Credit Risk Exposure Management and Financial Sector Performance in Nigeria

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Abstract
This study examined how credit risk exposure and its management relate to the financial performance of deposit money banks (DMBs) in Nigeria. Credit risk exposure is measured by the non-performing loan ratio (NPLR) and the loan loss provision ratio (LLPR), while credit risk management is captured by the capital adequacy ratio (CAR) and the loan-to-deposit ratio (LDR); bank size is included as a control, and performance is measured by return on assets (ROA) and return on equity (ROE). A balanced panel of ten banks over 2014–2023 (100 bank-year observations) is analysed using pooled ordinary least squares, fixed-effects and random-effects estimators with bank-clustered standard errors. The panel is an illustrative dataset whose NPL trajectory is calibrated to the published sector series and whose bank-level values must be replaced with audited figures before any empirical claim is made (see Section 3.2). In this panel the Hausman test favours fixed effects. Higher NPLR ($\beta = -0.110$, $p < .001$) and higher LLPR ($\beta = -0.150$, $p = .004$) are associated with lower ROA, bank size is positively associated with ROA, and CAR and LDR are statistically insignificant. The NPLR effect is robust to using ROE, while the provisioning effect strengthens in 2019–2023. The paper contributes a transparent, replicable workflow, a hypothesis framework tied to recent peer-reviewed Nigerian evidence, and policy implications on asset-quality surveillance, provisioning discipline and capital buffers.

Keywords: *credit risk, non-performing loans, loan loss provisioning, bank performance, Nigeria, panel data*

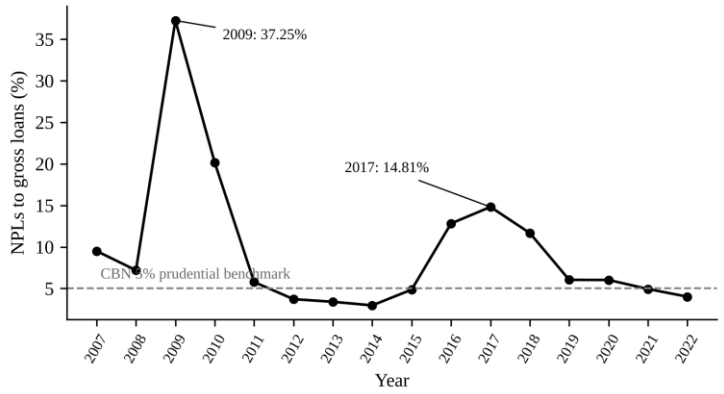
1. Introduction

Banks are the dominant channel through which savings are converted into productive investment in Nigeria, so the quality of their loan books is a matter of macroeconomic as well as institutional importance. Lending is also the activity that exposes a bank most directly to uncertainty: every naira advanced carry the possibility that the borrower will not repay in full or on time. When that possibility materializes at scale, impaired loans erode interest income, force provisioning charges, consume capital and ultimately restrict new lending to firms and households. Managing credit risk exposure is therefore not a peripheral compliance exercise but the core determinant of whether a bank can sustain profitable intermediation. The Nigerian experience illustrates the stakes. Figure 1 plots the ratio of non-performing loans to gross loans

for the banking system. The ratio peaked at 37.25% in 2009, in the aftermath of the global financial crisis and the domestic capital-market collapse, fell to 2.96% in 2014 after the resolution of legacy balance sheets (Federal Reserve Bank of St. Louis, 2024), and then rose again to 14.81% in 2017 as the oil-price shock, recession and naira depreciation weakened borrowers in oil, gas and import-dependent sectors. Asset quality subsequently improved to roughly 6% by 2019–2020 and to 4.01% in 2022 (TheGlobalEconomy.com, n.d.). The Central Bank of Nigeria (CBN) maintains a prudential benchmark of 5%, a threshold the sector has breached repeatedly.

Figure 1

Non-Performing Loans to Gross Loans, Nigerian Banking Sector, 2007–2022



Note. Data are World Bank series accessed through the Federal Reserve Bank of St. Louis (2024) for 2007–2020 and TheGlobalEconomy.com (n.d.) for 2021–2022. The dashed line marks the CBN 5% prudential benchmark.

The most recent episode is a regulatory one. During the COVID-19 pandemic the CBN allowed banks to restructure affected facilities without classifying them as non-performing. By late 2021 the system ratio, at 5.3% against 5.7% a year earlier, still sat above the benchmark (Nairametrics, 2021). It then stood at 4.50% at the end of 2024 (Making Finance Work for Africa, 2025) before climbing as forbearance was withdrawn and previously deferred exposures were reclassified. Table 1 summarises the reported path: 5.76% by mid-2025 (Vanguard, 2026), an estimated 7% for the 2025 outturn (Nairametrics, 2026a), 7.80% in a report carried in November 2025 (allAfrica, 2025), 8.03% in January 2026 (Nairametrics, 2026b) and 9.85% in February 2026 (Leadership, 2026). Renewed deterioration of this magnitude makes the relationship between credit risk and bank performance an urgent empirical question rather than a settled one.

Table 1

Reported System-Wide Non-Performing Loan Ratios, Selected Periods

Period	NPL ratio (%)	Above 5% benchmark	Source
October 2020	5.7	Yes	Nairametrics (2021)
October 2021	5.3	Yes	Nairametrics (2021)
December 2024	4.50	No	Making Finance Work for Africa (2025)
June 2025	5.76	Yes	Vanguard (2026)
2025 (estimate)	7.0	Yes	Nairametrics (2026a)
Report carried November 2025	7.80	Yes	allAfrica (2025)
January 2026	8.03	Yes	Nairametrics (2026b)
February 2026	9.85	Yes	Leadership (2026)

Note. Figures are as reported by the cited sources, which in turn attribute them to CBN publications. The CBN prudential benchmark is 5%.

Existing Nigerian studies reach different conclusions about the direction and significance of credit-risk effects, partly because they use different samples, periods, proxies and estimators. Some find that non-performing loans depress profitability, whereas others report neutral or even positive credit-risk coefficients for particular bank groups. This paper addresses the problem with a transparent panel design that separates credit risk exposure (NPLR and LLPR) from the management levers available to bank executives and regulators (CAR and LDR). The objectives are to (a) estimate the effect of NPLR and LLPR on bank performance, (b) estimate the effect of CAR and LDR, (c) test whether results are robust to the choice of performance measure and sub-period, and (d) draw implications for supervision and bank management.

