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Credit Risk Management and Financial Performance of Microfinance Banks in Nigeria

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Abstract

This study examined the impact of credit risk management on the financial performance of microfinance bank in Nigeria from the period of 1993 to 2022 (30years). The study used Loan-to-Deposit Ratio (LDR), Non-Performing Loan Ratio (NPLR), Loan Loss Provision Ratio (LLPR), Debt-to-Equity Ratio (DTER) and Capital Adequacy Ratio (CAR) as a proxied for credit risk management while financial performance proxied with Returns on Asset (ROA) of Microfinance Bank in Nigeria. The study made used of aggregate secondary data from CBN Statistical Bulletin, CBN Annual Report, CBN Financial Strategy Report and CBN Bank Supervisory Annual Report for the duration of the study. The descriptive statistics and the correlation analysis was used to determine the nature of relationship between the independent (Loan-to-Deposit Ratio (LDR), Non-Performing Loan Ratio (NPLR), Loan Loss Provision Ratio (LLPR), Debt-to-Equity Ratio (DTER) and Capital Adequacy Ratio (CAR)) and dependent (Return on Asset (ROA)) variables, followed by several diagnostics tests. After which, the study conducted a unit roots test for the time series data in order to ascertain if they are stationary or not and Johannsen Cointegration to the determined the long term effect of all the independent variables on the dependent variable. In view of the hypothesis formulated for this research, the method of data analysis chosen were the ordinary least squares multiple regression analysis which was used through the Regression model, using the computer software, E-VIEWs 9.0. The finding revealed that LDR with an associated p-value (sig. value) is 0.0020. This suggests that LDR have a positive significant effect on ROA; NPLR with an associated p-value (sig. value) of 0.8763. This suggests that NPLR have a negative insignificant effect on ROA; LLPR with an associated p-value (sig. value) is 0.2313. This suggests that LLPR have a negative insignificant effect on ROA; DTER with an associated p-value (sig. value) is 0.0252. This suggests that DTER have a positive significant effect on ROA and CAR with an associated p-value (sig. value) is 0.0176, this suggests that CAR have a positive significant effect on ROA. The study concluded that credit risk management has a significant impact on financial performance of microfinance bank in Nigeria. The study recommended that microfinance banks in Nigeria to maintain a healthy loan deposit ratio to improve their return on assets. By balancing their loan portfolio with their deposits, microfinance banks can potentially increase their profitability. A higher loan deposit ratio usually signifies that the bank is utilizing its deposits efficiently to generate interest income from loans, which can positively impact their return on assets.

Key Words: *Credit, Risk, Management, Financial and Performance*

Background to the Study

Microfinance banks offer savings, micro-credit, and other financial services to low-income groups and individuals to improve the economic standing of small-scale producers in rural and urban regions. They provide financial services to the poor who are usually excluded from formal finance (Abel, et al., 2023). Because they provide most credit to small and medium-sized businesses, microfinance banks are crucial to an economy. Microfinance banks are financial institutions that accept savings deposits and lend money to small enterprises to empower low-income earners and reduce poverty (Abubakar, et al., 2020). Banking companies aim to increase revenues through loan and advance interest, fees, and commissions. Banks earn most of their revenue from loan and advance interest (Adelowokan & Akinlo, 2021). Credit risk is associated with microfinance banks' major source of income, loan and advance interest. Several authors have attempted to explain credit risk (Adeoye, et al., 2020).

In Nigeria, microfinance institutions are vital to low-income people and small businesses. To continue serving their target clientele, Microfinance Banks (MFBs) must maintain financial stability and sustainability (Adeyemi, et al, 2021). MFBs struggle with credit risk, which can hurt their finances and stability. Understanding how credit risk affects MFB financial performance is essential for risk management and policy formulation in Nigeria's microfinance sector (Afolabi, et al., 2020). Economic growth and financial inclusion in Nigeria depend on microfinance banks. Credit, savings, and insurance are offered by these institutions to low-income individuals and microenterprises. However, credit risk can considerably impact microfinance banks' financial performance and sustainability (Agbamuche, et al, 2021).

Financial performance, according to Agbana, et al. (2023), is the extent to which a financial institution has achieved its financial goals and objectives. It matches income to the organization. The financial health of a company during a financial period is measured by it. Several scholars (Almekhlafi, et al 2016; Almshabbak & Chouaibi, 2023) measured financial performance with profitability ratios. Most banks and microfinance banks use these ratios to analyze loans since they are linked to results and financial success (Anh, 2023). Usually utilized are return on equity and return on assets. ROA shows a company's profitability relative to its assets. ROA shows how efficiently management uses assets to generate earnings. A company's ROE measures its efficiency at generating profits from shareholder equity (Anwer, et al., 2023). In this study, these proxies were chosen because they measure financial performance. This study examines how credit risk management affects the financial performance of listed microfinance banks in Nigeria. Good credit risk management leads to good financial performance, while poor credit risk management leads to poor financial performance (Bhatt, et al., 2023).

