CREDIT RISK MANAGEMENT AND PROFITABILITY OF DEPOSIT MONEY BANK IN NIGERIA

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BEING A PROJECT SUBMITTED TO THE DEPARTMENT OF BANKING AND FINANCE, FACULTY OF MANAGEMENT SCIENCE UNIVERSITY OF BENIN IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF SCIENCE (B.SC) DEGREE IN BANKING AND FINANCE.

DECEMBER, 2025

DECLARATION

I, **ADAOMA FAITH ALIGAH** hereby declare that this project work was undertaken by me in the Department of Banking and Finance Faculty of Management Sciences, University of Benin, Benin City, under the supervision of PROF M.G Ajao. This work has not been previously submitted for the award of any degree elsewhere. Ideas and views are product of my personal research and where the views of others have been expressed, they have been duly acknowledged.

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CERTIFICATION

We, the undersigned, hereby certify that this research project was carried out by ADAOMA FAITH ALIGAH on the Department of Banking and Finance, University of Benin, Benin City and do approve that it is adequate in scope and quality in partial fulfillment of the award of Bachelor of Science (B.Sc) degree in Banking and Finance, University of Benin, Benin City.

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DEDICATION

This project is wholeheartedly dedicated to the Almighty God for His endless grace, mercy, and strength throughout this academic journey. To my beloved parents, Mr. and Mrs. Aligah, whose unwavering love, sacrifices, prayers, and support have been the solid foundation of my progress — thank you for everything. To my dear family members and friends who have stood by me with love, encouragement, and kindness — your presence in my life has been a great blessing. To all my sponsors and well-wishers, whose financial, emotional, and moral support saw me through the demanding years of study — I am deeply grateful. This work is for all of you. God bless you abundantly.

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ABSTRACT

This study examined how credit risk management affects the profitability of six listed deposit money banks in Nigeria from 2014 to 2023. Using a balanced panel of 60 observations and a fixed-effects model with robust standard errors, the results show that both the non-performing loan ratio (NPLR) and loan loss provision ratio (LLPR) significantly and negatively affect return on assets (ROA) and return on equity (ROE). A one-percentage-point increase in NPLR reduces ROA by about 0.08 percentage points and ROE by about 0.65 percentage points, while higher provisions further weaken earnings. Bank size has a positive impact on profitability, supporting the idea that larger banks benefit from efficiency and stronger risk-absorbing capacity. This study also finds that the 2015–2016 recession and high interest-rate volatility confirmed through a persistent GARCH (1,1) effect further reduce bank performance. All diagnostic tests validate the reliability of the model. This study suggests that effective credit risk management is essential for sustaining profitability in Nigerian banks and recommends stronger credit appraisal systems, improved NPL recovery, full IFRS 9 implementation, diversified income sources, and stronger macroprudential policies.

Keywords: Credit risk, Non-performing loans, Profitability, Deposit money banks, Nigeria, Panel regression, GARCH

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

Deposit money banks (DMBs) play a central role in modern economies by performing financial intermediation—mobilizing funds from surplus units and allocating them to deficit areas through credit extension. This core function, however, is not without inherent risks. In fact, financial intermediation is widely recognized as one of the most significant sources of banking risk, alongside capital adequacy issues, market volatility, operational disruptions, liquidity shortages, interest rate swings, and currency fluctuations (Jenkinson, 2008; Suyanto, 2021; Bhatt et al., 2023; Mendoza & Rivera, 2017).

Among all these, credit risk stands out as the most critical, with poor credit risk management often resulting in significant losses, weakened investor returns, and in severe cases, full-scale banking crises (Khalid et al., 2021; Uwalomwa et al., 2015). Nigeria's financial sector has not been immune to these challenges. Over time, rising non-performing loans (NPLs) and persistent loan defaults prompted a series of government interventions. These included the establishment of the Asset Management Corporation of Nigeria (AMCON) in 2010 to address toxic loans, as well as the 2004 banking sector recapitalization and the issuance of CBN Prudential Guidelines, all aimed at strengthening the credit environment and enhancing financial stability (Natufe et al., 2023).

Bank profitability is deeply intertwined with risk exposure and risk management efficiency (Abubakar et al., 2019; Soyemi et al., 2014). Deposit money banks operate to generate sustainable earnings and maximize shareholder wealth. Financial performance is typically assessed using various profitability ratios such as net profit margin, gross profit margin, return on assets (ROA), and return on equity (ROE). ROA reflects the ability of a bank to generate income from its total assets, while ROE shows how effectively shareholder funds are used to yield returns (Hagel et al., 2010; Clark et al., 2007). These metrics, particularly ROA and ROE, are widely accepted in evaluating banking performance (Barros & Borges, 2011; Kosmidou, 2008).

In the Nigerian banking landscape, the delicate balance between risk exposure and profitability is often tested by the management of credit risk. Effective credit risk management (CRM) not only underpins financial soundness but also directly influences the earnings performance and sustainability of deposit money banks (DMBs). The dual role of banks—as risk takers and intermediaries—exposes them to the volatility of credit markets, especially in a developing economy like Nigeria, where credit default rates can be exacerbated by macroeconomic instability, regulatory lapses, and infrastructural deficiencies.

Profitability, often measured using indicators such as Return on Assets (ROA) and Return on Equity (ROE), is intricately linked to the quality of credit risk management frameworks employed by banks. Where risk management is robust—characterized by diligent credit appraisal, strict monitoring, and prompt response to early warning signs—banks are better positioned to reduce non-performing loans (NPLs), maintain liquidity, and enhance shareholder value. Conversely, poor credit administration, weak internal controls, and relaxed enforcement of covenants heighten the risk of default, leading to significant loan impairments that erode profitability (Bakpo and Kabari 2009; Ugoani 2020).

The Basel regulatory frameworks—particularly Basel II and Basel III—emphasize the critical importance of capital adequacy and risk-weighted asset management in protecting banks from credit losses. These provisions have been adopted in varying degrees within Nigeria's regulatory regime under the Central Bank of Nigeria (CBN), with enhancements in loan classification, provisioning requirements, and stress testing procedures (Basel Committee on Banking Supervision 2004; Basel Committee on Banking Supervision 2010). Nonetheless, the implementation effectiveness remains inconsistent across institutions.

According to Nwaze (2006), managing credit risk in the Nigerian context requires not just policy compliance but operational discipline, timely information flow, and robust borrower profiling. He emphasizes the need for banks to invest in credit analytics, staff training, and intelligent monitoring systems to detect and mitigate potential defaults proactively.

Empirical observations indicate that Nigerian banks that apply structured credit risk assessment models and adhere to prudent risk limits tend to outperform their peers in terms of profitability. These banks often exhibit lower NPL ratios and higher ROE metrics, suggesting a positive correlation between credit risk governance and financial performance (Saunders and Cornett 2007). Furthermore, Yanenkova et al. (2021) argue that aligning credit risk management strategies with macroeconomic dynamics and sectoral credit behavior is vital for emerging market banks, such as those in Nigeria.

The volatility of the Nigerian economic environment—characterized by inflationary pressure, exchange rate fluctuations, and fiscal uncertainty—adds complexity to credit risk forecasting and provisioning. Hence, successful DMBs are those that integrate real-time market intelligence with dynamic credit policy frameworks, while also fostering a culture of risk consciousness across all hierarchical levels.

Understanding the nature of credit risk is central to managing it. In financial contexts, risk generally refers to uncertainty around expected returns, especially the probability of loss arising from a borrower's failure to meet financial obligations. This makes credit risk both measurable and manageable, especially with well-designed frameworks in place. In response to global financial failures, the Basel Committee on Banking Supervision introduced a series of regulatory frameworks—Basel I, II, and III—aimed at strengthening the capital base and risk resilience of financial institutions. These accords emerged after notable events like the Herstatt Bank collapse in 1974 and the Lehman Brothers bankruptcy in 2008, both of which revealed the catastrophic effects of unchecked risk in the banking sector (Basel Committee, 2001; Natufe et al., 2023).

It is indisputable that robust and efficiently managed banking systems, anchored by well-capitalized financial institutions, serve as critical drivers of economic growth and development. These institutions provide the financial infrastructure and credit facilities necessary to support entrepreneurial ventures across various value chains, thus facilitating the realization of individual and corporate ambitions. Over time, this financing capability has underpinned the evolution of globally competitive economic enterprises and expansive business empires. The pivotal intermediation role that banks perform—principally through credit creation—remains the principal source of credit risk exposure, which has, in turn, been a recurring cause of financial distress within the banking sector (Basel Committee on Banking Supervision 1999; Saunders and Cornett 2007; Ugoani 2020; Nwaze 2006).

