçi et al., 2023). In this context, default risk continues to represent a major structural challenge for both financial institutions and the broader economy, with no definitive or permanent resolution in sight (Ahmed et al., 2021). At present, data from the Consumer Default Index (CDI) of Experian South Africa indicates that consumer indebtedness has reached approximately R1.9 trillion, with R20.4 billion recorded as newly defaulted debt between January and March 2024.

This study contributes to the fields of financial economics and banking regulation by generating empirical evidence that may support policymakers, regulators, and bank management in refining credit risk mitigation frameworks, enhancing financial stability mechanisms, and strengthening early warning systems for identifying banking-sector stress. Furthermore, the CDI (2022) data presented in Table 1 indicates that home loans

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constitute the largest share of average outstanding credit, whereas retail loans represent the smallest portion among all loan categories. The comparative analysis further shows variation in new default incidences, with retail loans recording the highest number of new defaulters, while credit card facilities exhibit the lowest default levels. In addition, a general decline in the number of defaulters was observed between 2021 and 2022.

Table 1: Consumer Default Index

Loan Type	Average Outstanding	New Defaulters	CDI (2021)	CDI (2022)
Home Loan	R1.04 Trillion	R4.23 Billion	1.73	1.63
Vehicle Loan	R444.63 Billion	R4.37 Billion	4.10	3.93
Retail Loan	R35.5 Billion	R97 Billion	12.11	10.97
Personal Loan	R298.78 Billion	R6.07 Billion	10.52	8.13
Credit Card	R152.93 Billion	R2.46 Billion	8.35	6.44

Source: Consumer Default Index Report (2022)

Non-performing loans (NPLs) serve as a key measure of default risk within commercial banks and act as an important indicator of overall financial system health. The Figure 1 depicts the annual trend of NPLs within the South African banking sector as illustrated.

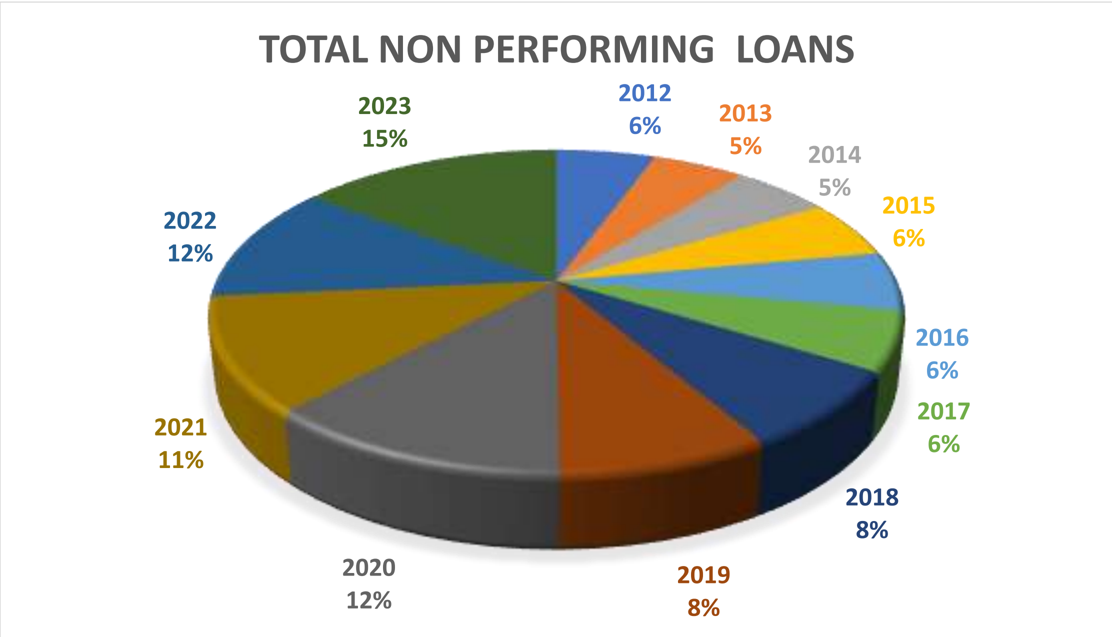

Figure 1: Overall Performance Non-Performing Loans
Source: Author's Computation, 2025

The graphical evidence indicates that NPLs remained relatively stable and subdued during the 2013–2014 period. This was followed by a gradual upward movement between 2015 and 2019, reflecting a progressive deterioration in credit quality over that interval. A pronounced escalation in NPLs is observed in 2020, representing a

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substantial deviation from prior trends. This sharp rise is plausibly associated with adverse macroeconomic disruptions and systemic shocks, most notably the COVID-19 pandemic, which commenced in March 2020 and significantly weakened repayment capacity across borrowers. Subsequently, a decline in NPLs is recorded in 2021, indicating partial recovery within the banking sector. However, a comparative assessment shows that NPLs increased again between 2022 and 2023, with an approximate rise of 3 percent, suggesting renewed pressure on credit performance during the later period.

The trajectory of NPLs shown in the Figure 2 reflects percentage changes over time. NPLs declined between 2016 and 2017, indicating improved credit conditions during that period. A more pronounced contraction is also observed between 2020 and 2021, reflecting a sharper reduction in default levels. Overall, the results demonstrate a cyclical pattern characterised by repeated peaks, troughs, and broader fluctuations across the study period. Marginal peaks are evident in 2013 and 2019, suggesting periodic increases in credit risk exposure. These variations may be linked to adjustments in banking policy instruments and regulatory frameworks over time, particularly in the post-COVID-19 environment, which contributed to structural shifts in the financial system. Furthermore, a significant percentage change in NPLs is recorded between 2022 and 2023, indicating renewed volatility in default behaviour.

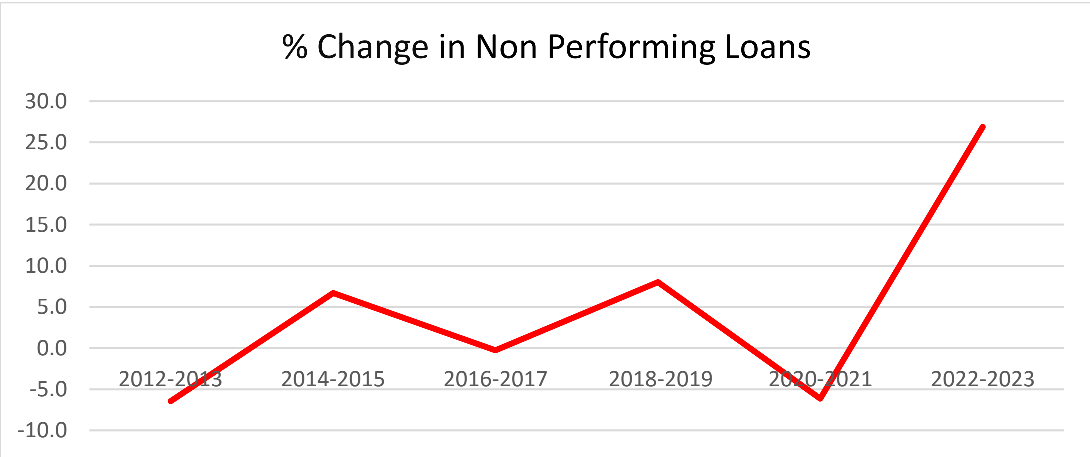

Figure 2: Year-on-Year Change in Non-Performing Loans
Source: Author’s Computation, 2025