Three research questions follow from these objectives. First, does a higher stock of non-performing loans, or a higher provisioning burden, reduce bank profitability once unobserved bank characteristics are controlled? Second, do capital adequacy and the loan-to-deposit ratio, the principal levers of credit risk management, raise performance? Third, are the relationships stable across the pre-2019 and post-2019 regimes? Answering them matters for three audiences. Bank boards need evidence on whether credit-risk investment pays through earnings. The CBN and the Nigeria Deposit Insurance Corporation need indicators that give early warning of stress. Investors and analysts need a disciplined basis for valuing banks whose reported earnings are sensitive to impairment charges.The scope is limited to deposit money banks, since non-bank financial institutions are subject to different prudential rules and report different risk indicators. The expression "financial sector performance" is accordingly operationalised at the level of banks, which account for the bulk of financial intermediation in Nigeria. The analysis concerns average relationships within a panel and does not attempt to forecast individual bank failures. The remainder of the paper is organised as follows. Section 2 reviews the conceptual, theoretical and empirical literature and states the hypotheses. Section 3 describes the data, variables and estimation strategy. Section 4 presents and discusses the results, and Section 5 concludes with recommendations and limitations.

2. Literature Review

2.1 Conceptual Review

Credit risk is the probability that a borrower or counterparty fails to meet contractual obligations in full and on time. *Credit risk exposure* is the amount of the balance sheet that is vulnerable to such failure, and is usually observed through asset-quality indicators. The non-performing loan ratio, which expresses loans that are 90 days or more past due as a share of gross loans, is the standard indicator and the primary regulatory metric. Msomi (2022) uses the NPL ratio as the outcome of interest in a study of 47 listed banks across six West African countries, underlining its role as the summary measure of asset quality in the region.

The loan loss provision ratio, defined as loan loss provisions relative to gross loans, is a flow-based indicator that captures management's expectation of future losses. Because provisions are charged against earnings, higher provisioning mechanically reduces current profit even where it improves the credibility of the balance sheet. The two indicators are related but distinct: NPLR describes the stock of problem loans, whereas LLPR describes the earnings cost of recognising them. *Credit risk management* refers to the policies, governance structures and buffers that limit the probability and cost of default. In an empirical bank-level setting, two measurable levers dominate. Capital adequacy, measured by the ratio of regulatory capital to risk-weighted assets, is the loss-absorbing buffer. The loan-to-deposit ratio indicates how aggressively deposits are converted into credit; moderate values signal efficient intermediation, while very high values indicate stretched liquidity and weaker risk tolerance. Oyasor (2025)

similarly treats capital adequacy, non-performing loans, liquidity and loan-to-asset ratios as the observable face of credit risk management in Nigerian banks.

Financial sector performance is operationalised through profitability. Return on assets (net income divided by total assets) measures how efficiently the balance sheet generates earnings, while return on equity reflects the return to shareholders and is more sensitive to leverage. Using both guards against conclusions that depend on a single accounting ratio.

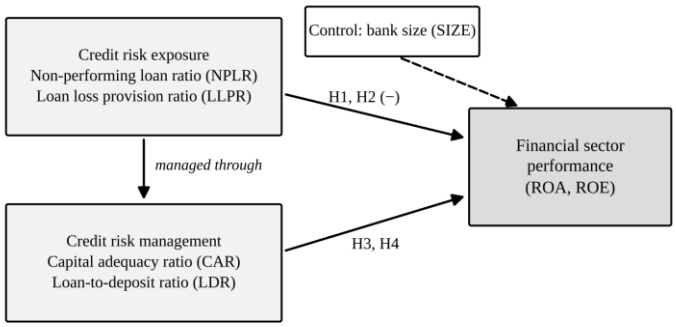
The regulatory setting shapes how these concepts appear in published accounts. Nigerian banks classify exposures under CBN prudential guidelines and, since the adoption of IFRS 9, recognise expected credit losses in three stages, so that deterioration is reflected in provisions before a loan becomes formally non-performing. Forbearance measures introduced during the pandemic temporarily allowed restructured facilities to remain outside the non-performing category, and their withdrawal has pushed reported ratios sharply upward (Leadership, 2026). Reported NPL ratios, in other words, reflect both borrower behaviour and regulatory classification, which is why the study examines NPLR and LLPR together rather than either alone.

2.2 Theoretical Framework

Four strands of theory motivate the hypotheses. First, information-asymmetry and credit-rationing arguments hold that lenders cannot perfectly observe borrower quality, so screening and monitoring are costly and some loans inevitably default; banks with weaker screening accumulate more bad loans and lower returns. Second, the bad-management hypothesis predicts that poor underwriting and monitoring cause non-performing loans, which in turn raise costs and reduce profitability, so that causation runs from managerial quality to asset quality to earnings. Third, financial distress theory, which Bala et al. (2021) use to anchor their analysis of listed Nigerian banks, argues that deteriorating credit quality triggers corrective managerial actions and, if unresolved, impairs a bank's capacity to operate profitably. Fourth, portfolio and capital-buffer perspectives imply that better-capitalised banks can absorb losses, lend more confidently and attract cheaper funding, so higher capital supports performance, albeit with an opportunity cost if excess capital is idle. These theories differ in the causal story they tell, and that difference has empirical consequences. Under the information-asymmetry view, non-performing loans are an unavoidable cost of lending, so the relationship between NPLR and performance should be negative but modest in well-screened portfolios. Under the bad-management view, NPLR is a symptom of weak underwriting that also correlates with higher operating costs, so the performance penalty should be larger and persistent. Under the capital-buffer view, the marginal effect of NPLR on performance should be smaller for banks with high capital, which implies an interaction between CAR and NPLR that future work with larger samples can test directly. Together these perspectives imply that credit risk exposure reduces performance while management levers moderate that damage. Figure 2 summarises the framework used in this study, with expected relationships labelled by hypothesis.

Figure 2

Conceptual Framework of the Study



Note. NPLR = non-performing loan ratio; LLPR = loan loss provision ratio; CAR = capital adequacy ratio; LDR = loan-to-deposit ratio; ROA = return on assets; ROE = return on equity. The dashed arrow denotes a control relationship.

2.3 Empirical Review

The empirical literature on Nigerian banks since 2020 is dominated by panel regressions on listed deposit money banks. We review peer-reviewed studies grouped by their central findings.