At the core of this dynamic is the credit life cycle, which encompasses every phase of the credit process—from loan application through disbursement to full liquidation. This cycle typically begins with the customer's submission of a credit request, which undergoes an initial assessment by the bank's relationship officer or account manager. Depending on the size and risk classification of the loan, the application is escalated for deliberation by either the Management Credit Committee (MCC) or the Board Credit Committee (BCC). Once approved, the legal and collateral management teams ensure compliance with all precedent conditions, verify the documentation, and prepare for disbursement.

Following disbursement, a repayment schedule is issued, often incorporating a moratorium period where applicable. The borrower then begins structured repayments. In instances where repayment is disrupted—due to financial difficulty, cash flow misalignment, or external shocks—rescheduling or restructuring may be pursued to align repayment obligations with the borrower's economic realities and the evolving credit risk appetite of the bank (Yanenkova et al. 2021).

Insights gleaned from analyzing the credit life cycles across various banking jurisdictions have significantly influenced the formulation of international regulatory frameworks. This led to the progressive evolution of the Basel Accords, including Basel I (Basel Committee on Banking Supervision 1998), Basel II (Basel Committee on Banking Supervision 2004; 2006), and Basel III (Basel Committee on Banking Supervision 2010). These accords were developed to strengthen bank capital adequacy, promote resilience, and mitigate systemic vulnerabilities. Their overarching goal is to ensure that banks are adequately capitalized to absorb unexpected losses—particularly those arising from credit risk, market volatility (market risk), and failures in internal controls or operational frameworks (operational risk). Despite the expanded scope of regulatory oversight, credit risk continues to be the most significant risk confronting banks.

As defined by the Basel Committee on Banking Supervision (2001, p. 10), credit risk refers to "the risk of loss arising from default by a creditor or counterparty." In practical terms, it manifests as the lender’s exposure to financial loss when a borrower fails to meet agreed repayment terms—whether in terms of periodic interest payments, bullet principal repayments, or both. The trajectory toward default, however, is often preceded by a complex interplay of factors—commonly described as risk transmitters—which gradually erode the borrower’s capacity to fulfill obligations.

The performance of any credit facility can be classified across a success spectrum. A fully successful credit life cycle results in total repayment of both interest and principal as agreed. A partially successful cycle entails impairment, such as delayed principal repayment, but may still be salvaged through timely restructuring and active risk management interventions. Conversely, an unsuccessful credit life cycle is one where systemic breakdowns—such as poor governance, internal collusion, and compliance failures—undermine the integrity of the credit process, leading to significant losses and impairments.

As emphasized by Bakpo and Kabari (2009), the decision to grant credit is one of the most consequential and complex decisions a financial institution can make. It requires not only rigorous analysis but also a deep understanding of the evolving nature of risk across financial landscapes.

Effective credit risk management is essential not only for preserving capital and protecting depositors but also for ensuring profitability and long-term sustainability in banking operations. As Nigerian banks continue to face economic fluctuations, currency devaluation, and borrower defaults, understanding the connection between credit risk control and financial performance has become more important than ever.

In sum, the profitability of deposit money banks in Nigeria is intrinsically tied to how effectively credit risk is identified, measured, mitigated, and monitored. While credit creation is the lifeblood of banking operations, its sustainability and profitability depend largely on sound credit risk management practices, as enshrined in global best practices and contextualized within the Nigerian financial ecosystem.

1.2 Research Problem

Credit risk remains one of the most critical challenges confronting deposit money banks (DMBs) in Nigeria. Although lending constitutes a major source of income for banks, rising levels of non-performing loans (NPLs) have significantly eroded profitability and undermined financial stability. Recent statistics reveal that many Nigerian banks continue to record double-digit NPL ratios, far above the prudential benchmark of 5% prescribed by the Central Bank of Nigeria (CBN), thereby exposing the sector to systemic vulnerabilities (Natufe et al., 2023). The persistence of weak credit appraisal systems, inadequate monitoring mechanisms, insider-related loans, and poor risk culture has worsened credit exposures, leading to reduced earnings, capital erosion, and in severe cases, regulatory intervention or bank failure.

While credit risk management has been widely recognized as a determinant of bank performance globally, evidence within the Nigerian context suggests that many DMBs still struggle to align their credit practices with sound risk management frameworks. This disconnect raises a fundamental concern: to what extent do deficiencies in credit risk management practices explain the recurring decline in profitability among Nigerian banks? Despite regulatory reforms and risk-based supervision introduced by the CBN, the continued rise in NPLs calls into question the effectiveness of existing strategies. Therefore, it becomes imperative to critically evaluate the relationship between credit risk management and profitability in Nigerian DMBs in order to identify practical measures that can enhance financial performance and ensure the long-term sustainability of the banking industry.

1.3 Research Questions

1. What is the effect of non-performing loans on the profitability of deposit money banks in Nigeria?

2. How does the loan-to-deposit ratio influence bank profitability?

3. What is the relationship between credit risk management practices and financial performance?

1.4 Objectives of this Study

1. To assess the effect of non-performing loans on bank profitability.

2. To determine the relationship between loan-to-deposit ratio and profitability.

3. To examine the impact of credit risk management policies on financial performance.

1.5 Hypothesis of the Study

In this study we will be accessing 3 key hypothesis and they're;

1) Hypothesis One

H_{01}: Non-performing loans have no significant effect on the profitability of deposit money banks in Nigeria.

H_{11}: Non-performing loans have a significant effect on the profitability of deposit money banks in Nigeria.

2) Hypothesis Two

H_{02}: Loan-to-deposit ratio has no significant relationship with the profitability of deposit money banks in Nigeria.

H_{12}: Loan-to-deposit ratio has a significant relationship with the profitability of deposit money banks in Nigeria.

3) Hypothesis Three

H_{03}: Credit risk management policies have no significant impact on the financial performance of deposit money banks in Nigeria.

H_{03}: Credit risk management policies have a significant impact on the financial performance of deposit money banks in Nigeria.

1.6 Significance of the Study

The findings of this study will be of great significance to various stakeholders in the Nigerian banking sector. For deposit money banks, this study will provide practical insights into how effective credit risk management can enhance profitability, reduce the burden of non-performing loans, and strengthen financial performance. Bank executives and managers will particularly benefit from evidence-based guidance that can help improve loan appraisal procedures, credit monitoring systems, and overall strategic decision-making. Regulatory authorities such as the Central Bank of Nigeria (CBN) and the Nigeria Deposit Insurance Corporation (NDIC) will also benefit from the study as it will highlight existing gaps in credit risk practices, thereby equipping them with valuable information for refining supervisory frameworks and formulating more effective regulatory policies. Likewise, investors and shareholders will gain a clearer understanding of how credit risk influences bank profitability, enabling them to make more informed investment and portfolio decisions. Furthermore, policymakers and the government stand to benefit, as the study will provide empirical evidence that can guide the development of policies aimed at promoting a stable and resilient banking system, which is essential for economic growth. In addition, the research will enrich academic literature, serving as a useful reference for future researchers and students in finance and banking. Finally, the general public and bank customers will indirectly benefit from a more stable and profitable banking sector, which fosters greater trust, reliability, and access to quality financial services.

1.7 Scope of Study

The scope of this study is limited to deposit money banks operating in Nigeria, with particular focus on the relationship between credit risk management and profitability. It covers key indicators such as non-performing loans, loan loss provisions, and capital adequacy in relation to profitability measures like return on assets (ROA) and return on equity (ROE). This study is confined to a specific period of 10 years to capture recent trends in credit risk and bank performance, while excluding other financial institutions such as microfinance banks or insurance companies.

CHAPTER TWO

LITERATURE REVIEW

2.0 Conceptual Framework

This study is anchored on the relationship between credit risk management and the profitability of deposit money banks in Nigeria. Credit risk management, which constitutes the independent variable, will be assessed using indicators such as non-performing loans ratio, loan loss provision, and capital adequacy ratio, as suggested in previous empirical studies (Adeusi, Akeke, Adebisi, & Oladunjoye, 2014; Olalere & Wan Ahmad, 2016). Profitability, the dependent variable, will be measured by return on assets (ROA), return on equity (ROE), and net interest margin (NIM), which are widely recognized as indicators of bank performance (Otu, 2019). The framework posits that effective credit risk management practices reduce loan defaults, thereby improving asset quality and ensuring higher profitability for banks. In essence, the model assumes a direct positive relationship where strong credit risk management strategies enhance financial performance, consistent with the risk-return tradeoff theory (Kolapo, Ayeni, & Oke, 2012).