Figure 3 illustrates the structural positioning of banks in South Africa. South Africa recorded the highest number of registered banks at that time. Over the following two decades, this number declined steadily, and by the end of 2021, registered banks had fallen by more than 50%, decreasing from 41 in 2001 to 18 in 2021, as shown in the figure. Over the past ten years, the number of mutual banks has remained largely stable; however, an expansion of approximately 20% in banking institutions began to emerge in 2012. In contrast, foreign bank branches have exhibited fluctuations over the last twenty years, reaching a peak of 16 branches in 2019, the highest level observed during the period. Meanwhile, representative offices of foreign banks have shown a declining trend over the same timeframe. At present, there are 29 representative offices of foreign banks, alongside 18 registered banks, of which 13 are locally controlled and 5 are foreign-controlled institutions. Despite the reduction in the total number of registered banks, the South African banking sector has remained competitive even during periods of economic disruption, including the pandemic and earlier financial crises. However, several studies suggest that the COVID-19 outbreak exerted significant pressure on the banking system. Baret et al. (2020) argue that COVID-19 increased credit risk exposure while simultaneously reducing the market value of collateral assets used in secured lending.

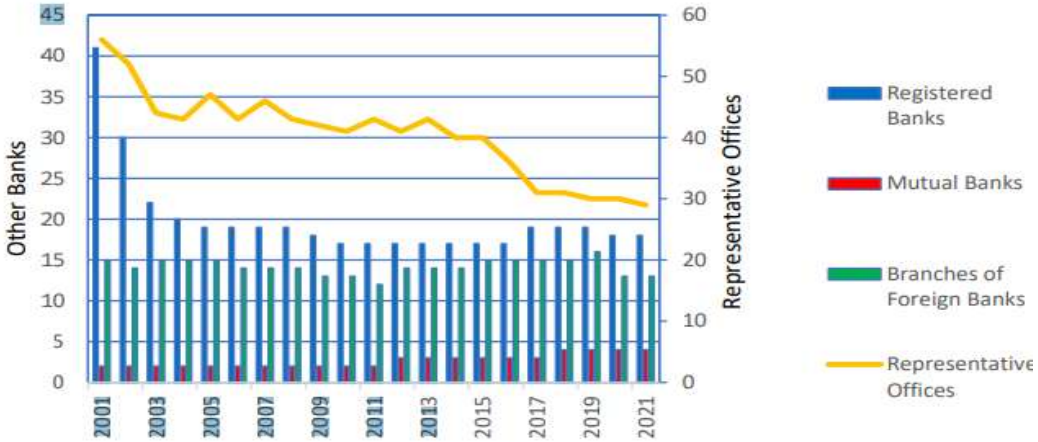

Figure 3: Structure of South African Banks
Source: Adapted from SARB, 2021

Figure 4 illustrates the movement of lending rates in South Africa over the observed period. Lending rates reached their lowest levels during the COVID-19 period (2020–2023), with a gradual downward adjustment already emerging from 2019 onwards. Despite fluctuations within the banking sector, the system remained broadly stable, maintaining a degree of consistency that supported confidence among borrowers relying on credit for both personal and corporate financing needs. Thereafter, lending rates began to increase slowly from early 2022 and reached their highest level in 2023. This upward adjustment may be linked to macroeconomic conditions, rising inflationary pressures, and policy rate decisions implemented by the South African Reserve Bank. Concurrently, banks have continued to face rising loan default pressures, which place strain on profitability and financial stability. However, despite this observed trend, there remains limited empirical consensus on whether loan defaults constitute a short-term cyclical issue or a more persistent long-run structural determinant of banks' financial health (Lawrence et al., 2024).

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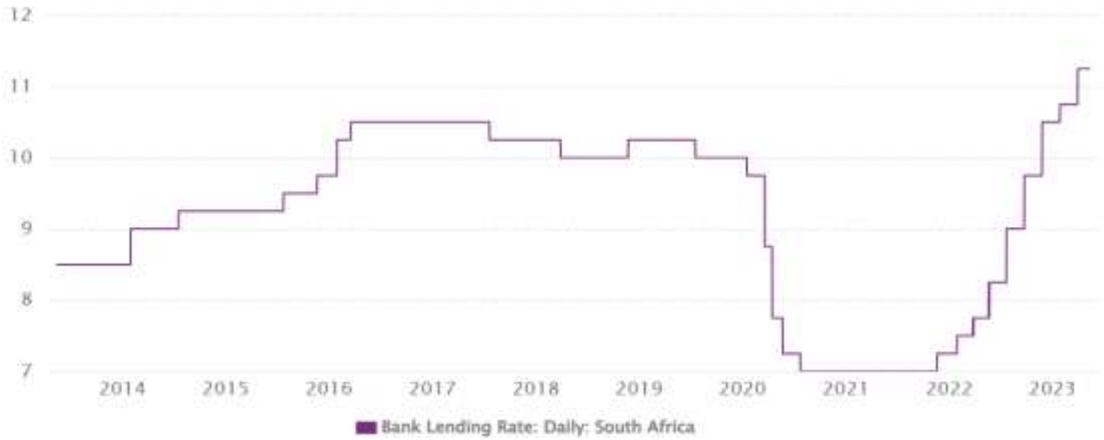

Figure 4: The South African Lending Rate From 2013-2024
Source: Adapted from CEIC,2023

LITERATURE REVIEW

This section comprises the pertinent literature on both the theoretical and empirical aspects of the area of the current research to analyse the relationship between loan default and banking performance.

Theoretical Literature

There are numerous theories that elucidate the relationship between bank performance and loan default. This study is driven by three pertinent theories to explain the relationship between loan defaults and bank performance which include asymmetry information theory, and loanable theories.

Asymmetry Theory

The theory of asymmetric information was established as an educational tool and to demonstrate how the existence of information gaps influences changes in financing decisions (Ahmad et al., 2023). According to Dari-Mattiacci et al. (2021), asymmetric information refers to a situation in which parties involved in a transaction do not possess equal access to the same information. This creates differing levels of knowledge between buyers and sellers regarding a financial security, thereby shaping perceptions of risk and return and influencing market behaviour. In this context, information asymmetry helps explain how unequal access to borrower information can lead to inefficient lending outcomes. It ensures that both parties are not operating on identical datasets, which may compromise transparency and decision-making quality. Accordingly, this framework allows the study to assess how limited information or awareness contributes to loan defaults. Where lenders possess insufficient information, their ability to accurately assess borrower creditworthiness becomes constrained, often

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restricted only to observable borrowing history or repayment behaviour. Such informational gaps may result in adverse selection and market inefficiencies.