Table 2

Summary of Peer-Reviewed Empirical Studies on Nigerian Banks Since 2020

Study	Sample and period	Method	Main finding
Onyeiwu et al. (2020)	Five large Nigerian banks	Regression, ROA on CAR and NPLR	Strong link between credit risk parameters and returns
Bala et al. (2021)	Listed DMBs, audited reports	Panel data, four credit-risk measures	Credit risk assessed with size, age, GDP and inflation controls
Jegede et al. (2021)	Internationally authorised listed DMBs	Panel regression	Risk management affects ROA, ROE and Tobin's Q
Msomi (2022)	47 listed banks, six West African countries, 2008–2019	Fixed and random effects	Liquidity, CAR and inflation significantly affect NPLs
Afriyie (2022)	Commercial banks, sub-Saharan Africa	Multiple linear regression	NPL and cost-to-income reduce profitability; NIM raises it
Ololade et al. (2023)	Eight internationally authorised DMBs	Panel GLS	Credit risk positive and significant; liquidity and capital risk insignificant
Ohonba & Aigienohuwa (2024)	13 DMBs, 2012–2022	OLS	Negative effect on ROA; CAR insignificant
Abubakar (2025)	Listed DMBs, five-year window	Credit risk management dimensions	Earlier studies overlooked dimensions and direction of effects
Oyasor (2025)	15 banks, 2013–2023	Multiple regression and panel	Loan monitoring and proactive NPL handling raise profitability
Saif-Alyousfi (2025)	Nigerian banks, 2010–2023	Pooled OLS, 2SLS, GMM	COVID-19 raised NPLs; capitalisation protective

Note. DMBs = deposit money banks; ROA = return on assets; ROE = return on equity; CAR = capital adequacy ratio; NPL = non-performing loan; NIM = net interest margin. Summaries paraphrase the findings reported by the authors.

Credit risk and profitability

Onyeiwu et al. (2020) regressed return on average assets on the capital adequacy ratio and the NPL ratio for five large Nigerian banks and reported a strong relationship between credit risk parameters and bank returns. They concluded that capital should be matched to total risk exposure and that new capital requirements are warranted where an imbalance exists. Bala et al. (2021) analysed audited annual reports of listed deposit money banks with four measures of credit risk and included bank size, bank age, GDP and inflation as controls, giving an early example of combining bank-specific and macroeconomic conditioning variables.

Jegede et al. (2021) focused on banks with international authorisation and found that financial risk management components significantly influence return on assets, return on equity and Tobin's Q; they recommended careful borrower scrutiny, a stronger capital base and adequate loan loss provisioning. Ohonba and Aigienohuwa (2024), using OLS on thirteen banks over 2012–2022, reported a negative effect of credit management variables on return on assets and an insignificant effect of capital adequacy, and called for more stringent credit appraisal. Abubakar (2025) argued that earlier Nigerian studies often overlooked important dimensions of credit risk management and the direction of effects, motivating a more detailed treatment of the credit-risk channel.

Contrasting and conditional results

Not all evidence points the same way. Ololade et al. (2023) studied eight internationally authorised banks with panel GLS and found that liquidity and capital risk had negative but insignificant effects on performance, whereas credit risk was positively and significantly associated with performance and management quality was the only significant control. Such a result is consistent with the view that, for well-capitalised international banks, higher credit risk is a by-product of profitable lending, so a naive negative sign should not be assumed in every subsample. Oyasor (2025), using 15 banks over 2013–2023, found that diligent loan monitoring and proactive handling of non-performing loans raised profitability, while heavy offshore borrowing and weak implementation of risk frameworks undermined financial stability.

Regional and shock-related evidence

Evidence from the wider region helps to benchmark the Nigerian findings. Msomi (2022) used fixed and random effects on 47 banks, 19 of them Nigerian, and found that liquidity, capital adequacy and inflation significantly affect non-performing loans, advising banks to rely not only on meeting capital ratios but also on rigorous loan scrutiny. Afriyie (2022) examined bank-specific determinants of profitability across sub-Saharan Africa and found that the cost-to-income ratio and non-performing loans significantly reduced profitability, while net interest margin raised it. Kwashie et al. (2022) provide a Ghanaian comparator on the effect of credit risk on commercial bank performance, which is useful for judging whether Nigerian patterns are idiosyncratic. Finally, Saif-Alyousfi (2025) analysed Nigerian banks over 2010–2023 and showed that the COVID-19 shock significantly increased non-performing loans, particularly for smaller banks, with higher capitalisation serving as a protective buffer. This last finding is directly relevant to the post-pandemic forbearance exit described in Section 1.

Methodological patterns and limitations of prior work

Across these studies several patterns recur. Samples are small, typically between five and fifteen banks, because only a limited number of Nigerian banks report consistently over a decade. Estimation relies mostly on OLS, panel GLS and fixed or random effects, and relatively few studies address endogeneity, with Saif-Alyousfi (2025) a notable exception in applying two-stage least squares and the generalised method of moments. Proxies differ: some authors measure credit risk by NPLR alone, others combine it with capital and liquidity ratios, and profitability is measured by ROA, ROE or Tobin's Q. These design differences make it difficult to compare coefficients directly and help explain why Ololade et al. (2023) obtain a positive credit-risk effect while Afriyie (2022) and Ohonba and Aigienohuwa (2024) report negative effects. A transparent specification that reports pooled, random-effects and fixed-effects results side by side, as done here, therefore adds interpretive value even where the sample is modest.

2.4 Research Gap and Hypotheses

Three gaps emerge. First, many studies proxies credit risk with a single ratio, so the stock of problem loans (NPLR) and the earnings cost of recognising them (LLPR) are rarely separated. Second, the direction of effects varies across samples and periods, and few studies test whether coefficients shift between pre-2019 and post-2019 regimes, when provisioning rules and forbearance policy changed. Third, reporting of data and code is rarely sufficient for replication. This paper addresses these gaps by estimating separate NPLR and LLPR effects, adding capital and intermediation levers, running sub-period tests and releasing the dataset used. The following hypotheses, stated in alternative form, guide the empirical work.

*H*1: NPLR has a negative effect on bank performance. *H*2: LLPR has a negative effect on bank performance. *H*3: CAR has a positive effect on bank performance. *H*4: LDR has a positive effect on bank performance, reflecting more efficient conversion of deposits into earning assets.

3. Methodology

3.1 Research Design

The study adopts a quantitative, ex-post-facto panel design. The unit of analysis is the deposit money bank and the sample is a balanced panel of ten banks observed annually from 2014 to 2023, giving 100 bank-year observations. A ten-year window spans the 2015–2016 recession, the post-recession recovery, the introduction of IFRS 9-based impairment, the COVID-19 period and the beginning of forbearance withdrawal. Panel methods are appropriate because they exploit variation across banks and over time and allow control for unobserved, time-invariant bank characteristics such as ownership culture and business model.