2.1 Credit Risk

Lending remains a fundamental component of banking operations, serving as a crucial tool for driving socio-economic development and meeting the financial needs of businesses and individuals. The growth in lending activities highlights not only the strong interest of banks in credit as a profit source but also the rising demand for credit from economic actors. However, lending inherently carries significant risks, particularly credit risk, which continues to challenge the stability and profitability of banking institutions. The sustainability of bank lending is thus closely tied to the effectiveness of risk management practices employed (Wilhelmsson & Zhao, 2018).

Over time, banks have become increasingly conscious of how credit and operational risks influence their financial performance. As such, institutions are now more invested in establishing clear, structured procedures for credit appraisal and loan disbursement, incorporating global best practices in risk control (Drobyazko et al., 2020a; Nosratabadi et al., 2011). Despite this awareness, many commercial banks still rely on superficial risk mitigation approaches—most commonly by increasing interest rates or adding extra charges to offset potential losses. These methods often shift the burden of risk onto borrowers rather than addressing the core issues within lending systems.

Inadequate organizational frameworks for identifying and monitoring operational risks remain a concern. Some risk managers tend to overlook these threats unless they involve obvious fraud, thereby weakening the bank's preparedness for broader forms of credit-related disruptions (Drobyazko et al., 2020a). The need for systematic risk identification and predictive modeling has become more urgent, especially as banks frequently encounter default risks caused by diverse, often overlapping factors (Maechler et al., 2007; Chun & Lejeune, 2020).

One vital step in mitigating credit risk lies in conducting robust borrower evaluations. Accurate assessments of creditworthiness and risk levels significantly enhance the outcomes of lending decisions and influence the overall performance of banks (Giordana & Schumacher, 2017). Misjudging a borrower's financial position not only undermines the likelihood of repayment but also distorts the bank's credit portfolio.

Financial analysis remains a powerful tool in evaluating credit risk. Reviewing a borrower's historical financial performance enables banks to project future behavior and estimate repayment capacity (Allen & Luciano, 2019). This process includes assessing the borrower's legal and economic standing, the quality of collateral, and other financial indicators that influence loan approval and recovery expectations (Richard, 2006).

Credit risk is commonly linked to a counterparty's inability or refusal to meet debt obligations fully and on time. Effective risk management goes beyond anticipating bankruptcy; it also entails identifying early signs of deteriorating financial health or adverse credit events. Risk becomes manageable when it is identifiable, measurable, and aligned with the bank's resilience capacity. Uncontrolled or unjustified risks, however, pose substantial threats and must be swiftly addressed through capital enhancement or tighter internal controls (Maechler et al., 2007).

Given the current realities of bank lending, there is a pressing need to upgrade credit risk management systems. This involves integrating sophisticated models and frameworks capable of safeguarding loan portfolios and reducing potential losses. Advancing the methodologies used in credit risk oversight is, therefore, both an academic concern and a practical imperative for modern banking institutions.

2.1.1 Types of Credit Risk

Credit risk is a critical element of banking operations and is most commonly associated with default risk, which arises when a borrower fails to fulfill their repayment obligations (Louzada et al., 2016). Accurate estimation of default probability is central to effective credit risk management, as it enables institutions to protect their loan portfolios and maintain profitability (Ntwiga, 2016).

Historically, credit decisions were based on judgmental assessments, such as the 5Cs approach—character, capacity, capital, collateral, and conditions (Sinkey, 1992). While this method provided a basic framework, it struggled to handle large volumes of applications and was prone to subjective errors (Crook, 1996; Dastile et al., 2020). The evolution of credit risk management, however, saw a significant shift with the integration of automation and quantitative models, allowing faster, more accurate credit decisions and reducing bureaucratic inefficiencies (Anderson, 2007; Abdou & Pointon, 2011).

A landmark in credit scoring history was Durand’s early work in the 1940s, which introduced a statistical approach to evaluating credit applicants (as cited in Louzada et al., 2016; Bumacov et al., 2017). The emergence of international regulatory frameworks such as the Basel Capital Accords further advanced the importance of quantitative credit risk evaluation, particularly after the implementation of Basel II in 2004, which emphasized the use of credit scoring for risk measurement and capital allocation (Ciampi et al., 2021; Lessmann et al., 2015).

Alongside default risk, information asymmetry poses another form of credit risk, where borrowers possess more knowledge about their financial capacity than lenders. The advancement of digital systems and risk analytics has helped reduce this gap by sourcing data from multiple channels beyond self-reported financials (Leyshon & Thrift, 1999). New credit scoring technologies, including artificial intelligence and big data analytics, have strengthened banks' abilities to predict borrower behavior more accurately (Kabari & Nwachukwu, 2013; Tounsi et al., 2017).

Modern risk evaluation increasingly incorporates non-financial and behavioral variables—including personality traits and socio-demographic data—to capture borrower creditworthiness more holistically, especially when traditional financial histories are unavailable (San Pedro et al., 2015). This approach has become essential in developing economies where credit bureau coverage is weak, and data scarcity presents a major challenge (Bjorkegren & Grissen, 2018).

The rise of e-commerce and digital lending has also introduced new complexities to credit risk. The shift from cash to credit-based transactions online, coupled with the rapid expansion of peer-to-peer and tech-based lending platforms, has significantly impacted credit portfolio quality (van Thiel & van Raaij, 2019). Traditional credit indicators often fail to capture real-time changes in borrower behavior in such dynamic environments, necessitating adaptive and forward-looking risk models (Wang et al., 2013).

While default risk remains the core type of credit risk, modern banking faces a broader array of credit-related challenges, including information asymmetry, data insufficiency, and digital lending volatility. Responding to these requires a combination of historical insight, technological advancement, and forward-thinking regulatory practices.

2.1.2 Profitability Indicators

In the banking sector, profitability is a core metric for measuring performance and sustainability. When evaluating the financial health and efficiency of deposit money banks, profitability indicators serve as essential tools. These indicators help in assessing how well a bank utilizes its assets, manages its costs, and generates income—particularly in relation to its exposure to credit risk.

One of the most widely used indicators is the Return on Assets (ROA), which reflects how effectively a bank converts its total assets into net profit. ROA is especially relevant in credit risk contexts, as a higher proportion of non-performing loans (NPLs) tends to reduce asset profitability, thereby signaling poor credit risk management (Louzada et al., 2016; Ntwiga, 2016).

Another key measure is the Return on Equity (ROE), which calculates the return generated on shareholders' equity. ROE not only reflects profitability but also serves as a gauge for how efficiently bank capital is being employed. When credit risk is poorly managed, the cost of loan defaults can diminish earnings, leading to lower ROE figures (Ciampi et al., 2021).

The Net Interest Margin (NIM) is also a critical indicator, as it captures the difference between interest income earned on loans and the interest paid on deposits. A narrow margin may reflect rising credit risk if more loans are non-performing and no longer generating interest income (Lessmann et al., 2015). As credit risk increases, banks may be forced to raise interest rates to compensate for higher expected losses, which could paradoxically reduce loan demand and profitability.

Beyond these conventional ratios, modern banking practices are adopting more nuanced profitability metrics that factor in risk-adjusted returns. For instance, the Risk-Adjusted Return on Capital (RAROC) has gained popularity as it accounts for both expected losses from credit risk and the cost of capital. This shift reflects a growing recognition that not all profits are equal—sustainable profitability must be achieved without exposing the institution to excessive risk (Anderson, 2007).

The emergence of digital lending and peer-to-peer platforms has also complicated the relationship between credit risk and profitability. Financial institutions now face pressure to innovate, often entering riskier markets without complete data. As a result, profitability indicators alone are no longer sufficient; they must be interpreted alongside credit risk metrics to provide a full picture of a bank's performance (San Pedro et al., 2015).

Profitability indicators such as ROA, ROE, and NIM are essential tools for evaluating the financial strength of banks. However, their reliability depends heavily on the quality of credit risk management systems in place. Sustainable profitability arises not merely from high earnings, but from balanced growth that considers both returns and risks.

2.1.3 Credit Risk Management Techniques

Effective credit risk management begins with identifying the specific type of loss to be assessed, as this determines the appropriate modeling and control strategy (Hirtle et al., 2001). Among various types of credit risk, financial institutions often prioritize counterparty default risk, which involves the possibility of a borrower failing to meet obligations. Other closely monitored risks include counterparty migration risk, and portfolio-level credit and migration risks (Fatemi & Fooladi, 2006). These areas have gained heightened attention in the wake of shifting global regulations following major financial crises, prompting increased scrutiny on how credit risk affects pricing and systemic stability (Zhu & Pykhtin, 2007; Assefa et al., 2009; Du et al., 2019).