MFBs are vital to people and small businesses that cannot access regular banking. Small loans, savings accounts, and other financial services improve financial inclusion and reduce poverty (Bhattarai, 2019). Credit risk is one of several hazards MFBs face as financial institutions. Credit risk comes when borrowers default on their loans. Inherent risk for all financial institutions, including MFBs. Academics and practitioners are interested in how credit risk affects microfinance banks' financial performance (Bimaruci, et al., 2020). Credit risk affects MFBs' profitability, solvency, and financial stability, therefore understanding it is vital. Loan defaults cost MFBs principle and interest. These losses can affect the bank's capital, ability to pay financial obligations, and sustainability (Bouteille & Coogan-Pushner, 2021). High credit risk also degrades loan portfolio quality, hurting the bank's finances. There may be more NPLs, higher provisioning needs, and lower profitability. Credit risk also prevents the bank from attracting low-cost deposits, limiting its lending capacity and expansion (Cheng, et al., 2020). Credit risk has a global influence on MFBs. Global microfinance bank credit risk management lessons can improve practices and policies worldwide.

In underdeveloped nations like Nigeria, microfinance banks (MFBs) are vital to individuals and small enterprises. Microfinance banks, like any financial institutions, have risks that might hurt their finances. A major risk for these institutions is credit risk. A microfinance bank may lose money if borrowers default on their loans. Through their diversified clientele of entrepreneurs, farmers, and low-income persons, microfinance banks are more susceptible to credit risk than conventional financial institutions. These banks lack regular banks' collateral requirements and credit evaluation systems, increasing credit risk. Credit risk is the possibility of borrowers defaulting on their loans, which can lead to NPLs, lower profitability, capital adequacy concerns, and bank collapses. Credit risk can hurt depositors, borrowers, and the financial system by hurting microfinance banks. Due to their target clientele, inadequate collateral, and informal lending, Nigerian microfinance banks struggle to manage credit risk. Credit risk in the microfinance sector has been studied, but deeper research on its effects on Nigerian microfinance institutions is needed.

Nigerian microfinance banks have high credit risk for several reasons. First, borrowers' creditworthiness is difficult to measure due to the informal economy and lack of trustworthy credit information. The lack of financial literacy among borrowers, limited repayment capacity, and unanticipated shocks like economic downturns and natural disasters increase microfinance bank credit risk. First, loan defaults and delinquencies diminish bank profits. The banks' capacity to fund operational costs and invest in expansion and outreach is affected. Credit risk can sap banks' capital, placing them at risk of insolvency. Credit risk also damages microfinance banks' credibility. Loan failures may cause borrowers to lose faith in the bank, reducing consumer loyalty and new business. Microfinance banks may have trouble getting funding from investors and financial institutions due to poor risk management and significant credit risk.
Global research have studied how credit risk affects MFB financial performance. For instance, Nteli and Onoja (2017) examined how credit risk affects Nigerian microfinance institutions' financial performance. Credit risk reduces MFB profitability, lowering their financial performance. Credit risk and Ghanaian microfinance institutions' financial stability were examined in another study by Sulemana et al. (2018). They found that excessive credit risk hurts MFB performance because it negatively impacts financial stability. Non-governmental organizations (NGOs), microfinance banks, and regulated financial institutions have various credit risk impacts. Analyzing the global impact of credit risk on MFBs is complicated by varied risk exposure and credit risk management methods for each institution. Credit risk directly affects microfinance banks' financial performance and stability. Most microfinance bank studies were done outside Nigeria, hence this study was needed to determine how credit risk management affects listed

microfinance banks in Nigeria. Given the conflicting and ambiguous outcomes, this study assessed the impact of credit risk management on Nigerian microfinance institutions' financial performance.

Review of Related Literature

Conceptual Review

Credit Risk Management

Credit risk is the failure of clients to repay their debt or borrowed funds to the bank on time. Due to the significant percentage of bank profit from credit giving due to interest generated, credit risk is considered the most important risk (Hasan, et al., 2018). Banking requires credit risk management to assess and minimize lending-related losses (Cheng, et al., 2020). By funding individuals, businesses, and governments, banks help economic growth. However, lending carries risk since borrowers may default, costing banks money (Saravia-Matus & Smith, 2020). Banks must manage credit risk to stay afloat and profitable. It entails recognizing, assessing, and minimizing lending risks (Dai, et al., 2023). We use credit scoring, analysis, loan structuring, collateral value, and early warning systems in our management framework. Complex financial markets and a worldwide banking industry make credit risk management harder (Dube & Kwenda, 2023). To manage credit portfolios efficiently, banks need advanced risk management techniques and systems. To stay safe, they must follow regulations and industry standards (Duho, et al., 2023).

Recently, banking events have highlighted the need of credit risk management. Credit risk management failures were highlighted by the 2008 financial crisis. Many banks lost money due to high default rates and poor risk management. To improve bank credit risk management, regulators and supervisory authorities have tightened regulations and recommendations (Echobu & Philomena, 2019). Basel II and Basel III standards from the Basel Committee on Banking Supervision (BCBS) give comprehensive credit risk management guidelines. AI and ML have also transformed credit risk management in recent years. These technologies allow banks to automate credit assessment, improve data analysis, and make more accurate loan choices (Ekinci & Poyraz, 2019). A number of studies have examined credit risk management best practices and how they affect banks' financial performance. Credit risk management has been studied in connection to bank profitability and the efficacy of specific instruments and strategies. The banking sector relies on credit risk management to reduce loan losses (Embaye, et al., 2017). A variety of methods are used to discover, assess, and mitigate credit risks. To guarantee financial stability and profitability, banks must adapt and improve credit risk management as financial markets and regulations become more complicated.