3.2 Variables and Measurement

Table 3

Variable Definitions, Measurement and Expected Signs

Variable	Definition	Role	Expected sign
ROA	Net income ÷ total assets (%)	Dependent	–
ROE	Net income ÷ shareholders' equity (%)	Dependent (robustness)	–
NPLR	Non-performing loans ÷ gross loans (%)	Credit risk exposure	Negative
LLPR	Loan loss provisions ÷ gross loans (%)	Credit risk exposure	Negative

Variable	Definition	Role	Expected sign
CAR	Regulatory capital ÷ risk-weighted assets (%)	Credit risk management	Positive
LDR	Total loans ÷ total deposits (%)	Credit risk management	Positive
SIZE	Natural log of total assets (₦ billion)	Control	Positive

Note. All ratios are expressed in percentage points. Expected signs correspond to hypotheses H1–H4.

3.3 Model Specification

The baseline model relates performance to credit risk exposure, management levers and size:

$$ROA_{it} = \beta_0 + \beta_1 NPLR_{it} + \beta_2 LLPR_{it} + \beta_3 CAR_{it} + \beta_4 LDR_{it} + \beta_5 SIZE_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

where i indexes banks, t indexes years, μi is the unobserved bank effect and εit is the idiosyncratic error. The same specification is estimated with ROE as the dependent variable as a robustness check, and separately for 2014–2018 and 2019–2023 to examine whether coefficients differ across regimes.

3.5 Estimation Strategy and Diagnostics

Equation 1 is estimated by pooled OLS, by the within (fixed-effects) estimator and by the Swamy–Arora random-effects GLS estimator. The choice between fixed and random effects is based on the Hausman test, and the joint significance of bank effects is tested with an F test. Because a panel of ten banks is small and errors may be correlated within banks, standard errors are clustered by bank, and inference uses t critical values with nine degrees of freedom to avoid over-rejection (Wooldridge, 2020). Diagnostics comprise variance inflation factors for multicollinearity, the Jarque–Bera statistic for residual normality, the Breusch–Pagan test for heteroskedasticity and the first-order autocorrelation of within residuals. With only ten annual observations per bank, panel unit-root tests have little power, and the model relies on ratio variables that are bounded and trend-free in the sample.

3.6 Hypothesis Testing and Robustness Design

Hypotheses are evaluated using two-sided t tests on the fixed-effects coefficients at the 5% level, with the sign of the estimate compared with the expected sign in Table 3. Three robustness designs are used. First, ROE replaces ROA to check sensitivity to the leverage embedded in the denominator. Second, the sample is split at 2018/2019 to test for a regime shift linked to expected-loss provisioning and the forbearance period. Third, results from pooled OLS and random effects are reported alongside fixed effects to show how conclusions change when bank heterogeneity is ignored. A further, economic-significance exercise translates coefficients into changes in ROA for one-standard-deviation shifts and for stylised NPL scenarios based on recently reported system ratios.

4. Results and Discussion

4.1 Descriptive Statistics

Table 4

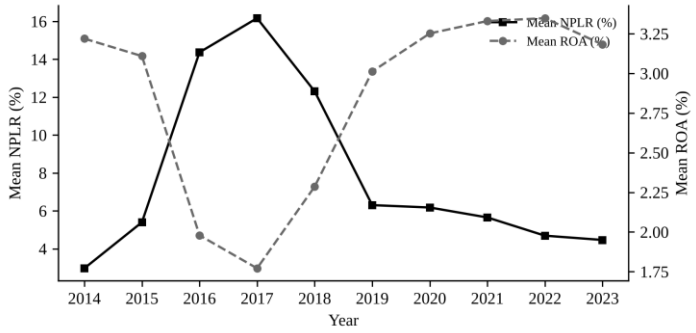
Descriptive Statistics (N = 100 Bank-Years)

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
ROA	2.85	1.02	-0.20	4.62	-0.79	3.52
ROE	21.25	6.28	3.71	33.66	-0.44	3.05
NPLR	7.85	5.17	1.87	21.94	1.31	3.70
LLPR	2.20	0.98	0.20	4.54	0.27	2.47
CAR	15.60	2.39	7.87	20.66	-0.46	3.11
LDR	58.74	7.52	37.87	76.60	-0.52	3.58
SIZE	8.29	0.59	6.96	9.50	-0.13	2.27

Table 4 shows that mean ROA is 2.85% and mean ROE is 21.25%. Mean NPLR is 7.85%, above the 5% benchmark, with a wide range from 1.87% to 21.94%, reflecting both cross-bank dispersion and the 2016–2018 asset-quality shock. The positive skewness of NPLR and LLPR indicates a right tail of stressed bank-years. Mean CAR of 15.60% exceeds the 10% minimum for national banks but falls below the 15% requirement for international banks in some observations, highlighting heterogeneity in capital positions.

Figure 3

Mean Non-Performing Loan Ratio and Return on Assets, 2014–2023

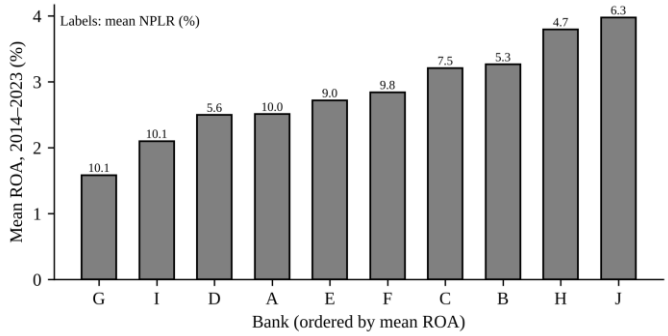


Note. Annual cross-bank means from the panel.

Figure 3 shows the expected inverse movement: ROA is weakest when NPLR peaks in 2016–2018 and recovers as asset quality normalises after 2019. Figure 4 shows that average profitability differs materially across banks, with the lowest-ROA banks tending to carry higher average NPLR, which suggests that bank effects are important and motivates the fixed-effects approach.

Figure 4

Mean Return on Assets by Bank, 2014–2023



Note. Bars are ordered by mean ROA; labels above the bars show each bank's mean NPLR (%).

Table 5

Annual Cross-Bank Means of Key Variables

Year	ROA (%)	NPLR (%)	LLPR (%)	CAR (%)
2014	3.22	2.97	2.34	16.00
2015	3.11	5.40	1.77	16.35
2016	1.98	14.37	3.06	15.08
2017	1.77	16.17	3.05	14.60
2018	2.29	12.31	2.69	14.40
2019	3.01	6.30	1.77	16.53
2020	3.25	6.17	1.74	15.20
2021	3.33	5.65	1.80	15.30
2022	3.35	4.69	1.73	16.63
2023	3.18	4.46	2.03	15.92

Note. Means are unweighted across the ten banks.