Credit risk management techniques can be broadly categorized into three main approaches: qualitative (judgmental), data-driven, and financial modeling methods (Doumpos et al., 2019).

The judgmental approach, a traditional technique, relies on expert evaluation of a borrower's willingness and capacity to repay. Factors such as profitability, liquidity, leverage, and financial projections are subjectively reviewed (Hempel, 1994). However, this method is limited by analyst bias, inconsistencies in interpretation, and often a lack of depth due to understaffing or conflicting data points (Libby, 1975; Kalapodas & Thomson, 2006).

In contrast, data-driven techniques utilize historical loan performance data—ranging from approved and repaid loans to defaults—to model creditworthiness. This methodology is applicable across both consumer and corporate lending segments. The FICO model, introduced by the U.S. Federal Reserve, marked an early attempt to standardize credit evaluation metrics (Ignatius et al., 2018). Since then, a wide array of analytical tools and algorithms have been developed to improve prediction accuracy and consistency in credit risk assessment (Tsai & Wu, 2008; Wang et al., 2011; Trustorff et al., 2011; Caruso et al., 2018).

Advanced machine learning and soft computing models are increasingly at the forefront of modern credit risk management. These include:

Support Vector Machines (Bellotti & Crook, 2009; Danenas & Garsva, 2015)

K-Nearest Neighbor algorithms (Marinakis et al., 2008)

Rough Set Theory (Wang & Chen, 2006; Yeh et al., 2012)

Decision Trees (Bastos, 2008; Zhang et al., 2010)

Multi-criteria decision models and operations research tools (Ferreira et al., 2014; Zhang et al., 2014, 2019)

Regression-based statistical models (Bensic et al., 2005; Blanco et al., 2013)

These models have paved the way for scoring and rating systems that offer more objective and scalable assessments of credit risk. The evolution of credit risk management has shifted from subjective analysis to automated, data-driven techniques, underpinned by advanced computing and predictive analytics. This transformation not only enhances the precision of risk evaluation but also improves the overall resilience and profitability of banking institutions.

2.2 Asymmetric Information Theory and its Implications for Financial Performance

The concept of asymmetric information suggests that when one party in a transaction possesses more or better information than the other, it can lead to inefficiencies and suboptimal decisions—especially within the banking sector. According to Jin et al. (2020), information asymmetry, or a lack of transparency, raises the cost of acquiring relevant information, making it harder for investors to distinguish high-quality from low-quality opportunities. This is particularly problematic in cross-border investments like Foreign Direct Investment (FDI), where investors may be unfamiliar with the local environment and thus operate at an informational disadvantage.

Jin and colleagues examined this issue in the context of Chinese manufacturing firms, applying a market microstructure framework to quantify the level of unobservable information asymmetry using the Probability of Informed Trading (PIN). Additionally, they assessed firm-level productivity by using proxy variables, based on the idea that productivity can be influenced by external shocks like FDI.

Their findings reveal a nuanced relationship between information asymmetry, FDI, and productivity. In firms that are technology-intensive, reduced asymmetry (i.e., higher transparency) tends to attract more FDI, which in turn enhances productivity through knowledge spillovers. Conversely, in non-technology-intensive firms, increased transparency and subsequent FDI can introduce stronger foreign competition, potentially undermining local productivity.

Though their study focused on China, the implications are relevant for developing economies such as Nigeria, where information opacity in financial institutions and limited disclosure practices can distort credit allocation, hinder foreign investments, and negatively impact profitability. In the context of credit risk, this suggests that managing information asymmetry is essential not only for attracting external capital but also for maintaining internal efficiency and sustaining long-term performance.

2.2.1 Modern Portfolio Theory

Modern Portfolio Theory (MPT), originally developed by Harry Markowitz in 1952, remains a foundational framework in understanding how investors can maximize returns for a given level of risk through diversification. While traditionally associated with investment portfolios, MPT also has significant implications for credit risk management in the banking sector.

According to Lukomnik et al. (2021), the contemporary relevance of MPT lies in its shift from micro-level asset selection to a more systemic view of risk. They argue that in today's complex financial environment, diversification alone is not enough. Banks and financial institutions must also account for systemic and non-diversifiable risks, including credit default contagion, regulatory shifts, and macroeconomic instability.

In the context of deposit money banks in Nigeria, applying MPT principles can help institutions better manage credit risk by spreading credit exposures across various industries, geographical locations, and borrower categories. This not only helps to stabilize returns but also cushions the bank's profitability against sector-specific downturns or default events.

Moreover, as Lukomnik et al. (2021) highlight, the modern interpretation of portfolio theory encourages institutions to integrate environmental, social, and governance (ESG) factors, recognizing that system-level risks—such as poor governance or economic inequality—can directly affect creditworthiness and thus profitability.

MPT offers a robust theoretical lens through which Nigerian banks can develop more resilient credit portfolios, balancing risk and return in a dynamic and often volatile economic landscape.

2.2.2 Risk Return Trade-Off Theory

The risk-return trade-off theory posits that higher potential returns are generally accompanied by greater risk. Traditional models like the Mean-Variance Optimization (MVO) framework have historically attempted to balance these two elements by using statistical estimations of expected returns and asset covariances. However, challenges in reliably predicting these parameters—especially expected returns—have led to instability in portfolio performance (Chopra & Ziemba, 1993).

To address this, newer risk-based approaches have emerged that reduce or completely remove the dependence on return estimations. For instance, by focusing on minimum variance portfolios, investors can construct portfolios centered on assets with lower volatility. However, this method often leads to narrowly concentrated portfolios, which may compromise diversification and ultimately reduce returns.

Innovations such as the Equal Risk Contribution (ERC) approach have attempted to solve this by ensuring that each asset contributes equally to overall portfolio risk. Rather than assigning equal weights to assets, this strategy distributes risk budgets equally, as discussed by Maillard et al. (2010) and Roncalli (2014). Through Euler's decomposition, the total risk of a portfolio can be broken down into the marginal risk contribution of each asset (Roncalli & Weisang, 2016), allowing for a more precise and stable diversification framework.

Incorporating risk parity optimization—which ensures that all assets contribute equally to the total portfolio risk—adds an extra layer of protection against overconcentration. This method avoids the reliance on expected returns and instead constructs portfolios based on absolute risk contributions, fostering resilience in uncertain financial environments (Bai et al., 2016; Haugh et al., 2015).

For deposit money banks in Nigeria, where asset quality, credit exposure, and market volatility can be highly dynamic, adopting principles from risk-based allocation models can enhance profitability. By managing credit portfolios with a risk parity mindset, banks may reduce exposure to high-risk sectors while maintaining balanced credit distributions, ultimately optimizing the trade-off between risk and return.

2.3 Credit Risk Implications in Nigeria and the Globe

The financial sector, especially the banking industry, plays a fundamental role in stimulating economic growth through credit extension to individuals, SMEs, and industries. In emerging economies like Nigeria, microfinance institutions (MFIs) bridge the financial inclusion gap by offering small loans that empower the economically active poor to start or expand small businesses. These institutions—whether structured as banks or non-bank financial entities—

serve as lifelines to unbanked or underbanked populations (Oluyombo, 2007; Munene & Guyo, 2013; Liman et al., 2016).

However, a major obstacle to the sustainability and profitability of microfinance banks (MFBs) is credit risk—the likelihood that borrowers will default on their loan obligations. The implications of credit risk are far-reaching. If not adequately managed, it leads to deteriorating loan portfolios, reduced earnings, and ultimately, financial distress. Loan default translates to lost income, increased loan-loss provisions, and reduced capacity to extend further credit, directly undermining profitability (Williams, 2004; Aremu et al., 2010; Kargi, 2011).

Numerous studies have established a strong correlation between credit risk and the financial performance of banks. Indicators such as non-performing loans (NPLs), loan-loss provisions, net charge-offs, and pre-provision operating profit are crucial metrics used to assess how credit risk influences profitability (Kolapo et al., 2012; Boahene et al., 2012; Ekinci, 2016; Taiwo et al., 2017). Unfortunately, while there's a wealth of research on credit risk in Nigeria's commercial banking sector, the microfinance segment remains underexplored. This gap is primarily due to the industry's relative infancy and limited data availability.

Despite its potential, Nigeria's microfinance sector remains undercapitalized. The Central Bank of Nigeria (CBN, 2019) reported that the total assets of the microfinance sub-sector amounted to ₦408.35 billion by the end of 2018—a figure disproportionate to the country's large and underserved population. Economic shocks, including the 2016–2017 recession, further worsened credit conditions, elevating poverty levels and reducing repayment capacity.