The Loanable Funds Theory

It is vital to note that the loanable funds theory lies at the core of mainstream monetary theory and informs the theoretical models employed by central banks in advanced economies in the formulation of monetary policy (Bertocco & Kalajzić, 2023). Furthermore, Bertocco (2007) outlines that Loanable Funds Theory (LFT) developed through three main stages. The first traces back to Wicksell's work in the late nineteenth and early twentieth centuries, focusing on the relationship between interest rates and inflation. The second stage emerged in the 1930s, when Robertson and Ohlin critically engaged with Keynesian monetary theory in comparison with LFT. The third stage, in the latter half of the twentieth century, involved economists such as Kohn, who examined the debate between Keynesian economics and LFT, ultimately showing a tendency towards the latter framework. The theory, originally formalised by (Gudgeon et al., 2020), posits that interest rates are determined by the interaction between the supply and demand of loanable funds within financial markets. In relation to this study, LFT provides a conceptual basis for understanding how the availability of lendable funds influences banking performance. It further suggests that rising loan defaults reduce the pool of available funds for lending, thereby constraining credit supply and negatively affecting bank profitability, since lending constitutes a primary source of banking revenue.

Empirical Literature Review

A limited body of empirical evidence exists on the relationship between loan default and bank performance. Prior to this study, some research examining the impact of loan default on bank profitability indicated a positive relationship between loan default and profitability (Ullah & Asghar, 2023), thereby diverging from conventional expectations and highlighting inconsistencies in empirical findings. However, broader empirical literature presents mixed outcomes, with studies reporting both positive and negative effects of loan default on bank performance. For instance, Moseti (2021) examined the effect of loan default on the profitability of commercial banks in Kenya using a descriptive research design covering 42 banks between 2016 and 2020. The study utilised secondary data from Central Bank of Kenya reports and applied regression analysis alongside descriptive statistics using SPSS 25 (Khan et al., 2023).

In contrast, Akehege (2011), using a literature-based approach in Galle, Sri Lanka, found that loan defaults have a significant negative effect on bank profitability. Similarly, Shrestha and Khadka (2024), employing a multiple linear regression model, reported that non-performing loans (NPLs), used as a proxy for loan default, significantly reduce bank profitability measured by return on assets (ROA). Conversely,

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Ullah and Asghar (2023), using a quantitative secondary dataset covering 1993–2022 in the UK banking sector, applied descriptive, correlational, and linear regression techniques. Their findings revealed that NPLs had a significant positive effect on both ROA and return on investment (ROI) for HSBC Bank, indicating context-dependent variations in outcomes (Akhter, 2023).

Overall, prior literature consistently finds that rising non-performing loans weaken profitability and financial stability. Evidence from Nigeria, Sri Lanka, Nepal, and Bhutan confirms that higher default rates reduce return on assets and equity, underscoring the importance of credit risk governance and monitoring systems (Akehege, 2011; Gautam, 2018; Ntiamoah, 2014; Shrestha & Khadka, 2024). Moseti (2021) further highlights that loan delinquency reduces profitability through increased provisioning costs. The theoretical underpinning of these findings is rooted in Akerlof's asymmetric information theory (Akerlof, 1978) which explains how information gaps between borrowers and lenders generate adverse selection and increase default risk, a perspective reinforced by Ahmad et al. (2023). Studies in developing economies also emphasise structural weaknesses, including weak regulatory frameworks and elevated borrower risk profiles, which intensify default risk (Balogun & Alimi, 1988; Erdas & Ezanoglu, 2022).

Nevertheless, some scholars present alternative perspectives regarding the broader implications of loan defaults. Bertocco and Kalajzić (2023) argue that loanable funds theory may oversimplify credit-market dynamics, as monetary conditions and institutional structures also shape financial outcomes. Moreover, macroeconomic shocks such as the COVID-19 pandemic can temporarily distort the relationship between credit risk and profitability, challenging linear interpretations (Abiola & Olausi, 2014; Baret et al., 2020). In the South African context, evolving banking structures, regulatory reforms, and digital transformation have also influenced how loan defaults affect financial performance (Experian, 2024; Mkele, 2024). From a methodological perspective, recent studies increasingly adopt advanced econometric techniques such as panel ARDL and pooled mean group estimators to capture both short-run and long-run relationships in banking performance (Pesaran, 1995; Zaman et al., 2020). This reflects a growing recognition that static models may fail to capture dynamic financial interactions. Overall, while there is broad agreement that loan defaults negatively affect banking stability and profitability, debate persists regarding the magnitude, channels, and contextual drivers of these effects across different financial systems (Ferreira, 2022).

METHODOLOGY

The study applied a quantitative research design to examine loan default and bank performance on an annual basis. South African commercial banks were selected as the focus of analysis, given that they account for the largest proportion of loan defaults within the banking sector and hold the dominant share of the market. To capture long-term trends and provide a clearer understanding of overall financial sector performance, the selected commercial banks were observed over the period 2012 to 2023. Secondary data were obtained from the published annual reports of individual commercial banks in South Africa. These reports are issued in compliance with the disclosure requirements of the South African Reserve Bank regarding financial reporting standards.

Model Specification

The study adopts a panel data modelling framework previously applied by Kolapo et al. (2012) to examine the impact of loan default, proxied by non-performing loans, on bank performance. However, this study extends the existing approach by implementing a three-stage modelling framework designed to capture the interrelationships between multiple variables more effectively. In this study, ROA, return on equity (ROE), and growth are used as dependent variables, while loan default serves as the primary independent variable. To enhance model robustness and reduce omitted variable bias, additional control variables are incorporated, including leverage ratio, funds available for lending, regulatory quality, board size, bank size, and bank nature. These controls are introduced to better isolate the effect of loan default on bank performance indicators.

Model 1: ROA=f (NPLR, LEVR, FTL, RQ, Bsize, BKsize, BN)
Model 2: ROE=f (NPLR, LEVR, FTL, RQ, Bsize, BKsize, BN)
Model 3: GRWTH= f (NPLR, LEVR, FTL, RQ, Bsize, BKsize, BN)

Model Estimation

$$ROA_{i,t} = \beta_0 + NPLR_{i,t}\beta_1 + LEVR_{i,t}\beta_2 + FTL_{i,t}\beta_3 +. RQ_{i,t}\beta_4 + Bsize_{i,t}\beta_5 + BKsize_{i,t}\beta_6 + BN_{i,t}\beta_7 + \varepsilon_i, \ldots\ldots(1)$$

$$ROE_{i,t} = \alpha_0 + NPLR_{i,t}\alpha_1 + LEVR_{i,t}\alpha_2 + FTL_{i,t}\alpha_3 +. RQ_{i,t}\alpha_4 + Bsize_{i,t}\alpha_5 + BKsize_{i,t}\alpha_6 + BN_{i,t}\alpha_7 + \varepsilon_i, \ldots\ldots(2)$$

$$\mathrm{GRWTH} = \delta_o NPLR_{i,t}\delta_1 + LEVR_{i,t}\delta_2 + FTL_{i,t}\delta_3 +. RQ_{i,t}\delta_4 + RQ_{i,t}\delta_5 + Bsize_{i,t}\delta_6 + Bksize_{i,t}\delta_7 + BN_{i,t}\delta_7\ \varepsilon_i, \ldots\ldots(3)$$

Where: ROA represents return on assets, ROE denotes return on equity, and GRWTH refers to growth. The variable NPLR measures the non-performing loan ratio, while LEVR captures the leverage ratio and FTLR indicates funds available for lending. Institutional and governance-related dimensions are represented by RQ for regulatory quality, BSIZE for board size, BKSIZE for bank size, and BN for bank nature. The symbol ε denotes the error term, t represents the time dimension of the panel, and i indicates the cross-sectional unit. The parameters β_0 denotes the constant term, while β_1–β_7, α_1–α_7, and γ_1–γ_7 represent the estimated coefficients for models 1, 2, and 3 respectively.