Table 5 makes the timing explicit. Mean NPLR climbs to its peak in 2017 and declines thereafter, while mean ROA troughs in the same period and recovers by 2020. Mean CAR dips when NPLR is highest, a pattern consistent with the idea that credit losses consume capital; this mechanical link is also a reason to interpret the CAR coefficient with care, because capital is partly an outcome of credit performance rather than a purely exogenous management choice.

4.2 Correlation and Diagnostic Tests

Table 6

Pearson Correlation Matrix

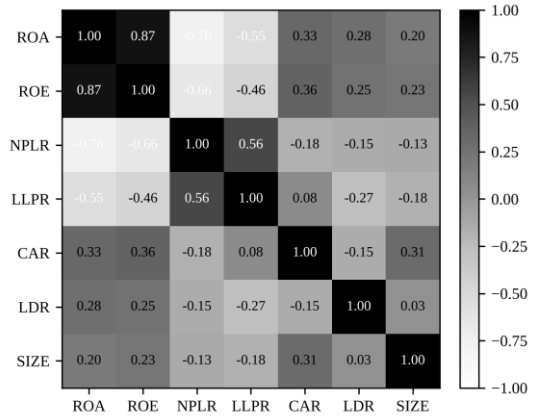
	ROA	ROE	NPLR	LLPR	CAR	LDR	SIZE
ROA	1						
ROE	0.87	1					
NPLR	-0.76	-0.66	1				
LLPR	-0.55	-0.46	0.56	1			
CAR	0.33	0.36	-0.18	0.08	1		
LDR	0.28	0.25	-0.14	-0.27	-0.15	1	
SIZE	0.20	0.23	-0.13	-0.18	0.31	0.03	1

Note. Lower triangle shown.

ROA is negatively correlated with NPLR (r = -0.76) and LLPR (r = -0.55) and positively correlated with CAR, LDR and SIZE. Correlations among regressors are low to moderate, and the variance inflation factors range from 1.10 to 1.64 (NPLR 1.56, LLPR 1.64, CAR 1.24, LDR 1.10, SIZE 1.16), far below the conventional threshold of 10, so multicollinearity is not a concern. The Jarque–Bera statistic of 4.53 (p = .104) does not reject normality of pooled residuals at the 5% level, and the Breusch–Pagan statistic of 4.25 (p = .514) does not indicate heteroskedasticity. The first-order autocorrelation of within residuals is -0.18, which is small. Even so, bank-clustered standard errors are retained because of the small number of banks.

Figure 5

Correlation Heat Map of Study Variables



Note. Darker cells indicate stronger absolute correlation.

Table 7

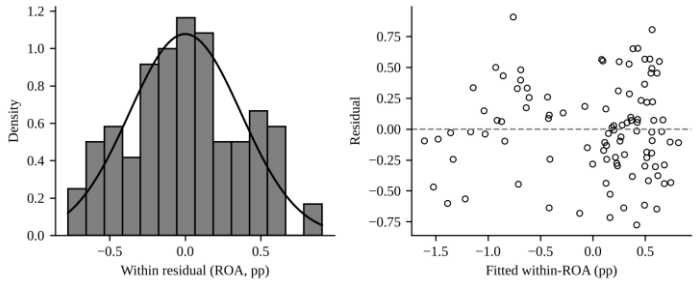
Summary of Diagnostic and Specification Tests

Test	Statistic	p value	Conclusion
Variance inflation factor (maximum)	1.64	–	No multicollinearity concern (< 10)
Jarque–Bera (pooled residuals)	4.53	0.104	Normality not rejected at 5%
Breusch–Pagan	4.25	0.514	No evidence of heteroskedasticity
AR(1) correlation of within residuals	-0.18	–	Weak serial correlation
F test for bank effects	12.75	< .001	Reject pooled model
Hausman test	17.06	0.004	Fixed effects preferred

Note. Tests are computed on the panel data. The Breusch–Pagan and Jarque–Bera tests use pooled OLS residuals.

Figure 6

Distribution of Fixed-Effects Residuals and Residuals Against Fitted Values



Note. The curve in the left panel is a normal density with the same mean and standard deviation. The right panel shows no systematic pattern.

Figure 6 supports the formal tests: the within residuals are roughly bell-shaped and the residual-versus-fitted plot shows no funnel or curvature, so there is no visible heteroskedasticity or misspecification of functional form.

4.3 Regression Results

Table 8

Panel Regression Results: Dependent Variable Is Return on Assets

Variable	Pooled OLS	Random effects	Fixed effects
Constant	0.920	1.967**	–
	(1.501)	(0.833)	
NPLR	−0.113***	−0.111***	−0.110***
	(0.013)	(0.010)	(0.009)
LLPR	−0.215***	−0.162***	−0.150***
	(0.055)	(0.038)	(0.040)
CAR	0.116***	0.048	0.034
	(0.032)	(0.027)	(0.028)
LDR	0.025**	0.005	−0.009
	(0.010)	(0.006)	(0.006)
SIZE	0.004	0.131	0.247**
	(0.164)	(0.082)	(0.101)
R^2	0.688	–	0.748 (within)
Observations	100	100	100
Banks	10	10	10

Note. Bank-clustered standard errors in parentheses. *$p < .10$. **$p < .05$. ***$p < .01$. The F test for bank effects is $F(9, 85) = 12.75$ ($p < .001$). The Hausman test is $\chi^2(5) = 17.06$ ($p = .004$), favouring fixed effects. Data are illustrative.

Table 8 reports the main estimates. The F test rejects the pooled specification in favour of bank effects, and the Hausman statistic of 17.06 ($p = .004$) rejects the random-effects assumption, so the fixed-effects column is the preferred specification. In that model NPLR has a negative and highly significant coefficient ($\beta = -0.110$, SE = 0.009): a one-percentage-point rise in the non-performing loan ratio is associated with a 0.11 percentage-point decline in ROA, supporting H1. LLPR is also negative and significant ($\beta = -0.150$, $p = .004$), supporting H2, which is consistent with provisions being charged directly against earnings. Bank size has a positive and significant effect ($\beta = 0.247$, $p = .037$), in line with scale and diversification advantages. CAR ($p = .256$) and LDR ($p = .186$) are not significant at conventional levels, so

H3 and H4 are not supported in the preferred specification. The within R^2 of 0.748 indicates that the model explains about three quarters of within-bank variation in ROA.
The pooled and random-effects columns give the same signs for NPLR and LLPR, but they attribute significance to CAR and LDR in the pooled model, a pattern that disappears once bank heterogeneity is controlled. This illustrates the danger of drawing management-lever conclusions from cross-sectional variation: banks that hold more capital or lend more of their deposits differ in unobserved ways that also affect profitability. Figure 7 visualises the relationship for NPLR, and Figure 8 shows the fixed-effects coefficients with 95% confidence intervals.