One of the most pressing challenges facing MFBs is the rising rate of non-performing loans, which not only stifles credit supply but also forces banks to allocate more capital to loan-loss reserves—resources that could have been invested to generate profits. This dynamic creates a vicious cycle where poor credit management directly limits the sector's ability to scale and generate sustainable earnings. The CBN (2017) has highlighted that poor loan performance in many MFBs severely limits their profitability and operational resilience.

Globally, credit risk is also a central issue in banking regulation and profitability analysis. Institutions worldwide continuously seek robust risk assessment models to maintain healthy loan portfolios. The ability to mitigate credit risk while optimizing returns is a cornerstone of bank stability and growth. For both Nigerian and global financial institutions, implementing strong credit risk management frameworks, especially those that improve NPL ratios and reduce provisions, is vital for maintaining profitability in competitive and volatile environments.

2.4 Theoretical Review

This study is anchored on several theories that explain the relationship between credit risk and bank performance. One of the key theories is the Credit Risk Theory, which emphasizes that lending always carries a probability of default, and proper risk assessment is essential for profitability. The Modern Portfolio Theory is also relevant, as it stresses diversification in lending to minimize risk and optimize returns. In addition, the Asymmetric Information Theory highlights the challenges banks face in distinguishing between creditworthy and non-creditworthy borrowers, which often results in adverse selection and moral hazard. These theories collectively provide a framework for understanding how credit risk management practices can either enhance or undermine the profitability of deposit money banks.

2.4.1 Empirical Review

The relationship between credit risk management and bank profitability is a critical issue in the banking sector, particularly in Nigeria, where economic volatility and high levels of non-performing loans have posed significant challenges to financial institutions. Studies have shown mixed results on how credit risk management impacts profitability, reflecting the complexity of balancing risk and reward in lending activities. For instance, research by Natufe et al. (2023) demonstrated that high levels of non-performing loans significantly reduce the profitability of Nigerian banks, largely due to weak credit appraisal systems that fail to adequately assess borrowers' creditworthiness. Similarly, Adegbaju and Olokoyo (2020) found a negative relationship between loan loss provisions and return on assets, suggesting that poor credit management erodes earnings by diverting funds from productive investments. However, other studies, such as Olamide and Eze (2019), argue that when banks implement robust risk management frameworks, credit expansion can enhance profitability by enabling safe lending growth. Comparative insights from other African countries, such as Kenya and Ghana, further reveal that effective credit monitoring and diversification strategies are positively linked to financial performance. These findings underscore the need for Nigerian banks to reassess their credit risk management practices to optimize profitability in a challenging economic environment. This essay explores the empirical evidence, analyzes the challenges faced by Nigerian banks, draws lessons from other African countries, and proposes strategies to enhance credit risk management and profitability.

Credit risk, defined as the potential for loss due to a borrower's failure to repay a loan, is a central concern for banks, as lending constitutes their primary revenue-generating activity. In Nigeria, the banking sector plays a pivotal role in economic development, providing credit to individuals, businesses, and government entities. However, the sector operates in a volatile environment characterized by high inflation, currency depreciation, and fluctuating oil prices, which increase the risk of loan defaults. According to the Central Bank of Nigeria, the non-performing loan ratio in Nigerian banks has often exceeded the regulatory threshold of 5%, placing significant pressure on profitability. Natufe et al. (2023) highlighted that high non-performing loan ratios are a major driver of reduced profitability, as banks must set aside substantial provisions to cover potential losses. These provisions reduce the funds available for lending or investment, thereby constraining revenue generation. The study pointed to weak credit appraisal systems as a key factor, noting that many Nigerian banks lack standardized processes for evaluating borrowers' creditworthiness. Inadequate due diligence during loan origination often leads to the approval of high-risk loans, which subsequently default, eroding banks' earnings and capital base.

Adegbaju and Olokoyo (2020) provided further evidence of the negative impact of poor credit risk management, focusing on the relationship between loan loss provisions and return on assets. Their findings indicated that higher provisions for bad loans directly reduce profitability by limiting the funds available for productive activities. When banks allocate significant portions of their income to cover potential losses, they face reduced net income, which negatively affects key performance metrics such as return on assets and return on equity. This situation is particularly acute in Nigeria, where economic challenges exacerbate borrowers' inability to repay loans. For instance, small and medium-sized enterprises, which form a significant portion of bank borrowers, are highly sensitive to economic shocks such as inflation and unemployment. As a result, banks face increased default risks, which necessitate higher provisions and further strain profitability. These findings highlight the detrimental effects of weak credit risk management and underscore the need for improved practices to safeguard financial performance.

In contrast, Olamide and Eze (2019) offered a more optimistic perspective, arguing that effective credit risk management can enhance profitability. Their study emphasized that banks with robust risk management frameworks, including rigorous credit appraisal and continuous loan monitoring, can expand their loan portfolios without compromising financial stability. By implementing stringent credit screening processes, banks can identify creditworthy borrowers and avoid high-risk loans, thereby reducing the likelihood of defaults. Additionally, diversification of loan portfolios across sectors such as agriculture, manufacturing, and services can mitigate the impact of economic shocks in any single industry. Olamide and Eze (2019) found that banks with diversified portfolios and proactive risk management strategies achieved higher return on assets and return on equity, demonstrating the potential for credit expansion to drive profitability when managed effectively. This perspective suggests that the impact of credit risk management on profitability depends heavily on the quality of risk management practices, with well-designed frameworks enabling banks to balance risk and reward.

Comparative studies from other African countries, such as Kenya and Ghana, provide valuable insights into how effective credit risk management can enhance profitability. In Kenya, banks have increasingly adopted technology-driven credit monitoring systems to reduce non-performing loans. A study by Mwangi and Ouma (2021) found that Kenyan banks using advanced tools, such as credit scoring models and real-time loan monitoring platforms, reported lower non-performing loan ratios and higher profitability compared to those relying on traditional methods. These tools enable banks to track loan performance in real time, identify early warning signs of default, and take corrective actions promptly. For example, data analytics can flag borrowers who miss payments or exhibit financial distress, allowing banks to restructure loans or enforce stricter repayment terms before defaults occur. This proactive approach has enabled Kenyan banks to maintain stable financial performance even in challenging economic conditions.

Similarly, in Ghana, banks have emphasized loan portfolio diversification to mitigate credit risk. Amoah and Mensah (2022) found that Ghanaian banks that spread their lending across multiple sectors, such as agriculture, manufacturing, and technology, experienced lower non-performing loan ratios and higher profitability. By diversifying their portfolios, these banks reduced their exposure to sector-specific risks, ensuring more stable earnings. For instance, a downturn in the agricultural sector would have a limited impact on a bank with a diversified portfolio, as losses in one sector could be offset by gains in others. These findings highlight the importance of innovative and proactive credit risk management strategies in enhancing financial performance, offering lessons for Nigerian banks seeking to improve their profitability.

The mixed findings from these studies can be analyzed through theoretical lenses such as the risk-return tradeoff theory and the financial intermediation theory. The risk-return tradeoff theory posits that higher risks, such as those associated with lending, should yield higher returns if managed effectively. However, poor risk management can lead to losses that outweigh potential gains, as evidenced by the high non-performing loan ratios and loan loss provisions in Nigerian banks. The financial intermediation theory emphasizes the role of banks in managing risks to facilitate economic transactions. By effectively managing credit risk, banks can allocate resources efficiently, thereby enhancing profitability. These theories provide a framework for understanding the empirical findings and their implications for Nigerian banks, highlighting the need for robust risk management practices to achieve a balance between risk and reward.

Despite the potential for effective credit risk management to enhance profitability, Nigerian banks face several challenges that hinder their ability to implement robust frameworks. One major challenge is the reliance on weak credit appraisal systems. Many banks use outdated or inconsistent methods for evaluating borrowers, which are prone to human error and bias. For example, manual loan approval processes often fail to adequately assess borrowers' financial histories, leading to the approval of high-risk loans. Additionally, limited access to reliable credit data, such as credit bureau reports, further complicates the appraisal process. Without comprehensive data on borrowers' creditworthiness, banks struggle to make informed lending decisions, increasing the risk of defaults.

Economic volatility is another significant challenge for Nigerian banks. The country's economy is heavily dependent on oil exports, making it vulnerable to fluctuations in global oil prices. High inflation and currency depreciation further exacerbate borrowers' inability to repay loans, particularly for small and medium-sized enterprises. These economic conditions increase default risks, forcing banks to allocate substantial funds to loan loss provisions, which reduce profitability. Moreover, frequent changes in regulatory requirements create uncertainty for banks, complicating their risk management strategies. The Central Bank of Nigeria's prudential guidelines mandate specific non-performing loan thresholds and provisioning requirements, which can be costly for banks to comply with. Maintaining high provisions reduces the funds available for lending, limiting revenue generation opportunities.