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The specified model framework further allows the application of the panel autoregressive distributed lag (ARDL) approach to examine the relationship between loan default and bank performance among South African commercial banks. According to Pesaran (1995), the panel ARDL model is a cointegration technique that incorporates both short-run dynamics and long-run equilibrium relationships through the inclusion of lagged variables (Foglia, 2022). Prior to model estimation, a series of formal and informal diagnostic tests were conducted to determine the statistical properties of the dataset and ensure its suitability for panel ARDL estimation.

Variable Definitions, Measurements Conceptual Framework

The study utilises NPLR as the independent variable. Bank performance is treated as the dependent variable and is measured through ROA, ROE, and GRWTH. To improve model robustness, control variables are included, namely BSIZE, BN, FTLR, and LEVR. In addition, RQ is incorporated as a moderating variable to capture its influence on the relationship between loan default and bank performance. All variables details source and measurement have been mentioned in Table 2.

Table 2: Measure of Variables

Variables	Definition	Data Source	Measurement
Return on Assets (ROA)	In order to assess the performance of banks, ROA is computed by dividing annual profit with the average assets that the firm recoded as per with annual financial statements. Mostly, this serves as a reflection to calculate the profit margin on assets. When banks report greater ROA, it is inferred that they are profitable and doing well.	Thomson Reuters	Profit for the Year / Average Assets
Return on Equity (ROE)	ROE is the ratio generated from bank's annual profit (revenue) to its total equity. These are other metrics that banks employ to gauge profitability. It indicates the proportion of shareholders' money that is returned from investments made in various securities and serves as a gauge of how successfully bank management has managed the cash contributed by shareholders.	Thomson Reuters	Profit for the Year / Shareholders' Equity
Growth (GRWTH)	Most banks utilize asset growth to show their performance. This ratio is measured by considering changes of assets from the previous year to the current and dividing by the current assets. This ratio helps the management even more in projecting and forecasting future performance	Thomson Reuters	Current Assets-Previous Assets/ Previous Assets
	It is the proportion of a bank's overall loan volume that is non-performing. The present net value ratio, or NPLR, gauges the likelihood of losing an existing loan whole or partially because of default or failure to uphold loan obligations.	Thomson Reuters	Non-Performing Loans/Total Loans x100

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Leverage Ratio(LEVR)	Banks use this ratio to gauge and evaluate their ability to pay short- and long-term debt. This ratio is computed. taking total liability over total equity.	Thomson Reuters	Total Liability/ Total Equity
Board Size(BDS)	The size of the board is important in banks. Determining whether a choice made by a majority may affect performance is helpful to position and predict the results.	Thomson Reuters	Logarithm of Board Members
Bank Nature (BN)	The notion aids in illustrating whether operating internationally can affect a bank's performance or not. It also helps banks become competitive and take up a large portion of the market.	Thomson Reuters	Dummy Variable
Bank Size (BS)	Banks use their size to assess if their growth is flattening or increasing favourably. The logarithm of assets is used to demonstrate bank size.	Thomson Reuters	Logarithm of Assets
Funds to Lend (FTL)	Banks use funds to lend as safe storage for funds while generating or accumulating more money through deposited funds to assist with their day-to-day service. The logarithm of deposit is used to demonstrate funds to lend.	Thomson Reuters	Logarithm of Total Deposit

Source: Author's Computation, 2024

Estimation Techniques

The Im, Pesaran and Shin (2003) unit root test is employed to assess stationarity in the dataset. This step is essential because estimation of the panel ARDL model requires that variables are either integrated of order zero, I(0), or at most integrated of order one, I(1).

The Autoregressive Distributive Lag (ARDL)

The specified model is reformulated into a panel ARDL (p, q_1, q_2, q_3, q_4, q_5, q_6, q_7) framework, where (p) denotes the lag order of the dependent variables (ROA, ROE, and GRWTH), while (q) represents the lag structure of the independent variables, including LEVR, NPLR, BN, FTLR, RQ, BSIZE, and BKSIZE. The panel ARDL estimation employs multiple techniques, including the Mean Group (MG) estimator, which assumes slope heterogeneity across groups while allowing coefficients to vary across cross-sectional units over time (Zaman et al., 2020). The second approach is the Pooled Mean Group (PMG) estimator, which constrains long-run coefficients to be homogeneous across groups while permitting short-run coefficients to differ. For the purpose of this study, the PMG estimator is adopted to evaluate short-run dynamic relationships among the variables. The MG estimator is also acknowledged as it provides consistent estimates of long-run average effects by allowing full parameter heterogeneity across groups. The general functional form of the MG estimator with higher-order lags, used to derive long-run parameters consistently, can be expressed as follows:

$$InROA_{it} = \Theta_{it} + \beta_{0,i} InROA_{1,t-1} + \beta_{1,i} InNPLR_{i,t-1} + \beta_{2,i} InLEVR_{1,t-1} + \beta_{3.i} InBN_{i.t-1} +$$

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$$\beta_{4.i}InFTL_{i.t-1}+\beta_{5.i}InRQ_{i.t-1}+$$
$$\beta_{6.i}InBSIZE_{i.t-1}+\beta_{7.i}InBKSIZE_{i.t-1}+\mu i \ldots\ldots\ldots\ldots\ldots \text{Model 1}$$
$$InROE_{it}= \Theta_{it}+\alpha_{0,i}InROE_{1,t-1}+\alpha_{1,i}InNPLR_{i,t-1}+\alpha_{2,i}InLEVR_{1,t-1}+\alpha_{3.i}InBN_{i.t-1}$$
$$\alpha_{4.i}InFTL_{i.t-1}+\alpha_{5.i}InRQ_{i.t-1}+$$
$$\alpha_{6.i}InBSIZE_{i.t-1}+\alpha_{7.i}InBKSIZE_{i.t-1}+\mu i \ldots\ldots\ldots\ldots \text{Model 2}$$
$$InGRWTH_{it}=\Theta_{it}+\delta_{0,i}InGRWTH_{1,t-1}+\delta_{1,i}InNPLR_{i,t-1}+\delta_{2,i}InLEVR_{1,t-1}+$$
$$\delta_{3.i}InBN_{i.t-1}+\delta_{4.i}InFTL_{i.t-1}+\delta_{5.i}InRQ_{i.t-1}+$$
$$\delta_{6.i}InBSIZE_{i.t-1}+\delta_{7.i}InBKSIZE_{i.t-1}+\mu i \ldots\ldots\ldots\ldots \text{Model 3}$$

Secondly, the Pooled Mean Group (PMG) estimator is employed to capture the long-run relationship among the variables. The functional form of the model can be expressed as follows.