Financial Performance

Financial performance is a key business indicator and management research variable. Hundal and Singh (2016) define financial performance as an organization's capacity to acquire and manage resources so as to obtain a competitive edge. Ahsan (2016) defined financial performance as how successfully a corporation uses its resources to bring investors rewards. Ratios measure a commercial bank's profitability. Profitability, dividend growth, sales turnover, asset base, capital employed, and others can be used to evaluate a company's financial success. Various disciplines disagree on how to quantify business performance and what factors affect financial success

(Bhattarai, 2016). Return on assets shows how well a company uses its resources to generate income, per Nzuve (2016). A firm with a high ROA maximizes shareholder wealth by efficiently using its assets/resources. Most ratios are ROE and ROA. This research will measure performance using ROA.

Theoretical Review

The Adverse Selection Theory

The 1981 Stiglitz-Weiss idea was adverse selection. When lending, a bank's clients or borrowers may have unobservable traits that could lead to loan repayment default, severely affecting its profitability. Assuming lenders cannot distinguish between bank loan clients with different risk levels, all bank loan contracts will have limited liability (Bhattarai, 2016). Banks can't tell safe from harmful borrowers, according to adverse selection theory. According to this argument, the lender, a bank, lacks information about loan applicants. Riskier loan customers should pay a higher interest rate to offset their higher default risk (Hasan et al., 2018). Thus, if they can be separated from other loan consumers, safer loan clients should pay less. Since banks don't know their borrowers' risk profiles, they charge all loan clients exorbitant average interest rates (Saravia-Matus & Smith, 2020). When loanable funds are limited, the interest rate may not rise enough to guarantee credit to all applicants, according to adverse selection theory. Credit volume and effort are below average. More wealthy borrowers can secure lower finance, work harder, and earn more (Lee & Wu, 2019). Credit markets project and may worsen asset inequalities in the borrowing class, which may perpetuate poverty (Adeleke & Akomolafe, 2021). Reduced informational asymmetries can reduce adverse selection in lending and change borrowers' incentives to repay by changing credit market competitiveness. Information asymmetry hinders MFIs' loaning (Adeusi et al., 2020).

According to Ayeni and Fatungase (2020), financial institutions require a business proposal, borrower credit history, and collateral before lending to reduce default risk. MFIs reduce adverse selection and substitute collateral by grouping loans. By providing MFIs with credit applicant data, Pagano et al. (2021) reduce adverse selection. Each bank collects confidential information on local credit applicants but not non-local applicants. MFIs can safely lend to non-local loan seekers by exchanging creditworthiness information. Information sharing can incentivize borrowers to serve MFI interests. According to Balogun and Suraju (2021), borrowers return their obligations since defaulters will be blacklisted, reducing external finance. When lenders can't tell good from bad borrowers, all borrowers are paid a typical interest rate based on their aggregate experience, according to De Carvalho and Lobo (2019). This rate will push some respectable borrowers out of the borrowing market if it is greater than they deserve, forcing banks to charge even higher rates to those who stay. Before lending, credit providers screen applicants thoroughly, which has been demonstrated to lower loan default in financial institutions. This study needs the idea since financial institutions must analyze customers to determine creditworthiness.

Empirical Review

In 2023, Anwer et al. examined how credit risk management affects Nigerian publicly traded microfinance institutions. Two Nigerian Stock Exchange-listed microfinance banks' annual reports and financial statements were analyzed from 2012 to 2017. Panel regression, multiple regression, and Pearson correlation were used to analyze the data. Insufficient capital adequacy had a major influence on financial performance. Financial success is affected by a positive NPL ratio. The negative loan loss provision ratio hurts Nigerian microfinance institutions. Financial performance is hurt by inflation, bank size, and the control variable. Our study showed that credit risk management affects Nigerian microfinance organizations' profitability.

According to Hermuningsih et al. (2023), credit risk impacts Nepal's commercial banks' financial stability. 160 observations from ten commercial bank balance panels from 2001 to 2016 were examined. A regression research found that Nepal's commercial banks' ROA, CAR, NPLR, and

MQR are highly connected. Commercial banks in Nepal are unaffected by the loan-to-deposit ratio (CDR) and risk sensitivity (RS).

Using data from Nigeria's five largest deposit money banks, Khan et al. (2023) examined their performance. From 2003 to 2017, Kwashie, et al. (2022) used financial data from Ghana Stock Exchange-listed banks to identify bank credit risk indicators and assess their influence on company financial performance. Credit risk lowers capital sufficiency, operational efficiency, profitability, and net interest margin, according to the 2SLS model. However, bank size and funding shortfall increase credit risk. An annual inflation adjustment usually boosts credit risk. According to the Basel accord, increased bank credit risk hurts business finances. To survive, banks must reduce credit risk.

In 2023, Agbana et al. evaluated how credit risk management influences Nigerian MFIs' financial performance. Based on a qualitative review, proactive risk assessment, complete credit evaluation, proper loan monitoring, and prompt loan recovery processes are essential to efficient credit risk management, which affects MFI performance. Clear laws, skilled workers, and enough technology increase credit risk management. The report addresses MFI problems such poor credit information, insufficient regulatory frameworks, and operational limits. Answering these questions can boost financial performance and sustainability. Intended improvements include credit information exchange, stakeholder cooperation, and capacity-building. Practitioners, regulators, and politicians can use this study's findings to improve credit risk management, financial performance, and Nigeria's long-term prosperity.

UAE commercial banks' credit risk management and financial performance were examined by Salem and Jamil (2021). Panel data from 2013 to 2019 was used to examine how independent factors such capital adequacy ratio, non-performing loans ratio, cost-income ratio, liquidity ratio, and loans-to-deposit ratio affected sixteen UAE commercial banks' financial performance. Descriptive statistics and the random effect model for hypothesis testing were used to analyze bank secondary data. Non-performing loans and cost-income ratios have a significant negative impact on commercial bank profitability in the UAE, while capital adequacy, liquidity, and loans-to-deposits ratios have a weak positive relationship on return on assets but a low statistical impact.