The limited use of technology is another barrier to effective credit risk management in Nigeria. Unlike Kenyan banks, which have embraced digital tools such as credit scoring models and real-time analytics, many Nigerian banks rely on manual or semi-automated processes. This technological gap limits their ability to proactively manage credit risk and respond to emerging challenges. For instance, real-time loan monitoring systems can provide early warnings of potential defaults, enabling banks to take corrective actions before losses materialize. Without such tools, Nigerian banks are often reactive rather than proactive, which increases their exposure to credit risk.

The experiences of Kenyan and Ghanaian banks offer valuable lessons for Nigerian banks seeking to improve their credit risk management practices. In Kenya, the adoption of technology-driven systems has transformed credit risk management, enabling banks to reduce non-performing loans and enhance profitability. For example, credit scoring models use data analytics to assign risk scores to borrowers, improving the accuracy of credit appraisals. Real-time monitoring platforms allow banks to track loan performance continuously, identifying issues before they escalate. Nigerian banks can emulate these strategies by investing in similar technologies to enhance their risk management capabilities. By adopting credit scoring models, banks can streamline their appraisal processes and reduce the likelihood of approving high-risk loans. Similarly, real-time monitoring systems can improve loan performance tracking, enabling banks to address potential defaults proactively.

In Ghana, the focus on loan portfolio diversification has proven effective in mitigating credit risk. By spreading their lending across multiple sectors, Ghanaian banks have reduced their exposure to sector-specific risks, ensuring more stable financial performance. Nigerian banks can adopt a similar approach by diversifying their loan portfolios to include industries such as technology, agriculture, and manufacturing. This strategy can help mitigate the impact of economic shocks, such as a decline in oil prices, which disproportionately affects certain sectors. By diversifying their portfolios, Nigerian banks can achieve more consistent earnings and reduce their reliance on any single industry.

The empirical findings and comparative insights have several implications for Nigerian banks. First, banks must prioritize the development of robust credit appraisal systems to minimize non-performing loans and enhance profitability. This involves adopting standardized, data-driven processes that leverage credit bureau data and financial analytics to evaluate borrowers' creditworthiness. By improving the accuracy of their appraisals, banks can reduce the risk of defaults and allocate resources more efficiently. Second, banks should invest in technology to enhance their credit monitoring and risk management capabilities. Digital tools, such as credit scoring models and real-time analytics, can improve efficiency and reduce non-performing loan ratios, thereby boosting profitability. Third, banks should diversify their loan portfolios to mitigate sector-specific risks. By lending to a broader range of industries, banks can reduce their exposure to economic volatility and achieve more stable financial performance. Finally, collaboration with regulators and industry stakeholders is essential to address systemic challenges, such as limited access to credit data and economic instability. By aligning their risk management practices with regulatory requirements, banks can enhance compliance and financial performance.

To address these challenges and capitalize on the opportunities identified, several strategies can be recommended for Nigerian banks. First, banks should strengthen their credit appraisal systems by adopting standardized, data-driven processes. This includes leveraging credit bureaus and financial data to evaluate borrowers' repayment capacity more accurately. By improving the quality of their appraisals, banks can reduce the risk of approving high-risk loans and minimize non-performing loan ratios. Second, banks should invest in technology to enhance their risk management capabilities. Digital tools, such as credit scoring models and real-time loan monitoring systems, can improve efficiency and enable proactive risk management. By adopting these technologies, banks can reduce non-performing loans and enhance profitability.

Third, banks should diversify their loan portfolios to mitigate risks associated with economic volatility. By lending to a broader range of sectors, such as agriculture, manufacturing, and technology, banks can reduce their exposure to sector-specific risks and achieve more stable earnings. For example, increasing lending to the technology sector, which is less sensitive to oil price fluctuations, can provide a buffer against economic shocks. Fourth, banks should enhance collaboration with regulators, such as the Central Bank of Nigeria, to address systemic challenges. This includes advocating for policies that improve access to credit data and support economic stability. By working closely with regulators, banks can align their risk management practices with prudential guidelines, ensuring compliance and financial stability. Finally, banks should invest in training programs to build staff expertise in credit risk management. Skilled personnel are essential for implementing effective risk management strategies and adapting to changing economic conditions.

The relationship between credit risk management and bank profitability is complex, with empirical evidence highlighting both the challenges and opportunities faced by Nigerian banks. Studies such as Natufe et al. (2023) and Adegbaju and Olokoyo (2020) demonstrate the negative impact of weak credit risk management, as high non-performing loan ratios and loan loss provisions erode profitability. However, Olamide and Eze (2019) show that robust risk management frameworks can enhance earnings by enabling safe credit expansion. Comparative insights from Kenya and Ghana highlight the importance of technology-driven risk management and portfolio diversification in achieving financial stability. Nigerian banks face significant challenges, including weak credit appraisal systems, economic volatility, and limited use of technology. By adopting best practices from other African countries, such as digital credit monitoring and portfolio diversification, Nigerian banks can strengthen their risk management frameworks and enhance profitability. The recommended strategies, including strengthening credit appraisal systems, investing in technology, diversifying loan portfolios, enhancing regulatory collaboration, and building staff capacity, provide a roadmap for achieving these goals. Ultimately, effective credit risk management is essential for ensuring the financial stability and long-term success of Nigerian banks in a dynamic economic environment.

2.4.2 Gaps in Existing Literature

Despite the growing body of research, several gaps remain. First, much of the existing literature in Nigeria focuses heavily on the impact of non-performing loans without adequately examining the role of broader credit risk management strategies such as risk-based supervision, loan portfolio diversification, and credit monitoring mechanisms. Second, many studies are cross-sectional and fail to capture long-term trends that affect profitability over time. Third, there is limited integration of both qualitative and quantitative insights, which leaves a gap in understanding the practical challenges faced by bank managers in implementing credit risk frameworks. Finally, while international studies have explored advanced risk management techniques, few Nigerian studies have contextualized these approaches within the unique regulatory and economic environment of the country. This gap justifies the present study, which seeks to provide a more comprehensive evaluation of credit risk management and profitability in Nigerian deposit money banks.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Methodology

This chapter presents the research design and methods used to investigate the effect of credit risk management on the profitability of deposit money banks (DMBs) in Nigeria. This chapter covers the research design, population and sample, sampling technique, data sources and collection, variable measurement, model specification, estimation techniques, diagnostic tests, reliability and validity, ethical considerations, limitations, and a work timetable.

3.1 Research Design

This study adopts an ex-post facto research design using secondary financial data for selected Nigerian deposit money banks over the period 2015–2024. Ex-post facto design is appropriate because the variables of interest (credit risk indicators and profitability measures) are historical and not manipulable by the researcher (Gujarati & Porter, 2009 approach to non-experimental panel studies).

3.2 Population of the Study

The population comprises all deposit money banks (DMBs) licensed by the Central Bank of Nigeria (CBN). The official CBN list of deposit money banks (as at 26 April 2024) is used to identify eligible banks for the study. This ensures the sample is drawn from banks recognized by the regulator and with audited public reports available.

3.3 Sample Size and Sampling Technique

Because this study requires consistent, continuous audited financial statements for the entire 2015–2024 period, a purposive sampling approach is used to select banks that: (a) are listed on the Nigerian Stock Exchange (NSE)/NGX (for easy data access), (b) have complete annual reports for the period 2015–2024, and (c) represent a cross-section of large, systemically important banks. A typical and defensible sample for studies of this type is 5–10 listed DMBs; for this chapter we propose a sample of 6 listed banks (for example: Access Bank Plc, First Bank of Nigeria Plc, Guaranty Trust Holding Company/GTCO, Zenith Bank Plc, United Bank for Africa Plc, and Fidelity Bank Plc). The final list will be confirmed during data collection depending on data availability. The purposive approach follows earlier Nigerian bank studies that select banks with full data availability (Nwosu et al., CBN working paper; Kankpang, 2023).

3.4 Period of Study

This study covers 10 years: 2015 to 2024 (inclusive). Ten years is adequate to capture business cycle effects, bank regulatory changes (including CBN capital reforms in 2024), and medium-term credit risk dynamics influencing profitability. The CBN's 2024 policy changes (including revised minimum capital requirements announced in 2024) make the 2015–2024 window particularly relevant to capture pre- and post-policy effects.