$$InROA_{it}= \alpha_i+\sigma_{j=1}^{p}\lambda_{ij}InROA_{i,t-j}+\sigma_{j=0}^{q1}\delta_{1ij}InNPLR_{1,t-j}+\sigma_{j=0}^{q2}\delta_{2ij}InLEVR_{2,t-j}+$$
$$\sigma_{j=0}^{q3}\delta_{3ij}InBN_{3,t-j}\sigma_{j=0}^{q4}\delta_{4ij}InFTL_{4,t-j} + \sigma_{j=0}^{q5}\delta_{5ij}InRQ_{5,t-j} +$$
$$\sigma_{j=0}^{q6}\delta_{6ij}InBSIZE_{5,t-j} + \sigma_{j=0}^{q7}\delta_{7ij}InBKSIZE_{7,t-j}+\mu_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Model 1}$$
$$InROE_{it}= \alpha_i+\sigma_{j=1}^{p}\lambda_{ij}InROE_{i,t-j}+\sigma_{j=0}^{q1}\delta_{1ij}InNPLR_{1,t-j}+\sigma_{j=0}^{q2}\delta_{2ij}InLEVR_{2,t-j}+$$
$$\sigma_{j=0}^{q3}\delta_{3ij}InBN_{3,t-j}\sigma_{j=0}^{q4}\delta_{4ij}InFTL_{4,t-j} + \sigma_{j=0}^{q5}\delta_{5ij}InRQ_{5,t-j} +$$
$$\sigma_{j=0}^{q6}\delta_{6ij}InBSIZE_{5,t-j} + \sigma_{j=0}^{q7}\delta_{7ij}InBKSIZE_{7,t-j}+\mu_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Model 2}$$
$$InGRWTH_{it}= \alpha_i+\sigma_{j=1}^{p}\lambda_{ij}InGRWTH_{i,t-j}+\sigma_{j=0}^{q1}\delta_{1ij}InNPLR_{1,t-j}+\sigma_{j=0}^{q2}\delta_{2ij}InLEVR_{2,t-j}$$
$$+\sigma_{j=0}^{q3}\delta_{3ij}InBN_{3,t-j}\sigma_{j=0}^{q4}\delta_{4ij}InFTL_{4,t-j} + \sigma_{j=0}^{q5}\delta_{5ij}InRQ_{5,t-j} +$$
$$\sigma_{j=0}^{q6}\delta_{6ij}InBSIZE_{5,t-j} + \sigma_{j=0}^{q7}\delta_{7ij}InBKSIZE_{7,t-j}+\mu_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Model 3}$$

The above function indicates that *i* represents the number of banks (i = 1, 2, 3, …, 8), while *t* denotes the time dimension measured in years. The lag structure (p, q_1, q_2, q_3, q_4, q_5) captures the optimal lag length for the dependent and independent variables. In addition, α_i represents the bank-specific fixed effects, and μ_{it} denotes the error term.

The following specification represents the short-run dynamics of the model, incorporating the error correction mechanism. The functional form of the model is expressed as follows.

$$\Delta InROA_{it}=\alpha_i+\Phi_i(\Delta InROA_{i,t-1}\text{-}\beta_1 InNPLR_{i,t-1}\text{-}\beta_2 InLEVR_{i,t-1}\text{-}\beta_3 InBN_{i,t-1}\text{-}$$
$$\beta_4 FTL_{i,t-1}\text{-}$$
$$\beta_5 InRQ_{i,t-1}\beta_6 InBSIZE_{i,t-1}\beta_7 BKSIZE_{i,t-1})+\sigma_{j=0}^{q1}\lambda_{ij}\ \Delta InROA_{it-j}+$$
$$\sigma_{j=0}^{q1}\delta_{1ij}\ \Delta InNPL_{it-j}+\sigma_{j=0}^{q2}\ \delta_{2ij}\ \ \Delta InLEVR_{it-j} + \sigma_{j=0}^{q3}\ \delta_{3ij}\ \Delta InBN_{it-j}+\sigma_{j=0}^{q4}\ \delta_{4ij}$$
$$\Delta InFTL_{it-j}\ +\sigma_{j=0}^{q5}\ \delta_{5ij}\ \ \Delta InRQ_{it-j} + \sigma_{j=0}^{q6}\ \delta_{6ij}\ \Delta InBSIZE_{it-j}\ +\sigma_{j=0}^{q7}\ \ \delta_{7ij}$$
$$\Delta InBKSIZE_{it-j}\ +\varepsilon it \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

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$$\Delta InROE_{it}=\alpha_i+\Phi_i(\Delta InROE_{i,t-1}-\beta_1 InNPLR_{i,t-1}-\beta_2 InLEVR_{i,t-1}-\beta_3 InBN_{i,t-1}-\beta_4 FTL_{i,t-1}-\beta_5 InRQ_{i,t-1}\beta_6 InBSIZE_{i,t-1}\beta_7 BKSIZE_{i,t-1})+\sigma_{j=0}^{q1}\lambda_{ij}\ \Delta InROE_{it-j}+\sigma_{j=0}^{q1}\delta_{1ij}\ \Delta InNPL_{it-j}+\sigma_{j=0}^{q2}\ \delta_{2ij}\ \ \Delta InLEVR_{it-j}+\sigma_{j=0}^{q3}\ \delta_{3ij}\ \Delta InBN_{it-j}+\sigma_{j=0}^{q4}\ \delta_{4ij}\ \Delta InFTL_{it-j}+\sigma_{j=0}^{q5}\ \delta_{5ij}\ \ \Delta InRQ_{it-j}+\sigma_{j=0}^{q6}\ \delta_{6ij}\ \Delta InBSIZE_{it-j}+\sigma_{j=0}^{q7}\ \ \delta_{7ij}\ \Delta InBKSIZE_{it-j}+\varepsilon it \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$\Delta InGRWTH_{it}=\alpha_i+\Phi_i(\Delta InGRWTH_{i,t-1}-\beta_1 InNPLR_{i,t-1}-\beta_2 InLEVR_{i,t-1}-\beta_3 InBN_{i,t-1}-\beta_4 FTL_{i,t-1}\beta_5 InRQ_{i,t-1}\beta_6 InBSIZE_{i,t-1}\beta_7 BKSIZE_{i,t-1})+\sigma_{j=0}^{q1}\lambda_{ij}\ \Delta InGRWTH_{it-j}+\sigma_{j=0}^{q1}\delta_{1ij}\ \Delta InNPL_{it-j}+\sigma_{j=0}^{q2}\ \delta_{2ij}\ \ \Delta InLEVR_{it-j}+\sigma_{j=0}^{q3}\ \delta_{3ij}\ \Delta InBN_{it-j}+\sigma_{j=0}^{q4}\ \delta_{4ij}\ \Delta InFTL_{it-j}+\sigma_{j=0}^{q5}\ \delta_{5ij}\ \ \Delta InRQ_{it-j}+\sigma_{j=0}^{q6}\ \delta_{6ij}\ \Delta InBSIZE_{it-j}+\sigma_{j=0}^{q7}\ \ \delta_{7ij}\ \Delta InBKSIZE_{it-j}+\varepsilon it \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

The function presented above captures the short-run dynamics through an error correction framework, where λ_i represents the long-run coefficients, while ε_{it} denotes the error correction term. Φ_i reflects the speed of adjustment, indicating the rate at which deviations in the dependent variable are corrected to restore long-run equilibrium with the independent variables. A statistically significant and negative value of Φ_i confirms the existence of co-integration among the variables. To ensure the reliability and robustness of the model estimates, a series of diagnostic tests were conducted. These include tests for heteroscedasticity, autocorrelation, and overall model stability.