Three objectives and hypotheses were proposed by Agbamuche et al. (2021) to examine how credit risk affects financial performance. From 2010 to 2019, this Ex-Post Facto study examined ten years. This study includes the nineteen listed Nigerian DMBs as of December 31, 2020. The study focused on all first-tier Listed Deposit Money Banks on the Nigerian Stock Exchange (NSE) using purposive sampling. Data was analyzed using descriptive statistics, correlation analysis, and panel regression analysis from five first-tier listed banks' audited financial reports. For listed banks, non-performing loans and impairment loan charge-offs had a negative and large impact, while capital adequacy had a positive but negligible impact. The report advises banks to be more vigilant when assessing loans and alter their terms and conditions to reflect new realities that may increase nonperforming loans.

In Nigeria, Afolabi (2021) examined credit risk and bank performance using nonperforming loans, loan loss reserves, loans and advances, and equity as proxy variables. A panel research design was utilized to empirically analyze bank annual reports from 2009 to 2018. Capital and non-performing loans boost profitability, whereas loan-to-deposit ratios hurt it, according to the study.

Chang et al. (2020) examined how credit, liquidity, and operational risk affect bank profitability using 2012-2018 JSE-registered bank data. To determine how the dependent variable affected the independent factors, Smart PLS-SEM was utilized. Credit risk favorably affects bank profitability, the study found. Also, liquidity risk boosts bank profits tremendously. Operational risk hurts bank profits. Bank-specific risk is positively correlated with credit, operational, and liquidity risk, but profitability is not.

Research Methodology

This investigation used ex-post facto methods. After the fact, researchers examine how previous events affected the present. This study used this research design because it is the best when it is impossible to choose, control, and manipulate all independent variables or when laboratory control is impractical, costly, or ethically unacceptable. This study employed time series data from the CBN Statistical Bulletin, Annual Report, and Bank Supervisory Annual Report for 1993-2022. This study used secondary data to measure credit risk management [Loan-to-Deposit Ratio (LDR), Non-Performing Loan Ratio (NPLR), Loan Loss Provision Ratio (LLPR), Debt-to-Equity Ratio (DTER), and Capital Adequacy Ratio (CAR)] and Returns on Asset (ROA) proxied for the financial performance of Microfinance Bank in Nigeria of events that happened and were recorded from their secondary sources. Due to its reliability and accuracy, the CBN Statistical Bulletin, Annual Report, and Bank Supervisory Annual Report were chosen for the study. Statistics were used in this study. Next, descriptive statistics and correlation analysis were used to determine the relationship between the independent (Loan-to-Deposit Ratio (LDR), Non-Performing Loan Ratio (NPLR), Loan Loss Provision Ratio (LLPR), Debt-to-Equity Ratio (DTER), and Capital Adequacy Ratio (CAR)) and dependent (Return on Asset (ROA)) variables. Later, the study performed a unit roots test to determine if the time series data were stationary and Johannsen Cointegration to evaluate the long-term effect of all independent factors on the dependent variable. According to the research hypothesis, ordinary least squares multiple regression analysis will be used through the Regression model in E-VIEWs 9.0. For the study, this is the right data analysis. The model for this study was modified from Abubakar, et al., 2020, Effect of credit risk management on financial performance in listed microfinance banks in Nigeria. The model which specifies that financial performance of microfinance banks in Nigeria [proxy by Return on Asset (ROA)] is significantly influenced by the credit risk management measures (Loan-to-Deposit Ratio (LDR), Non-Performing Loan Ratio (NPLR), Loan Loss Provision Ratio (LLPR), Debt-to-Equity Ratio (DTER) and Capital Adequacy Ratio (CAR)) is formulated as follows;

ROA = f(LDR, NPLR, LLPR, DTER, CAR)

$$ROA = \beta_0 + \beta_1 LDR + \beta_2 NPLR + \beta_3 LLPR + \beta_4 DTER + \beta_5 CAR + U$$

Where:
ROA = Return on Asset
β_0 = Constant Term
β_1 = Coefficient of Loan-to-Deposit Ratio
LDR = Loan-to-Deposit Ratio
β_2 = Coefficient of Non-Performing Loan Ratio
NPLR = Non-Performing Loan Ratio
β_3 = Coefficient of Loan Loss Provision Ratio
LLPR = Loan Loss Provision Ratio
β_4 = Coefficient of Debt-to-Equity Ratio
DTER = Debt-to-Equity Ratio
β_5 = Coefficient of Capital Adequacy Ratio
CAR = Capital Adequacy Ratio
U = Disturbance Term (other variable not mentions in the model)
The a priori expectation is $\beta 1, \beta 2, \beta 3, \beta 4, \beta 5 > 0$

Table 3.1: Variable Descriptions

Variables	**Category of Variables**	**Description**
Return on Asset (ROA)	Dependent Variable	Is a proxy on banks performance, measures how effectively a company has used the owner's resources. It is used as a measure of performance or profitability of the deposit banks.
Loan-to-Deposit Ratio (LDR)	Independent Variable	LDR is described in the study as the percentage of a bank's total loans to its deposit base of Microfinance banks as calculated in CBN Publications.
Non-Performing Loan Ratio (NPLR)	Independent Variable	NPLR is described in the study as the total value of non-performing loans (loans with delayed payment or default) to the total loan portfolio of Microfinance banks as calculated in CBN Publications.
Loan Loss Provision Ratio (LLPR)	Independent Variable	LLPR is described in the study as the total value of the bank's provision for loan losses to its average loan portfolio of Microfinance banks as calculated in CBN Publications.
Debt-to-Equity Ratio (DTER)	Independent Variable	DTER measures the proportion of a bank's total debt to its equity capital of Microfinance banks as calculated in CBN Publications
Capital Adequacy Ratio (CAR)	Independent Variable	The CAR calculates the bank's capital as a percentage of its risk-weighted assets of Microfinance banks as calculated in CBN Publications

Source: Researchers Compilation, 2024.