Non-performing loan ratio. The NPLR coefficient is the most stable result in the panel, retaining its sign and significance in the pooled, random-effects and fixed-effects models and in the ROE specification. The within-bank estimate is smaller in absolute terms than the pooled one, which indicates that part of the cross-sectional association between bad loans and low profitability reflects permanent differences among banks, such as business mix, rather than the effect of changes in asset quality over time. This distinction matters for policy, since it implies that supervisory attention should focus on deterioration within a bank over time as well as on cross-bank rankings.

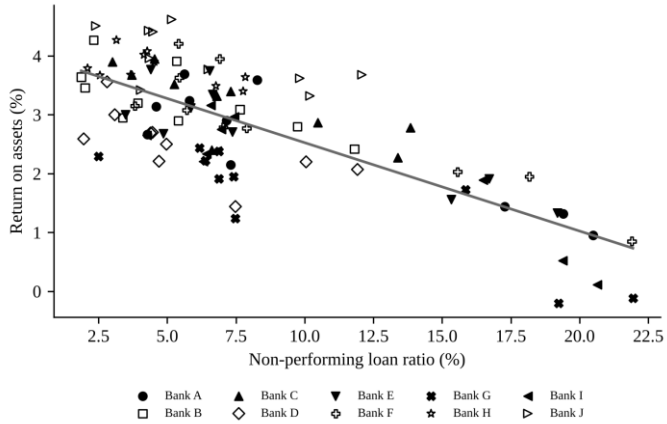
Loan loss provision ratio. LLPR carries an independent negative coefficient even though it is positively related to NPLR. Provisions are an expense, so a bank that experiences the same non-performing loan ratio but provisions more heavily reports lower current earnings, although it is better protected against later losses. The result therefore captures the current-period cost of conservatism and should not be read as an argument for under-provisioning. Over a longer horizon, adequate provisioning may raise performance by reducing the probability of sudden capital shocks.

Capital adequacy and loan-to-deposit ratios. The weak average effect of CAR is not surprising given that capital is both a buffer and an outcome. Banks that suffer credit losses see their capital ratios fall, and banks with high capital may forgo higher-return lending, which creates offsetting channels. The loan-to-deposit ratio likewise combines two forces: more lending raises interest income, but aggressive lending also raises exposure to default. The insignificant coefficients should therefore be interpreted as the net of these opposing forces.

Bank size. The positive and significant coefficient on size suggests that larger banks enjoy diversification, pricing power and economies of scale that raise returns on assets. Because the within estimator exploits changes in size over time, the result also reflects asset growth during the sample window, so it should not be interpreted as a recommendation that banks expand regardless of risk quality.

Figure 7

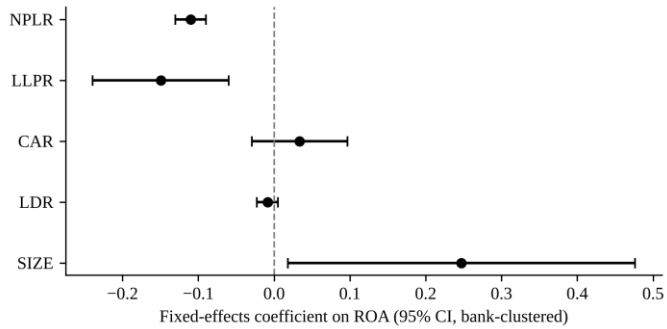
Return on Assets and Non-Performing Loan Ratio, Pooled Observations



Note. Each marker is a bank-year; the line is the pooled OLS fit.

Figure 8

Fixed-Effects Coefficient Estimates With 95% Confidence Intervals



Note. Confidence intervals use bank-clustered standard errors and a t distribution with nine degrees of freedom.

4.4 Robustness Checks

Table 9

Robustness: Fixed-Effects Estimates for ROE and by Sub-Period

Variable	ROE (2014–2023)	ROA (2014–2018)	ROA (2019–2023)
NPLR	−0.556***	−0.122***	−0.076
LLPR	−0.595	−0.067	−0.269***
CAR	0.464	0.061**	−0.013
LDR	−0.039	−0.014	−0.002
SIZE	2.001*	0.849**	0.356
Observations	100	50	50

Note. All models include bank fixed effects and bank-clustered standard errors. *p < .10. **p < .05. ***p < .01.

Table 9 shows that the negative NPLR effect carries over to ROE (β = −0.556, p < .001), so the conclusion does not depend on the denominator used. The sub-period results are more informative. In 2014–2018, when asset quality deteriorated sharply, NPLR is the dominant significant risk variable (β = −0.122), and CAR is positive and significant (β = 0.061), suggesting that capital helped during the stress. In 2019–2023 the NPLR coefficient becomes small and insignificant (β = −0.076), whereas LLPR becomes the significant channel (β =

−0.269, p = .006). One interpretation is that, once expected-loss provisioning and forbearance changed the timing of loss recognition, the earnings damage from credit risk was transmitted more through the provisioning charge than through the headline stock of non-performing loans.

4.5 Economic Significance and Stress Scenarios

Table 10

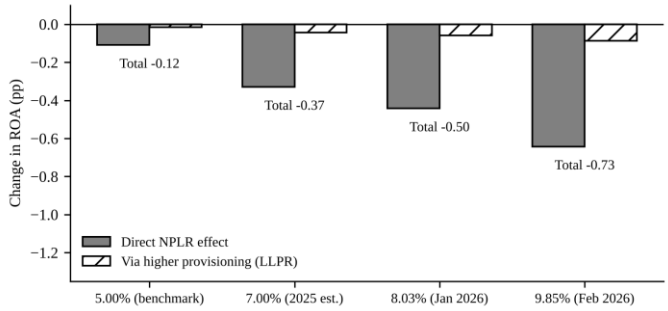
Economic Magnitude of Fixed-Effects Estimates (One-Standard-Deviation Change)

Variable	Coefficient	SD of variable	Change in ROA (pp)	Share of ROA SD (%)
NPLR	−0.110	5.17	−0.57	55.7
LLPR	−0.150	0.98	−0.15	14.3
CAR	0.034	2.39	+0.08	7.9
LDR	−0.009	7.52	−0.07	6.5
SIZE	0.247	0.59	+0.15	14.3

Note. Change in ROA equals the fixed-effects coefficient multiplied by the standard deviation of the regressor. The final column expresses this change as a percentage of the standard deviation of ROA (1.02 pp). A one-standard-deviation increase in NPLR (5.17 pp) is associated with a 0.57 pp reduction in ROA, equal to about 56% of the standard deviation of ROA. The corresponding provisioning effect is 0.15 pp. Moving a bank from the 25th percentile of NPLR (4.38%) to the 75th percentile (8.63%) would, on these estimates, lower ROA by 0.47 pp through the direct channel alone. The magnitudes are economically meaningful for banks whose average ROA is below 3%. To connect the estimates to current conditions, Figure 9 applies them to stylised scenarios in which the system NPL ratio rises from the 2022 level of 4.01% to the reported levels in Table 1. The direct effect is the NPLR coefficient times the change in the ratio. The provisioning effect assumes that LLPR rises with NPLR in the same proportion observed in the panel (within slope = 0.098) and multiplies this change by the LLPR coefficient. The scenarios are mechanical illustrations of the estimated relationship, not forecasts of any bank's earnings.