PRESENTATION OF EMPIRICAL RESULTS AND DISCUSSION

This study investigates the relationship between loan defaults and bank performance. Loan defaults are represented by the non-performing loan ratio (NPLR), while bank performance is evaluated using ROA, ROE, and GRWTH.

Descriptive Statistics

The descriptive statistics of the independent and dependent variables are presented in Table 3, while the correlation matrix is reported in Table 7 (Appendix). Each variable is based on 105 observations, corresponding to annual data covering the 2012–2023 period.

Table 3 (descriptive statistics) and Table 7 (correlation matrix) summarise the statistical properties of the dataset. It is important to note that all variables included in the descriptive analysis exhibit a positive mean over the study period, with the exception of ROA, ROE, and bank growth (GRWTH), which recorded negative average values during the sample period. Table 3 presents the comparative summary statistics of the dependent, independent, and control variables used in the study. The results show that all variables, except RQ and ROA, exhibit negative skewness. This indicates that values

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are more concentrated above the mean, resulting in a left-skewed distribution. The Jarque–Bera probability values suggest that the variables are normally distributed. It is also important to note that BN, RQ, and FTLR are platykurtic, as their kurtosis values are below three. This reflects negative excess kurtosis, indicating flatter peaks and lighter tails relative to a normal distribution. In contrast, NPLR, ROE, GRWTH, LEVR, BKSIZE, BSIZE, ROA, and bank type are leptokurtic, with kurtosis values exceeding three. This indicates positive excess kurtosis, characterised by sharper peaks and heavier tails compared to a normal distribution. Based on these statistical characteristics, the study proceeds to formal trend analysis and stationarity testing of all variables.

Table 3: Descriptive Statistics

Variables	Mean	Median	Max	Min	SD	Skewness	Kurtosis	Jarque-Bera	Prob
lnROA	-3.6260	-4.4274	0.0000	-9.4896	1.9368	0.6692	3.0110	8.9576	0.0013
lnROE	-1.9166	-1.9583	0.0000	-8.4434	1.1512	-1.2377	10.5461	312.7358	0.0000
lnGROWTH	-1.9167	-2.1925	2.2786	-8.4035	1.6102	-0.4513	4.1348	10.5119	0.0052
lnNPLR	0.5194	0.5141	3.1235	-2.9161	0.9136	-0.0783	4.3456	9.1767	0.0001
lnLEVR	1.1086	2.4423	2.6993	-6.3977	2.5553	-2.0853	6.0555	129.1938	0.0000
lnFTL	19.9162	23.3540	28.0966	0.0000	10.479	-1.2866	2.8764	33.1806	0.0000
lnRQ	0.0991	0.0701	0.3987	-0.1851	0.1741	0.2885	2.1352	5.3992	0.0072
lnBS	23.9427	26.2329	28.3066	0.0000	6.5155	-2.9713	11.3487	503.2011	0.0000
lnBDS	2.2493	2.4849	3.0910	0.0000	0.7854	-2.1189	6.6128	149.8874	0.0000
BN	0.5917	1.0000	1.0000	0.0000	0.4936	-0.3730	1.1391	20.0968	0.0000

Source: Author’s Computations in EViews 10

Stationarity Tests

A unit root test is conducted to examine whether each panel series used in the study is stationary. The analysis is performed on both level and first-difference specifications of the variables. The Im–Pesaran–Shin (IPS) test is applied to detect the presence of unit roots in panel datasets, which is indicative of non-stationarity. Unlike conventional unit root procedures, the IPS approach allows for heterogeneity in the autoregressive coefficients across cross-sectional units. It generates individual unit root statistics for each cross-section and aggregates them to produce an overall panel-level inference regarding stationarity. The IPS test is based on a null hypothesis that all series contain a unit root, implying non-stationarity. Rejection or non-rejection of this null depends on the associated p-values obtained from the test statistics. A statistically significant result provides evidence against the null hypothesis, indicating stationarity in the series.

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Key outputs of the IPS procedure include the t-bar, t-tilde-bar, and z-tilde-bar statistics, along with corresponding critical values at the 1%, 5%, and 10% significance levels. These thresholds are used to determine whether the null hypothesis of non-stationarity can be rejected. Table 4 presents the results of the unit root tests based on the Im–Pesaran–Shin (IPS) approach, used to assess stationarity in the panel dataset across all variables. The findings indicate that, at levels, the variables are non-stationary. As a result, the analysis proceeds by applying first differencing to the series. This transformation is necessary in econometric modelling to achieve stationarity, which is a prerequisite for reliable statistical inference. Examination of the level-form results for variables such as ROA, ROE, GRWTH, and others shows that most p-values exceed 0.05. Accordingly, the null hypothesis of a unit root cannot be rejected, confirming non-stationarity at levels.

Table 4: Panel Unit Root Test (Im-Pesaran-Shin (IPS))

Variables	Statistic			Fixed-N Exact Critical Values			P-Value
	T-Bar	T-Tilde-Bar	Z-Tilde-Bar	1%	5%	10%	5%
lnROA	2.2794	1.9081	2.0031	2.240	2.020	1.900	0.0466
D.lnROA	3.9620	2.4058	4.8518	2.240	2.020	1.900	0.0000
lnROE	2.0884	1.7368	1.8651	2.240	2.020	1.900	0.0611
D.lnROE	3.8973	2.3769	4.7266	2.240	2.020	1.900	0.0000
lnGRWTH	2.9204	2.0827	1.3553	2.240	2.020	1.900	0.0544
D.lnGRWTH	4.2993	2.4106	4.8727	2.240	2.020	1.900	0.0000
lnNPLR	0.7601	0.7143	2.5409	2.240	2.020	1.900	0.9945
D.lnNPLR	3.5953	2.0726	3.4046	2.240	2.020	1.900	0.0003
lnLEVR	1.9266	1.5767	1.2176	2.240	2.020	1.900	0.4311
D.lnLEVR	4.1126	2.4292	4.9535	2.240	2.020	1.900	0.0000
lnFTLR	1.2323	1.2335	1.2337	2.240	2.020	1.900	0.5466
D.lnFTLR	3.4532	2.4331	2.2232	2.240	2.020	1.900	0.0003
lnRQ	1.0398	1.0277	1.1904	2.240	2.020	1.900	0.8831
D.lnRQ	4.9708	2.6019	5.7039	2.240	2.020	1.900	0.0000
lnBSIZE	1.9630	1.0278	1.1188	2.240	2.020	1.900	0.9121
D.lnBSIZE	4.7702	2.5427	5.4466	2.240	2.020	1.900	0.0000
lnBKSIZE	2.1535	1.4021	0.4768	2.240	2.020	1.900	0.3261
D.lnBKSIZE	3.5499	2.0127	3.2198	2.240	2.020	1.900	0.0021

Source: Author's Computations in Stata 17.0

However, after first differencing (e.g., D.ROA, D.ROE, D.GRWTH), the p-values consistently fall below 0.05, leading to rejection of the null hypothesis and indicating stationarity at first difference. This pattern suggests that ROA, ROE, GRWTH, NPLR, LEVR, FTLR, RQ, BSIZE, and BKSIZE are integrated of order one, I(1), as they become stationary only after differencing. Given that the variables share the same order of integration, the study proceeds to examine the existence of a long-run relationship among the panel variables using correlation analysis and further panel-based estimations.