Results and Discussion

Under this sub-heading, various analyses was conducted, this was done below;

Table 4.2: Descriptive Statistics

	LOGROA	LOGLDR	LOGNPLR	LOGLLPR	LOGDTER	LOGCAR
Mean	0.596159	1.952713	1.481054	1.488207	1.433866	0.999477
Median	0.245400	1.906519	1.492251	1.597749	1.450940	1.314073
Maximum	2.152288	2.513444	1.975432	1.915505	1.591843	1.553762
Minimum	-0.698970	1.694430	0.745075	0.798651	1.224533	-0.585027
Std. Dev.	0.962328	0.186847	0.389649	0.387036	0.088887	0.707172
Skewness	0.367575	1.146943	-0.255815	-0.435208	-0.820338	-1.272287
Kurtosis	1.548682	4.257049	1.735000	1.619817	3.267481	3.222964
Jarque-Bera	3.308460	8.552605	2.327490	3.328163	3.454206	8.155713
Probability	0.191239	0.013894	0.312314	0.189365	0.177799	0.016944
Sum	17.88477	58.58139	44.43163	44.64622	43.01599	29.98430
Sum Sq. Dev.	26.85620	1.012445	4.402961	4.344112	0.229125	14.50266
Observations	30	30	30	30	30	30

Source: EVIEW, 9.0 Outputs, 2024.

Table 4.2 shows descriptive data format. The mean ROA was 0.5962, with an SD of 0.9623. LDR mean and SD are 1.9527 and 0.1868. NPLR has a mean of 1.4811 and SD of 0.3896. LLPR has a mean of 1.4882 and SD of 0.3870. DTER averages 1.4339 with an SD of 0.0889. Finally, CAR averages 0.9995 and SDs 0.7072. All variables' Std. Dev. values are greater than their means, indicating that the data is broadly distributed except for ROA, whose mean value is lower. The normal distribution has neither heavy or light tails due to its three-kurtosis value. If kurtosis exceeds three, a distribution has heavier tails than the normal distribution. Table 4.2 shows that ROA, NPLR, LLPR, DTER, and CAR have thin tails since their kurtosis coefficients are smaller than 3. LDR has a thick tail since its kurtosis is greater than 3 relative to the normal distribution.

Table 4.3: Correlation Output

	LOGROA	LOGLDR	LOGNPLR	LOGLLPR	LOGDTER	LOGCAR
LOGROA	1.000000					
LOGLDR	0.678161	1.000000				
LOGNPLR	-0.655602	-0.710550	1.000000			
LOGLLPR	0.691254	0.456667	-0.888467	1.000000		
LOGDTER	0.434429	0.493802	-0.320095	0.171713	1.000000	
LOGCAR	0.668460	0.296454	-0.701676	0.917131	0.048933	1.000000

Source: EVIEW, 9.0 Outputs, 2024.

Table 4.3 shows that correlation values below 0.8 indicate no multicollinearity. The results also show that LDR, LLPR, DTER, and CAR positively affect MFB ROA in Nigeria. NPL has a strong negative association with MFB ROA in Nigeria.

Table 4.4: Multicollinearity Test

Variance Inflation Factors
Date: 05/23/24 Time: 19:28
Sample: 1993 2022
Included observations: 30

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	11.91690	2207.137	NA
LOGLDR	0.544797	388.1543	3.405263
LOGNPLR	0.594983	357.8931	1.617313
LOGLLPR	0.154153	504.3839	2.395345
LOGDTER	0.961054	367.3175	1.359457
LOGCAR	0.122524	338.63909	1.397014

Source: EVIEW, 9.0 Outputs, 2024.

Multicollinearity was tested in the study's annual time series data. Refer to Table 4.4 for test findings. In multiple regression models, multicollinearity occurs when two or more independent variables are strongly correlated. According to Table 4.4, the variance inflation factor (VIF) was calculated to verify the study's findings. All independent variables' Centered Variance Inflation Factor (CVIF) statistical range is 1.3596 to 3.4053. CVIF values for LDR, NPLR, LLPR, DTER, and CAR are 3.4053, 1.6173, 2.3953, 1.3595, and 1.3970. Multicollinearity is unlikely because the VIF is < 10. Multicollinearity is suggested by VIFs over 10.

Table 4.5a: Breusch-Godfrey Serial Correlation LM Test

F-statistic	1.919407	Prob. F(2,22)	0.1705
Obs*R-squared	4.457031	Prob. Chi-Square(2)	0.1077

Source: E-VIEW, 9.0 Outputs, 2024.

To test serial correlation, variable residuals were determined before estimating models. This was done by serial correlation LM. In Table 4.5a, the serial correlation LM test shows that the models have no serial correlation because the f-statistics p-values are insignificant at 5%.