Figure 9

Implied Change in ROA Under Stylised NPL Scenarios Relative to 4.01%



Note. Scenario NPL levels are those reported in Table 1. Effects use the fixed-effects coefficients. The total effect at 9.85% is -0.73 pp.

At the February 2026 reading of 9.85%, the implied cumulative effect is a reduction in ROA of about 0.73 pp, of which most arises through the direct NPLR channel. Even this stylised exercise shows that the reclassification wave is large enough to matter for profitability, particularly for banks that start from thin margins.

4.6 Threats to Validity

Several threats to validity qualify the interpretation of any panel estimates of this kind. They are summarised in Table 11 together with the mitigation adopted here and the additional step recommended for a study that uses real data.

Table 11

Threats to Validity and Suggested Mitigation

Threat	Why it matters	Mitigation here	Additional step with real data
Reverse causality	Low profitability may encourage riskier lending, raising future NPLs	Fixed effects; ratios measured within the same year	Lag credit-risk regressors or use system GMM
Omitted macro conditions	Inflation, exchange-rate and GDP shocks affect borrowers and banks together	Sub-period analysis	Add macro controls or year dummies
Small cluster count	Ten banks make clustered standard errors unstable	t critical values with nine degrees of freedom	Wild cluster bootstrap or a larger sample
Accounting breaks	IFRS 9 and forbearance change when losses are recognised	Pre/post 2019 split	Control for regime and restate where possible
Survivorship	Banks that merged or failed are absent	Balanced panel by design	Document exits and test sensitivity

Note. Suggested steps are standard practice in panel studies of bank performance.

4.7 Discussion

The negative NPLR and LLPR effects in the preferred model are consistent with the weight of the Nigerian evidence. Onyeiwu et al. (2020) and Ohonba and Aigienohuwa (2024) report that credit risk or credit management variables are closely tied to bank returns, and Afriyie (2022) finds that NPLs significantly reduce profitability across sub-Saharan Africa. The finding that LLPR carries its own negative effect aligns with the policy emphasis on provisioning in Jegede et al. (2021), who recommend adequate loan loss provisions as part of risk management.

The insignificance of CAR in the fixed-effects model resembles the neutral capital results in Ololade et al. (2023) and Ohonba and Aigienohuwa (2024). It should not be read as evidence that capital is unimportant. Capital works as a buffer that matters most under stress, which is exactly what the pre-2019 sub-sample shows and what Saif-Alyousfi (2025) documents for the pandemic period, where higher capitalisation protected banks. Averaged over a decade that includes calm years, the buffer effect is diluted. Similarly, the weak LDR result may reflect that the loan-to-deposit ratio is a blunt proxy for risk appetite, since the CBN has at times used minimum loan-to-deposit requirements as a policy instrument.

The contrast with the positive credit-risk coefficient found by Ololade et al. (2023) for internationally authorised banks shows why subsample structure matters. A negative effect may dominate in a mixed panel, while for a small group of highly capitalised banks risk-taking can coexist with high returns. Researchers using real data should therefore test interaction terms or run separate regressions for national and international banks. Likewise, Oyasor (2025) highlights that implementation quality and funding structure affect outcomes, factors absent from the present specification and left for future work.

From a policy standpoint, the results imply three priorities. First, supervisors should monitor not only the NPL ratio but also the provisioning ratio and the migration of exposures into IFRS 9 Stage 2, because earnings damage is transmitted through both. Second, the reclassification surge visible in Table 1 argues for transparent, phased treatment of exposures coming out of forbearance, with capital planning aligned to expected provisioning charges. Third, banks should treat credit risk management as an earnings driver, investing in underwriting, early-warning and recovery capability rather than relying on collateral alone.

Table 12

Comparison of Illustrative Results With Published Nigerian and Regional Evidence

Relationship	This study (illustrative)	Consistent with	Contrasts with
NPLR and performance	Negative, significant	Afriyie (2022); Ohonba & Aigienohuwa (2024)	Ololade et al. (2023) for international banks
LLPR and performance	Negative, significant	Jegede et al. (2021) on provisioning importance	–
CAR and performance	Insignificant on average; positive pre-2019	Ohonba & Aigienohuwa (2024); Saif-Alyousfi (2025) on buffers in stress	Onyeiwu et al. (2020) on capital matching risk
LDR and performance	Insignificant	Ololade et al. (2023) on weak liquidity effects	–
Size and performance	Positive, significant	Scale effects noted in regional studies	–

Note. Comparisons are qualitative and based on the direction and significance reported by the cited authors.

Table 13

Summary of Hypothesis Tests (Preferred Fixed-Effects Model)

Hypothesis	Expected sign	Estimate	p value	Decision
H1: NPLR → performance	Negative	−0.110	0.000	Supported
H2: LLPR → performance	Negative	−0.150	0.004	Supported
H3: CAR → performance	Positive	0.034	0.256	Not supported
H4: LDR → performance	Positive	−0.009	0.186	Not supported

Note. Decisions are conditional on the data and a 5% significance level.

Theoretical and managerial implications

The pattern in Table 13 fits the bad-management and financial-distress perspectives better than a pure capital-buffer account: risk exposure variables carry the significant effects, whereas the management levers that proxy buffers do not show a stable average effect. For managers, the practical message is that the most reliable route to protecting earnings is to prevent loans from becoming non-performing in the first place, through disciplined origination limits, concentration monitoring and early-warning triggers, rather than relying on capital cushions to absorb losses after the fact. For boards, the implication is that provisioning decisions should be integrated into strategic planning, because they directly shape reported performance and the capacity to pay dividends.