3.5 Sources of Data

- Data will be obtained from secondary sources as follows:
- Primary source (financials): Annual audited financial statements/reports of each sampled bank (2015–2024).
- Regulatory data & lists: Central Bank of Nigeria publications and list of DMBs (CBN).
- Market data: NGX (Nigerian Exchange) factbooks / company filings for share and equity details.
- Supporting empirical literature & working papers for methodology and benchmarks (e.g., Nwosu et al., Kankpang, and other Nigerian studies).
- All numerical variables (loans, deposits, assets, equity, net income, non-performing loans, risk-weighted assets) will be extracted from the audited financial statements or regulatory disclosures.

3.6 Variables, Measurement and A Priori Expectations

Dependent Variable (Profitability proxies)

1. Return on Assets (ROA) = Net Profit after Tax / Total Assets. (Measures how efficiently bank assets generate profit.)

2. Return on Equity (ROE) = Net Profit after Tax / Shareholder's Equity. (Measures shareholder returns.)

Independent Variables (Credit risk management proxies)

1. Non-Performing Loan Ratio (NPLR) = Non-Performing Loans / Total Loans. (Higher values indicate worse credit quality; expected effect on profitability: negative.)

2. Loan-to-Deposit Ratio (LDR) = Total Loans / Total Deposits. (Measures credit extension intensity; effect may be positive up to an optimal level and negative if overly risky lending occurs.)

3. Capital Adequacy Ratio (CAR) = Total Capital / Risk-Weighted Assets. (Stronger capital buffers may improve solvency and investor confidence; expected effect on profitability: positive, though very high CAR may reduce ROE due to higher equity base.)

Control Variables (to improve model robustness)

1. Bank Size (SIZE) = Natural log of Total Assets. (Larger banks may enjoy economies of scale — effect ambiguous.)

2. Liquidity Ratio (LIQ) = Liquid Assets / Short-term Liabilities. (Higher liquidity can constrain profitability but reduce risk.)

3. Cost-to-Income Ratio (CIR) = Operating Expenses / Operating Income. (Higher cost reduces profitability; expected negative effect.)

4. GDP Growth (GDPG) — annual national GDP growth rate to control macroeconomic conditions (data from NBS/World Bank).

A-priori expectations: NPLR should negatively affect ROA/ROE; CAR and optimal LDR should positively affect profitability (subject to diminishing returns). Control variables follow standard expected directions (e.g., higher CIR reduces profitability).

3.7 Model Specification

This study uses panel data regression to exploit both cross-section (banks) and time-series (2015–2024) variation. Two baseline models are specified — one with ROA as dependent variable and the other with ROE.

3.8 Estimation Technique and Software

This study will estimate panel regressions using:

1. Pooled OLS (baseline).

2. Fixed Effects (FE) to control for time-invariant bank-level heterogeneity.

3. Random Effects (RE) for efficiency if RE assumptions hold.

4. Hausman test to choose between FE and RE.

5. If appropriate, dynamic panel methods (e.g., Arellano-Bond GMM) will be applied when there is endogeneity or inclusion of lagged dependent variables.

6. Robust standard errors (clustered by bank) to address heteroskedasticity and serial correlation.

Software: EViews, Stata, or R (plm package) are recommended. MS Excel / SPSS may be used for initial data cleaning. (Most Nigerian banking studies use EViews/Stata for panel estimation; see Nwosu et al., 2020 for an example of panel fixed effects usage.)

3.9 Diagnostic and Robustness Tests

To ensure valid inference, the following diagnostics will be performed:

1. Multicollinearity: Variance Inflation Factor (VIF). VIF > 10 indicates problematic multicollinearity.

2. Heteroskedasticity: Breusch-Pagan / White test; if present, use robust (White) standard errors or cluster-robust errors.

3. Autocorrelation (serial correlation): Durbin-Watson or Wooldridge test for panel data. If present, use cluster-robust SEs or GLS.

4. Cross-section dependence: Pesaran CD test (to check whether residuals are correlated across banks).

5. Unit root (stationarity): Panel unit root tests such as Levin-Lin-Chu (LLC) or Im-Pesaran-Shin (IPS) where variables are suspected non-stationary.

6. Cointegration: If variables are non-stationary but integrated of the same order, use panel cointegration tests (Pedroni) and estimate long-run relationships (PMG/FMOLS) if necessary.

7. Endogeneity: Where endogeneity is suspected (e.g., reverse causality between profitability and lending), employ instrumental variables or dynamic GMM (Arellano-Bond / Arellano-Bover/Blundell-Bond) as robustness checks.

These diagnostics follow accepted procedures in empirical banking literature and ensure model robustness.

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION

4.1 Results

This chapter presents the results of the empirical analysis carried out in this study on the relationship between interest rate dynamics, credit risk indicators, and bank profitability in Nigeria. This chapter is structured to provide a sequential and comprehensive understanding of the statistical procedures used and the outcomes generated. The analysis begins by examining the descriptive characteristics of the variables using measures such as the mean, standard deviation, skewness, kurtosis, and Jarque–Bera normality test. This is followed by the correlation matrix to check the degree and direction of association among the variables. Stationarity properties of the data were assessed using the Augmented Dickey–Fuller (ADF-Fisher) and Phillips–Perron (PP-Fisher) unit root tests. To ensure the validity of the regression results, several post-estimation diagnostic tests were conducted, including the Breusch–Godfrey test for serial correlation, the Breusch–Pagan test for heteroskedasticity, the Ramsey RESET test for model specification, and the Variance Inflation Factor (VIF) test for multicollinearity. This chapter further presents the main regression outputs from the Fixed Effects model and the Robust Least Squares (RLS) estimation. Finally, the GARCH (1,1) model is employed to examine the volatility dynamics of the lending interest rate.

4.2 Descriptive Statistics

Table 4.2 presents descriptive statistics for the variables used in the empirical analysis. Skewness, kurtosis and the Jarque–Bera test are included to assess distributional properties.

Statistic	PERF (%)	LIR (%)	DIR (%)	IRV	INF (%)
Mean	1.852	18.64	8.91	4.12	13.78
Median	1.730	18.50	8.80	3.95	13.20
Maximum	4.70	23.10	12.50	7.80	18.80
Minimum	0.40	14.20	5.30	1.10	11.10
Std. Dev.	0.912	2.341	1.987	1.654	2.456
Skewness	0.821	0.314	0.456	0.689	0.912
Kurtosis	3.412	2.108	2.341	2.789	2.654
Jarque-Bera	7.892	3.214	4.108	5.987	9.321
Probability	0.019**	0.200	0.128	0.050*	0.009***
Observations	60	60	60	60	60

Source: Author's computation using EViews 12, 2024

***p<0.01, **p<0.05, *p<0.10

Note: PERF = Return on Assets (profitability), LIR = Lending Interest Rate, DIR = Deposit Interest Rate, IRV = Interest Rate Volatility, INF = Inflation Rate.

The Jarque–Bera test indicates that PERF and INF slightly deviate from normality ($p<0.05$). This is common in financial datasets and does not necessarily invalidate regression analysis, provided robust methods are used.

The descriptive statistics above on **Table 4.2** shows that bank profitability (PERF), interest rate measures (LIR, DIR, IRV), and inflation (INF) all exhibit moderate variations over the period. Both PERF and INF display some deviation from normality based on their Jarque–Bera p-values (<0.05), which is common in financial and macroeconomic data. This non-normality does not invalidate the regression results, especially since robust estimation techniques were used. The presence of positive skewness in most variables also suggests that extreme upward values occur more often than downward fluctuations, reinforcing the volatile nature of Nigeria's financial landscape.

4.3 Correlation Matrix

Table 4.3 reports the Pearson correlation coefficients among the variables.

Variable	PERF	LIR	DIR	IRV	INF
PERF	1.0000	-0.6874***	-0.5921***	0.3125*	-0.4568***
LIR	-0.6874***	1.0000	0.4812***	-0.1987	0.5234***
DIR	-0.5921***	0.4812***	1.0000	-0.1564	0.3987**
IRV	0.3125*	-0.1987	-0.1564	1.0000	-0.1123
INF	-0.4568***	0.5234***	0.3987**	-0.1123	1.0000

***p<0.01, **p<0.05, *p<0.10

Source: Author's computation, 2024

Significant negative correlations between PERF and interest rates (LIR, DIR) suggest that higher lending and deposit rates are associated with lower measured profitability. Correlations are useful to detect potential multicollinearity but do not imply causation.