Table 4.5b: Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.116830	Prob. F(5,24)	0.9874
Obs*R-squared	0.712835	Prob. Chi-Square(5)	0.9823
Scaled explained SS	0.289534	Prob. Chi-Square(5)	0.9978

Source: E-VIEW, 9.0 Outputs, 2024.

A variable's variability is not uniform over the range of values of a second variable that predicts it, causing heteroskedasticity. Situation causes issue. Breusch-Pagan-Godfrey heteroskedasticity tests ensured that the proposed model estimation is homoscedastic. Because the f-statistics p-values are not significant at 5%, the models do not have heteroskedasticity.

Table 4.5c: Ramsey RESET Test
Equation: UNTITLED
Specification: LOGROA C LOGLDR LOGNPLR LOGLLPR
LOGDTER
LOGCAR
Omitted Variables: Squares of fitted values

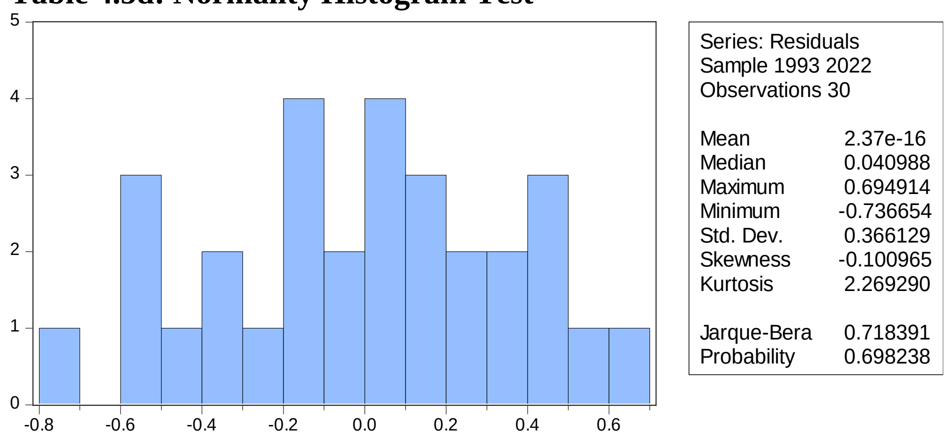
	Value	df	Probability
t-statistic	1.467103	23	0.1559
F-statistic	2.152392	(1, 23)	0.1559
Likelihood ratio	2.683764	1	0.1014

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.332666	1	0.332666
Restricted SSR	3.887466	24	0.161978
Unrestricted SSR	3.554799	23	0.154556

Source: E-VIEW, 9.0 Outputs, 2024
The model is homoskendastic because three parameters have probability values above 0.05. The prior table 4.5.1c supports this conclusion. Ramsey test results show that our regression model is stable, confirming its accuracy.

Table 4.5d: Normality Histogram Test



Source: E-VIEW 9.0 Output, 2024.

The residuals were tested for normality to check if the model residuals were normal. Not regularly distributed residuals indicate large outliers. These affect standard errors, which affect coefficient significance. The test suggests that the residuals are normally distributed because the histogram is bell-shaped and the J-B statistic probability value is 0.3728, which is more than (5). We reject the null hypothesis that residuals are not regularly distributed. The residuals were tested for normality to check if the model residuals were normal. Not regularly distributed residuals indicate large outliers. These affect standard errors, which affect coefficient significance. The test suggests that the residuals are normally distributed because the histogram is bell-shaped and the J-B statistic probability value is 0.6982, which is greater than 0%. We reject the null hypothesis that residuals are not regularly distributed.

Table 4.6: ADF Unit root Test

Group unit root test: Summary
Series: LOGROA, LOGLDR, LOGNPLR, LOGLLPR, LOGDTER, LOGCAR
Date: 05/23/24 Time: 19:21
Sample: 1993 2022
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.91281	0.1807	6	173
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.03568	0.8498	6	173
ADF - Fisher Chi-square	15.2271	0.2293	6	173
PP - Fisher Chi-square	21.6385	0.0418	6	174

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Group unit root test: Summary
Series: LOGROA, LOGLDR, LOGNPLR, LOGLLPR, LOGDTER, LOGCAR
Date: 05/23/24 Time: 19:24
Sample: 1993 2022
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-9.98001	0.0000	6	164
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.88828	0.0000	6	164
ADF - Fisher Chi-square	99.4707	0.0000	6	164
PP - Fisher Chi-square	102.849	0.0000	6	168

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Source: E-VIEW, 9.0 Outputs, 2024

Unit roots indicate non-stationary time-series data, while zero indicates stationary stochastic processes. ADF was used for the unit root test (table 4.6). LDR, NPLR, LLPR, DTER, and CAR all had unit root tests at their first difference 1(1), according to the ADF unit root group test output summary because their ADF values exceed the crucial value of 5%, this is evident. The p-value for all variables is less than 5% and better than 95% confidence, lending further evidence of stationary series. Each reached stationarity at order one, the initial difference. The variables are integrated at order one, therefore we may use Johansen cointegration.