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Lag Order Selection

To determine the appropriate lag length for the panel data model, several lag order selection criteria were applied using the pvarsoc command in Stata. These criteria are designed to identify the optimal lag structure by minimising model specification errors while avoiding overfitting. The lag selection procedure evaluates competing lag lengths based on statistical information criteria to ensure efficient model estimation. The results of this lag order selection process, which indicate the preferred lag structure based on the applied tests, are presented in Table 5.

The results presented in Table 5 summarise the lag order selection criteria for the panel data analysis, generated using the pvarsoc command in Stata. The likelihood ratio (LR) test indicates that the inclusion of an additional lag significantly improves model performance up to Lag 1. Similarly, Lag 1 is identified as the optimal lag length by the final prediction error (FPE), Akaike information criterion (AIC), Hannan–Quinn information criterion (HQIC), and Schwarz Bayesian information criterion (SBIC), as all criteria reach their minimum values at this lag. This evidence suggests that Lag 1 provides an appropriate balance between model parsimony and explanatory power, avoiding over-parameterisation while still capturing the dynamic behaviour of the panel data. Consequently, Lag 1 is selected as the most suitable lag structure for the panel VAR framework, forming a robust foundation for subsequent empirical analysis. The next section presents the ARDL model results of the study.

Table 5: Lag Order Selection

Lag	LogL	LR	FPE	AIC	HQIC	SBIC
0	-856.124		1.2e-03	3.247	3.289	3.354
1	-812.045	88.158*	6.8e-04*	2.967*	3.051*	3.178*
2	-801.324	21.442	7.1e-04	3.003	3.128	3.316
3	-795.112	12.424	7.5e-04	3.047	3.213	3.462

Source: Author's Computations in Stata 17.0

Note:

LR = Likelihood Ratio Test Statistic
FPE = Final Prediction Error
AIC = Akaike Information Criterion
HQIC = Hannan-Quinn Information Criterion
SBIC = Schwarz/Bayesian Information Criterion

The * indicates the optimal lag length selected by each criterion.

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Panel ARDL Results

The study employs the panel ARDL approach to examine the relationship between bank performance and loan defaults, capturing both short-run dynamics and long-run equilibrium effects as shown in Table 6.

Table 6: Panel ARDL Results

EQUATIONS	Eq1: (ROA)			Eq2: (ROE)			Eq3: (Growth)		
Long-Term-Effects									
Variables	Coef	Std. Error	Prob	Coef	Std. Error	Prop	Coef	Std. Error	Prob
lnNPLR	-0.4865	0.2067	0.0049	-0.6270	0.1014	0.0000	0.0235	0.1612	0.5826
lnLEVR	-0.1855	0.1129	0.1038	0.0964	0.1780	0.3451	0.1418	0.1344	0.2938
lnFTL	-0.0541	0.0339	0.0261	-0.0750	0.0185	0.0001	-0.0183	0.0435	0.6740
lnRQ	0.6312	0.6857	0.3597	1.2151	0.6261	0.0566	2.8262	1.1283	0.0139
lnBDS	-0.2300	0.2182	0.9812	1.1594	0.3143	0.0005	-0.1508	0.2258	0.5059
lnBS	-0.1383	0.0348	0.2947	-0.7019	0.0205	0.0011	-0.0311	0.0422	0.5071
BN	0.9666	0.2993	0.0017	2.3791	0.7473	0.0022	1.3371	0.4537	0.0040
C	0.1899	0.3819	0.6202	-0.0685	0.3860	0.8596	-0.1694	0.6017	0.7790

Source: Author's Computations in Stata 17.0

ROA=-0.4865*lnNPLR-0.1855*lnLEVR-0.0541*lnFTL+0.6312*lnRQ-0.2300*lnBDS-0.1383*lnBS 0.9666*lnBN

LNROE=-0.6270*lnNPLR+0.0964*lnLEVR-0.0750*lnFTL+1.2151*lnRQ+1.1595*lnBDS-0.7019*BS +2.3791*lnBN

LNGROWTH=0.0235*lnNPLR+0.1418*lnLEVR-0.0183*lnFTL+2.8262*lnRQ-0.1508*lnBDS-0.0311*lnBS + 0.1694*lnBN

Source: Author's Construct from Computations in EViews 10

The long-run results indicate that credit risk, funding structure, and governance-related variables exert differentiated effects across the selected measures of bank performance. The coefficient of lnNPLR is negative and statistically significant for both ROA and ROE, indicating that an increase in non-performing loans reduces profitability and confirming that higher credit risk undermines banks' financial stability (Ozurumba, 2016). However, its insignificant relationship with GRWTH suggests that loan defaults do not directly constrain long-term expansion in the sample. The leverage ratio (lnLEVR) is statistically insignificant across all specifications, implying that capital structure alone does not exert a meaningful long-run influence on bank performance

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within the studied context. Similarly, lnFTL exhibits a significant negative effect on profitability indicators, suggesting that higher lending exposure or aggressive liquidity deployment may increase risk and reduce returns, while its effect on GRWTH remains statistically insignificant.

Institutional quality, proxied by lnRQ, shows a positive and significant relationship with GRWTH, highlighting that stronger regulatory environments support long-term expansion. However, its influence on profitability measures remains comparatively weak. Governance variables present mixed outcomes: lnBDS is positive and significant for ROE but insignificant for ROA and GRWTH, indicating that board structures may enhance shareholder returns more than operational efficiency. lnBS has a negative and significant effect on ROE, suggesting potential diseconomies of scale or increased managerial complexity in larger banks. In contrast, BN is positive and significant across all equations, indicating that structural differences in bank type play an important role in shaping both profitability and growth outcomes. Overall, the findings suggest that credit risk and institutional factors are key long-run determinants of banking performance, while governance and structural variables exert selective effects depending on the performance metric.

Focusing specifically on NPLR and ROA, the results confirm a negative and statistically significant long-run relationship. A 1% increase in NPLR reduces ROA by 0.4865 units, indicating that rising loan defaults significantly erode bank profitability. These findings are consistent with (Akehege, 2011), who report that loan defaults negatively affect financial institution profitability, and Gautam (2018), who emphasises that default risk weakens banks' funding capacity. However, the findings contrast with Moseti (2021), who report a positive but insignificant relationship between loan defaults and bank performance. Overall, the study concludes that loan defaults have a negative and significant long-run impact on ROA in South African commercial banks.

Secondly, the results indicate that loan defaults have a negative and significant effect on ROE. Holding other factors constant, a 1% increase in NPLR reduces ROE by 0.6270 units. These findings are consistent with theoretical expectations and are supported by Ullah and Asghar (2023), who also report a significant adverse relationship between loan defaults and profitability. However, they contrast with Moseti (2021), who finds a positive but statistically insignificant association. Accordingly, the study concludes that loan defaults significantly and negatively affect ROE. Lastly, regarding GRWTH, the results indicate that the relationship between loan defaults and bank growth is statistically insignificant, even at the 10% significance level, suggesting that loan defaults do not exert a direct long-run influence on growth performance.