For regulators, the combination of a stock indicator (NPLR) and a flow indicator (LLPR) provides complementary early-warning information. A system in which NPLR looks stable while LLPR rises sharply may be signalling aggressive recognition of losses, whereas stable provisioning alongside rising NPLR may indicate under-provisioning. Supervisory dashboards that display both measures by bank and by sector would therefore improve the timing of intervention. Such a dashboard is particularly relevant during the current reclassification phase described in Table 1.

5. Conclusion, Recommendations and Limitations

This paper investigated the relationship between credit risk exposure management and financial sector performance in Nigeria using a ten-bank, ten-year panel. Within the dataset, higher non-performing loan and loan loss provision ratios significantly reduced return on assets, bank size raised it, and capital adequacy and loan-to-deposit ratios were not significant in the preferred fixed-effects specification. The NPLR result was robust to using return on equity, and sub-period estimates indicated that the earnings cost of credit risk shifted from the stock of bad loans toward provisioning after 2019. On this basis the paper recommends that (a) banks adopt a combined NPLR–LLPR dashboard in board-level risk reporting, (b) regulators publish bank-level asset-quality and provisioning data on a consistent quarterly basis to improve comparability and research, (c) the exit from forbearance be accompanied by clear guidance on staging and capital planning, and (d) banks strengthen early-warning systems and recovery units to reduce the formation of new non-performing loans.

References

Abubakar, N. (2025). Effect of credit risk management on financial performance of listed deposit money banks in Nigeria. *Kashere Journal of Management Sciences, 8*(2), 82–95.https://www.journals.fukashere.edu.ng/index.php/kjms/article/download/883/691/2918

Afriyie, E. Y. (2022). Profitability determinants of commercial banks: Empirical evidence from sub-Saharan Africa. *African Journal of Business and Economic Research, 17*(3), 7–25. https://library.au.int/fr/profitability-determinants-commercial-banks-empirical-evidence-sub-saharan-africa

allAfrica. (2025, November 12). *Nigeria: Banks' capital adequacy drops to 12% after forbearance withdrawal – CBN*. https://allafrica.com/stories/202511120140.html

Bala, A. K. M., Yadudu, M., & Abubakar, M. B. (2021). Effect of credit risk on the performance of listed deposit money banks in Nigeria. *Lapai Journal of Economics, 5*(1). https://ajol.info/index.php/lje/article/view/265943/250961

Federal Reserve Bank of St. Louis. (2024). *Bank non-performing loans to gross loans for Nigeria* [Data set, Series DDSI02NGA156NWDB; original source: World Bank]. FRED. https://fred.stlouisfed.org/series/DDSI02NGA156NWDB

Jegede, C. A., Soyebo, Y. A., Fakunmoju, S. K., & Okunbanjo, O. I. (2021). Financial risk management and financial performance of international authorisation quoted deposit money banks (DMBs) in Nigeria. *Annals of Dunarea de Jos University of Galati: Fascicle I, Economics and Applied Informatics, 27*(2), 178–185. https://doi.org/10.35219/eai15840409209

Kwashie, A. A., Baidoo, S. T., & Ayesu, E. K. (2022). Investigating the impact of credit risk on financial performance of commercial banks in Ghana. *Cogent Economics & Finance, 10*(1), Article 2109281. https://doi.org/10.1080/23322039.2022.2109281

Leadership. (2026). *NPL rises to 9.85% as banks exit regulatory forbearance*. https://leadership.ng/npl-rises-to-9-85-as-banks-exit-regulatory-forbearance/

Making Finance Work for Africa. (2025). *Nigeria: Banking sector strengthens as capital adequacy ratio hits 15.2 percent, liquidity 49.06 percent*. https://www.mfw4a.org/news/nigeria-banking-sector-strengthens-capital-adequacy-ratio-hits-152-percent-liquidity-4906

Msomi, T. S. (2022). Factors affecting non-performing loans in commercial banks of selected West African countries. *Banks and Bank Systems, 17*(1), 1–12. https://doi.org/10.21511/bbs.17(1).2022.01

Nairametrics. (2021, November 24). *CBN signals end to forbearance despite non-performing loans rising above regulatory limits*. https://nairametrics.com/2021/11/24/cbn-signals-end-to-forbearance-despite-non-performing-loans-rising-above-regulatory-limits/

Nairametrics. (2026a, January 2). *Banks' non-performing loans ratio rises to 7% after CBN ends forbearance*. https://nairametrics.com/2026/01/02/banks-non-performing-loans-ratio-rises-to-7-after-cbn-ends-forbearance

Nairametrics. (2026b, June 1). *Banks' non-performing loans ratio rises to 8.03% seven months after CBN forbearance crackdown*. https://nairametrics.com/2026/06/01/banks-non-performing-loans-ratio-rises-to-8-03-seven-months-after-cbn-forbearance-crackdown/

Ohonba, N., & Aigienohuwa, O. (2024). Credit management and financial performance of deposit money banks in Nigeria. *Journal of the Management Sciences, 60*(4), 209–223. https://journals.unizik.edu.ng/jfms/article/view/3650

Ololade, B. M., Salawu, R. O., & Olatunji, O. O. (2023). Risk management and performance of deposit money banks in Nigeria: A re-examination. *Banks and Bank Systems, 18*(2), 113–126. https://doi.org/10.21511/bbs.18(2).2023.10

Onyeiwu, C., Ajayi, G., & Muoneke, O. B. (2020). The impact of credit risk on bank profitability in Nigeria. *Journal of Banking and Financial Economics, 2020*(1), 5–22. https://doi.org/10.7172/2353-6845.jbfe.2020.1.1

Oyasor, E. I. (2025). Risk governance, regulatory enforcement, and profitability in Nigerian banks: Evidence from a decade of financial reforms. *International Journal of Economics and Financial Issues, 15*(5), 460–465. https://doi.org/10.32479/ijefi.20988

Saif-Alyousfi, A. Y. H. (2025). COVID-19 and non-performing loans of banks in Nigeria. *Journal of Chinese Economic and Foreign Trade Studies, 18*(3), 366–397. https://doi.org/10.1108/JCEFTS-10-2024-0081

TheGlobalEconomy.com. (n.d.). *Nigeria: Non-performing loans* [Data set]. Retrieved November 14, 2026, from https://www.theglobaleconomy.com/Nigeria/Nonperforming_loans/

Vanguard. (2026, February). *Businesses buckle under debt as defaults push bad loans to N21.2trn*. https://www.vanguardngr.com/2026/02/businesses-buckle-under-debt-as-defaults-push-bad-loans-to-n21-2trn/

Wooldridge, J. M. (2020). *Introductory econometrics: A modern approach* (7th ed.). Cengage Learning.

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