Table 4.7: Summary of Johansen Cointegration Test Output

Date: 05/23/24 Time: 19:25
Sample (adjusted): 1995 2022
Included observations: 28 after adjustments
Trend assumption: Linear deterministic trend
Series: LOGROA LOGLDR LOGNPLR LOGLLPR LOGDTER LOGCAR
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.814165	116.9773	95.75366	0.0008
At most 1 *	0.649181	69.85620	69.81889	0.0497
At most 2	0.553695	47.52664	40.85613	0.0242
At most 3	0.272497	31.93756	29.79707	0.0507

At most 4	0.230201	19.29722	15.49471	0.0326
At most 5	0.059049	9.704189	3.841466	0.0117

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.814165	47.12113	40.07757	0.0069
At most 1	0.649181	39.32956	33.87687	0.0487
At most 2	0.553695	32.58908	27.58434	0.0317
At most 3	0.272497	28.07838	21.13162	0.0398
At most 4	0.230201	17.25533	14.26460	0.0414
At most 5	0.059049	9.704189	3.841466	0.0117

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
Source: E-views 9.0 Output, 2024.

Once the variables' time series features are known, this study uses Johansen and Juselius (1990)'s (Trace Statistics) and (Maximum Eigenvalue) to determine if they have a long-term relationship. The cointegration test is summarized in Table 4.7. The multivariate cointegration test by Johansen and Juselius cointegration technique showed that both the trace statistic and the Maximum Eigenvalue statistic show evidence of two cointegration relationships (at None and at most 1), where their values are greater than their respective critical values at 5% significance level. These findings support a steady long-term link between ROA, LDR, NPLR, LLPR, DTER, and CAR.

Table 4.8: Multiple Regression Analysis

Dependent Variable: LOGROA
Method: Least Squares
Date: 05/23/24 Time: 19:26
Sample: 1993 2022
Included observations: 30

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.348795	3.452087	-2.418478	0.0235
LOGLDR	2.562324	0.738104	3.471496	0.0020
LOGNPLR	-0.121405	0.771351	-0.157393	0.8763
LOGLLPR	-1.319557	1.074315	-1.228278	0.2313
LOGDTER	1.993792	0.980334	2.033788	0.0252

LOGCAR	0.586194	0.250034	2.344457	0.0176

R-squared	0.855249	Mean dependent var	0.596159
Adjusted R-squared	0.825092	S.D. dependent var	0.962328
S.E. of regression	0.402465	Akaike info criterion	1.194437
Sum squared resid	3.887466	Schwarz criterion	1.474677
Log likelihood	-11.91656	Hannan-Quinn criter.	1.284088
F-statistic	28.36035	Durbin-Watson stat	1.676699
Prob(F-statistic)	0.000000		

Source: EVIEW, 9.0 Outputs, 2024.

In Table 4.8, multiple regression analysis reveals an LDR coefficient of 2.5623, t-value of 3.4715, and p-value of 0.0020. Therefore, LDR boost ROA significantly. 0.0020 is below 0.05 (5%), making the link notable. Our alternative hypothesis challenges the null hypothesis that LDR does not influence Nigerian MFB ROA. ROA and LDR correlate positively (2.5623). MFB ROA in Nigeria would rise 256.23% with 1% LDR. According to commercial loan theory, banks should only lend short-term, self-liquidating paper. The loan-to-deposit ratio boosts microfinance banks' ROI. Changes in loan-to-deposit ratios can enhance Nigerian microfinance bank profits. Increased loan portfolio compared to deposits may enhance asset returns. Microfinance institutions must risk more deposits to increase profitability. Avoid non-performing loans and credit risk by managing lending.. Good loan-to-deposit ratios increase Nigerian microfinance banks' return on assets, stressing the need for careful lending, risk management, regulatory control, financial inclusion, and capital. Knowing this link would help microfinance institutions grow sustainably and enhance Nigeria's economy. Normal firms shouldn't liquidate all loans because bank deposits are stable. Not all demand depositors can demand payment (Lee & Wu, 2019). Given deposit stability, banks can extend funds for a while. Jamil and Salem (2021) disagree with Hermuningsih, Sari, and Rahmawati (2023).

The NPLR variable's coefficient is -0.1214, with a t-value of -0.1574 and a p-value of 0.8763 in Table 4.6's multiple regression analysis. ROA appears unaffected by NPLR. The association is insignificant because 0.763 exceeds 0.05 (5%). We reject the alternative hypothesis and accept the null hypothesis that NPLR will not affect MFB ROA. A negative ROA correlation with NPLR of -0.1214. A 1% NPLR increase lowers Nigerian MFB ROA 12.12%. Thus, microfinance institutions must control risk. The NPL ratio does not significantly affect ROA, suggesting financial institutions are riskier. Rethinking risk assessment may help microfinance institutions manage all operational risks. The NPL ratio's insignificant effect on Nigerian microfinance banks' ROA emphasises the necessity for a holistic approach to risk management, regulatory monitoring, investor relations, operational efficiency, and research in this vital sector. Commercial loan theory's theories, models, and frameworks help lenders, borrowers, and governments lend. This approach helps banks evaluate businesses' creditworthiness, set interest rates, schedule repayment, and manage commercial loan risks. Unlike Anwer and Hermuningsih (2023), Salem and Jamil (2021) and Agbamuche (2021) agree.

Table 4.6's multiple regression analysis shows the LLPR variable's coefficient -1.3196, t-value -1.2283, and p-value 0.2313. ROA is scarcely affected by LLPR. This association is statistically insignificant because the p-value exceeds 0.05 (5%). Null hypothesis: LLPR does not affect MFB ROA; alternate hypothesis rejected. Since LLPR is -0.3196, ROA suffers. Increasing LLPR by 1% reduces Nigerian MFB ROA by 31.96%. Nigerian microfinance banks' ROA is poor due to loan loss provision rates. These banks may not minimise credit risk using risk management. Reworking credit risk management may aid microfinance enterprises. If loan loss provision ratio somewhat affects return on assets, Nigerian microfinance banks may be unstable. The loan loss provision ratio's modest impact on Nigerian microfinance banks' ROA highlights risk management, financial stability, regulatory control, and investor trust. Microfinance organisations can strengthen resilience and performance to increase financial inclusion and alleviate poverty. Results support Anwer et al. (2023) but contradict Agbamuche (2021).