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CONCLUSION

Loan default is a persistent challenge for the banking sector globally, not only in South Africa. Based on the empirical findings, NPLR has a negative and statistically significant effect on the performance of South African commercial banks. This implies that an increase in loan defaults leads to a decline in ROA and ROE. However, the results further show that NPLR has an insignificant effect on GRWTH, suggesting that loan defaults do not directly constrain bank expansion in the long run. Based on these findings, several policy and managerial implications are proposed to strengthen credit risk management and improve ROA and ROE as key indicators of bank performance:

- First, regulators should enforce stricter standards for assessing borrower creditworthiness and strengthen loan monitoring systems by requiring more frequent and transparent reporting of NPLs and early warning indicators.
- Commercial banks should enhance loan recovery mechanisms by streamlining recovery processes, supported by strong legal frameworks and efficient collateral liquidation procedures.
- Regulatory frameworks should be reinforced to ensure closer monitoring of lending practices and compliance with prudential regulations. Given the observed upward trend in NPLs, stronger oversight can help maintain financial stability, reduce systemic risk, protect customers, and support a resilient banking environment that encourages sustainable innovation.
- Banks should promote financial literacy initiatives to educate borrowers on responsible borrowing behaviour and repayment obligations.
- Incentive mechanisms, such as reduced interest rates or loyalty-based benefits, can be introduced to encourage timely repayment behaviour among borrowers.
- Loan restructuring options should be made available for borrowers experiencing temporary financial distress to reduce default risk and improve repayment continuity.
- Banks should diversify their loan portfolios across multiple sectors to reduce concentration risk and exposure to high-risk industries.
- Credit assessment systems should be strengthened through advanced credit scoring models to improve borrower screening and minimise default probability.

Finally, the study acknowledges several limitations, including data constraints, potential endogeneity concerns, and the use of aggregated banking indicators, which may not fully capture bank-specific risk management practices or structural heterogeneity. Future research could address these limitations by incorporating bank-level microdata, applying nonlinear econometric techniques, and integrating macro-financial variables such as climate-related risks or digital banking adoption to better understand the evolving determinants of loan defaults and financial stability.

DECLARATIONS

All authors declare that they have no conflicts of interest.

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APPENDIX

Correlation Matrix

The results in Table 7 presents results on correlation analysis, which examines the strength and direction of linear relationships between pairs of variables. The Pearson correlation analysis was used for the correlation matrix. The correlation between bank performance and various variables are shown on Table 7 (correlation matrix). It can be deduced from the correlation matrix that NPLR, LEVR, FTL, BDS, BS and BN negatively correlate with bank performance indicators, thus ROA, ROE and GRWTH. On the other hand, only regulatory quality positively correlates with ROA, ROE and GRWTH. Overall, it is deduced that all reported coefficients are below 0.6 indicating that there are no multicollinearity problems.

Table 7: Correlation analysis (Pearson correlation)

	lnROA	**lnROE**	**lnGROTH**	**lnNPR**	**lnLER**	**lnFTL**	**RQ**	**InBDS**	**BS**	**BN**
lnROA	1.0000									
lnROE	0.5956	1.0000								
lnGROWT	0.3068	0.2030	1.0000							
lnNPLR	-0.1280	-0.0682	-0.0495	1.0000						
lnLEVR	-0.0610	-0.2046	-0.1948	0.1948	1.0000					
lnFTL	-0.2364	-0.3649	-0.2583	0.3041	0.2784	1.0000				
lnRQ	0.1504	0.1546	0.0728	-0.1812	-0.0608	-0.1390	1.0000			
InBDS	-0.3826	-0.2894	-0.2938	0.0582	0.0714	0.3215	-0.0758	1.0000		
lnBS	-0.4614	-0.4462	-0.3971	0.2298	0.2967	0.1516	-0.1754	0.0452	1.0000	
BN	-0.4074	-0.0796	-0.4225	0.0509	0.5286	0.5230	0.0670	0.3568	0.5067	1.0000

Bank performance of banks includes Return on Assets (ROA), Return on equity (ROE) and Growth (in terms of assets)
Source: Author's computations in EViews 10

Diagnostic Test Results

To ensure that the estimated model is correctly stated, and the findings were validated, a number of diagnostic tests were carried out.

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Table 8: Diagnosis Analysis Equation 1

Test	Hypothesis	Test statistics	P-Value	Finding
Breusch-Pagan-Godfrey	No statistical significance evidence of heteroskedasticity	F=0.8151	0.7309	No statistical significance evidence of heteroskedasticity, therefore residuals are homoscedastic
Breusch-Godfrey Serial Correlation LM Test	Random effects not statistically significant	F=0.9290	0.2204	Pooled model is statistically significant
Ramsey test	The model is correctly specified	F=1.2034	0.2336	The model is correctly specified (P value less than the significant value of 0.05, no significance evidence that the model is misspecified)
Breusch-Godfrey	No significant evidence of autocorrelation in the residuals	F-statistic = 0.3857	0.5361	Residuals are not autocorrelated

Source: Author’s construct from computations in EViews 10

Table 9: Diagnosis Analysis Equation 2

Test	Hypothesis	Test Statistics	P-Value	Finding
Breusch-Pagan-Godfrey	No heteroscedasticity in the model	F=0.9272	0.4892	Model correctly specified, no error variance
Breusch-Godfrey Serial Correlation LM Test:	Random effects not statistically significant	F= 0.2635	0.6969	Pooled model is statistically significant
Ramsey test	The model is correctly specified	F= 0.3190	0.5749	The model is correctly specified (P value less than the significant vale(o=0.05)
Breusch-Godfrey	No significant evidence of autocorrelation in the residuals	F-statistic = 0.7125	0.8633	Residuals are not autocorrelated

Source: Author’s construct from computations in EViews 10

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Table 10: Diagnosis Analysis Equation 3

Test	Hypothesis	Test statistics	p-Value	Finding
Breusch-Pagan-Godfrey	No heteroscedasticity in the model	F=0.6417	0.8018	No statistical significance evidence of heteroskedasticity
Breusch-Godfrey Serial Correlation LM Test:	Random effects not statistically significant	F= 0.9648	0.3847	Pooled model is statistically significant
Ramsey test	The model is correctly specified	F=0.0683	0.7944	The model is correctly specified
Breusch-Godfrey test	P value > 0.05 therefore No autocorrelation in the residuals	F= 0.9648	0.3847	No autocorrelation in the residuals

Source: Author's construct from computations in EViews 10

Based on Table 8, 9 and 10 diagnostic tests confirmed the model's strength: there was no heteroscedasticity in the model per the Breusch-Pagan-Godfrey test, and no autocorrelation according to the Breusch-Godfrey LM test. The Ramsey RESET test verified accurate model specification, and the pooled model showed statistical significance. These findings validate that the model is trustworthy in examining the changing and consequential connections between loan defaults and banks' success, providing practical suggestions for risk control and policy development.