Multiple regression gives DTER a coefficient of 1.9938, t-value of 2.0338, and p-value of 0.0252. This suggests DTER enhances ROA. Links p-value is 0.0252, below 0.05. DTER influences Nigerian MFB ROA, thus we reject the null hypothesis and accept the alternative. Positive correlation between DTER and ROA is 1.9938. 1% DTER modification boosts Nigerian MFB ROA 199.38%. Financial performance can be improved by strategically managing Nigerian microfinance banks' capital structure, as debt to equity ratios raise return on assets. Debt financing can boost these banks' return on assets, a critical profitability and efficiency measure. Ideal leverage may help microfinance banks. Microfinance banks should optimise capital structure to maximise asset returns, say studies. Balanced debt-equity can minimise these companies' capital costs, improve financial stability, and boost performance. Financial planning and capital allocation matter. The positive return on assets from debt to equity ratio of Nigerian microfinance banks illustrates the complex interaction between capital structure, financial performance, risk management, and investor relations. Microfinance organisations need financial responsibility to thrive. These findings contradict Agbamuche et al. but support Salem and Jamil (2021).

CAR has a coefficient of 0.5862, t-value of 2.3445, and p-value of 0.0176 after multiple regression. CAR increases ROA. Because 0.0176 is smaller than 0.05 (5%), the association is significant. Our alternative hypothesis challenges the null hypothesis that CAR does not influence Nigerian MFB ROA. ROA and CAR correlate favourably (0.5862). MFB ROA in Nigeria would rise 58.62% with 1% CAR. Improved capital adequacy helps Nigerian microfinance firms weather financial storms. Well-capitalized microfinance institutions that can weather economic downturns and unexpected shocks stabilise the financial system. CAR and ROA are positively connected, demonstrating microfinance banks can benefit from risk. Microfinance institutions need money and good risk management to reduce credit and operational risks. Capital management is essential for financial stability, risk resilience, investor trust, regulatory compliance, growth, and competitiveness. Capital adequacy ratio increases Nigerian microfinance banks' return on assets. These findings indicate that Nigerian microfinance companies need major funding. Anwer et al. (2023) agree, Salem and Jamil (2021) and Agbamuche (2021) disagree.

Conclusion

This study analysed how credit risk management affected Nigerian microfinance bank financial performance from 1993 to 2022. Loan-to-Deposit Ratio (LDR), Non-Performing Loan Ratio (NPLR), Loan Loss Provision Ratio (LLPR), Debt-to-Equity Ratio (DTER), and Capital Adequacy Ratio (CAR) were used to calculate credit risk and Microfinance Bank of Nigeria Returns on Asset

(ROA) for financial performance. Secondary data from CBN Statistical Bulletin, Annual Report, Financial Strategy Report, and Bank Supervisory Annual Report was used throughout the study. This study used statistical data analysis. Later, descriptive statistics and correlation analysis were performed to assess the association between the independent (LDR, NPLR, LLPR, DTER, and CAR) and dependent (ROA) variables, followed by multiple diagnostics tests. The study next tested the time series data for stationaryness using unit roots and Johannsen. Cointegration determined the long-term effect of all independent variables on the dependent variable. The hypothesis for this research led to the choice of ordinary least squares multiple regression analysis for the Regression model in E-VIEWs 9.0. LDR was found with a p-value of 0.0020. This implies that LDR positively affect ROA and NPLR with a p-value of 0.8763. LLPR has a 0.2313 p-value, suggesting that NPLR has a negative negligible effect on ROA. A p-value of 0.0252 implies that LLPR has a negative negligible influence on ROA. This implies that DTER and CAR have positive significant effects on ROA. CAR's p-value (sig. value) is 0.0176. The study found that credit risk management affects Nigerian microfinance bank financial performance.

Recommendations

From the objectives and findings, we suggest:

1. I urge Nigerian microfinance banks maintain a healthy loan deposit ratio to boost return on assets. To boost profits, microfinance banks should balance their lending portfolio and deposits. Banks with a high loan deposit ratio use their deposits efficiently to create loan interest, which can boost their return on assets.

2. To lower non-performing loans and loan loss provisions, microfinance banks should improve credit risk management. Detailed credit assessment, monitoring, and collection can accomplish this. Decrease concentration risk and dependence on specific sectors or clientele by diversifying microfinance banks' loan portfolios. The quality of assets and loan default risks can be improved by diversifying.

3. Nigerian microfinance institutions should assess and maybe change their provisioning procedures to capture loan losses. More accurate and reflective provisioning can improve return on assets.

4. Nigerian microfinance banks should aim for a balanced debt-to-equity ratio that meets industry targets and regulations. They can reduce financial risk and financing costs by optimising loan and equity financing. Leveraging available money to boost returns can improve the institution's financial performance with moderate debt.

5. A good capital adequacy ratio helps Nigerian microfinance banks and their finances. More capital means the bank can sustain losses, minimising the chance of insolvency. Stability boosts investor trust, attracts new investors, and boosts profitability and ROA.

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