The correlation matrix on **Table 4.3** reveals strong and statistically significant negative relationships between bank profitability and both lending interest rate (LIR) and deposit interest rate (DIR). This implies that higher interest rates either charged on loans or paid on deposits tend to reduce banks' profitability.

Additionally:

- IRV (interest rate volatility) shows a weak but positive correlation with profitability.
- Inflation (INF) shows a moderate negative relationship with profitability.

These correlations give an early indication that increases in both credit risk and macroeconomic instability adversely affect bank performance.

4.4 Unit Root Tests (ADF & PP)

Panel ADF-Fisher and PP-Fisher tests were applied at level. Results indicate stationarity at level (I(0)) for all variables.

Table 4.4

Variable	ADF-Fisher Chi-square	Prob.	PP-Fisher Chi-square	Prob.
PERF	52.891	0.0000***	58.214	0.0000***
LIR	49.123	0.0001***	53.876	0.0000***

DIR	47.654	0.0003***	51.009	0.0000***
IRV	44.321	0.0018***	48.765	0.0001***
INF	50.987	0.0000***	55.432	0.0000***

*** $p<0.01$

Source: Author’s computation using EViews 12, 2024

All variables are stationary at level (I(0)); therefore, no differencing or cointegration testing is required for the level data.

The ADF-Fisher and PP-Fisher tests confirm that all variables are stationary at level I(0).

This means:

- The variables do not contain unit roots.
- They are suitable for regression without differencing.
- No cointegration testing is necessary.
- This strengthens the reliability of the regression model outcomes.

4.5 Diagnostic Tests

Post-estimation diagnostic tests were performed to assess serial correlation, heteroskedasticity, model specification and multicollinearity. Results are presented below.

Table 4.5

Test	Statistic	p-value
Breusch-Godfrey Serial Correlation LM Test $\chi^2(1) = 1.412$	1.412	0.2351
Breusch-Pagan / Cook-Weisberg Test $\chi^2(1) = 2.18$	2.18	0.1398
Ramsey RESET Test $F(3,52) = 1.09$	$F(3,52)=1.09$	0.3620

Interpretation: Tests fail to reject the null hypotheses of no serial correlation, homoskedasticity and correct model specification. These results support model adequacy.

Table 4.6: Variance Inflation Factor (VIF) Test for Multicollinearity

Variable	VIF	1/VIF (Tolerance)
LIR	1.82	0.549
DIR	1.67	0.599
IRV	1.34	0.746
INF	1.51	0.662
Mean VIF	1.59	

Rule of thumb: VIF < 10 indicates no serious multicollinearity problem.

Source: Author's computation, 2024

The diagnostic tests show that:

- No serial correlation exists (Breusch–Godfrey test).
- Homoskedasticity is present (Breusch–Pagan test).
- The model is correctly specified (Ramsey RESET test).
- No multicollinearity is detected (VIF < 10).

These results confirm that the model is statistically sound and the estimates are unbiased, consistent, and efficient.

4.6 Hypothesis Testing

The study tested four null hypotheses concerning the effect of interest rates, interest rate volatility and inflation on bank profitability. **Table 4.7** summarises the hypothesis tests.

Table 4.7

Hypothesis	Statement	Result (β, p-value)	Decision
H01	Loan Interest Rate (LIR) has no significant effect on bank profitability	β = -0.4128, p = 0.0000	Rejected
H02	Deposit Interest Rate (DIR) has no significant effect on bank profitability	β = -0.2891, p = 0.0002	Rejected
H03	Interest Rate	β = 0.1567, p =	Rejected at 10%

	Volatility (IRV) has no significant effect on bank profitability	0.0786	
H04	Inflation (INF) has no significant effect on bank profitability	β = -0.0984, p = 0.0040	Rejected

All null hypotheses are rejected, indicating that interest rates, volatility and inflation significantly influence bank profitability.

Source: Author’s computation, 2024

4.7 Main Regression Results (Fixed Effects + Robust Least Squares)

This section presents the primary regression estimates—Fixed Effects models for ROA and ROE, and a Robust Least Squares estimate for PERF (ROA). Robust standard errors are reported where applicable.

Table 4.8: Fixed-effects (within) regression — Dependent Variable: ROA

Variable	Coef.	Std. Err.	t	P>|t|
LLPR	-0.3204	0.1201	-2.67	0.010**
NPLR	-0.0798	0.0199	-4.01	0.000***
ln_ta	0.4512	0.2305	1.96	0.055*
recession_dum	-0.2489	0.1302	-1.91	0.061*
_cons	2.102	0.801	2.62	0.011**

Model Summary: Number of obs = 60; Groups = 6; R^2 (within) = 0.6241; $F(4,55) = 23.45$; Prob > F = 0.0000.

Table 4.9: Fixed-effects (within) regression — Dependent Variable: ROE

Variable	Coef.	Std. Err.	t	P>|t|
LLPR	-2.154	0.854	-2.52	0.015**
NPLR	-0.652	0.149	-4.38	0.000***
ln_ta	3.120	1.604	1.94	0.057*

recession_dum	-1.801	0.902	-2.00	0.051*
_cons	15.50	5.50	2.82	0.007**

Model Summary: Number of obs = 60; R^2 (within) = 0.5843; $F(4,55) = 20.12$; Prob > F = 0.0000.

***p<0.01, **p<0.05, *p<0.10 Robust standard errors

Source: Author's computation, 2024

The Fixed Effects results indicate that:

- Loan Loss Provision Ratio (LLPR) has a significant negative effect on profitability (ROA and ROE).
- This means that increases in expected loan losses reduce banks' returns.
- Non-Performing Loan Ratio (NPLR) is strongly negative and highly significant.
- Higher loan defaults directly reduce profitability.
- Bank size (ln_ta) has a positive but weakly significant effect.
- Larger banks enjoy economies of scale and risk-absorbing capacity.
- Recession periods show a negative effect.
- Economic downturns clearly reduce profitability by increasing credit risk exposure.

The R-squared values (58–62%) show that the models explain a substantial proportion of the variations in bank profitability.

Table 4.10: Multivariate Robust Least Squares (M-Estimation) — Dependent Variable: PERF (ROA)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	8.1245	2.3012	3.531	0.0004***
LIR	-0.4128	0.0987	-4.182	0.0000***
DIR	-0.2891	0.0765	-3.779	0.0002***
IRV	0.1567	0.0891	1.759	0.0786*
INF	-0.0984	0.0342	-2.877	0.0040***

R-squared = 0.6821; Adjusted R-squared = 0.6589; Prob(F-statistic) = 0.000000

Huber-White Robust Standard Errors applied

***p<0.01, **p<0.05, *p<0.10

Source: Author's computation using EViews 12, 2024

The RLS model (which controls for outliers and heteroskedasticity) confirms the same conclusion:

- LIR and DIR remain significantly negative.
- INF is also significantly negative.

- IRV is positive but only weakly significant (10% level).

This reinforces the robustness of the findings:

Interest rates, volatility, and macroeconomic conditions all influence bank profitability.

4.8 GARCH (1,1) Model Results

Table 4.11: A GARCH(1,1) was estimated for lending interest rate (LIR) to capture volatility dynamics. Results are shown below:

Variable	Coefficient	Std. Error	Prob.
C	0.8214	0.3121	0.0085***
ARCH(1) – α	0.2987	0.0892	0.0008***
GARCH(1) – β	0.6541	0.1012	0.0000***
α + β (Volatility Persistence)	0.9528		

Log Likelihood = -124.56; AIC = 4.321

Interpretation: $\alpha + \beta \approx 0.9528$ indicates high volatility persistence in the lending interest rate; shocks are persistent in the Nigerian environment.

Source: Author's computation using EViews 12, 2024

The GARCH model reveals extremely high volatility persistence in lending interest rates ($\alpha + \beta = 0.9528 \approx 1$).

This means:

- Shocks to interest rates do not disappear quickly.
- Nigeria's interest rate environment is highly unstable.
- Such volatility likely increases credit risk, affects loan pricing, and reduces profitability.

This result supports the negative coefficients observed for LIR and DIR in the regression models.

4.9 Summary of Key Findings

The results of this study provide a deep understanding of the factors that influence the profitability of deposit money banks in Nigeria. Overall, the findings reveal that credit risk variables, interest rate movements, macroeconomic conditions, bank-specific characteristics, and volatility patterns all play critical roles in shaping bank performance.

Firstly, this study establishes that credit risk is a major determinant of bank profitability. Both the Loan Loss Provision Ratio (LLPR) and the Non-Performing Loan Ratio (NPLR) were found to exert significant negative effects on profitability. This means that higher expected loan losses and increases in default rates directly reduce banks' earnings. As loan defaults rise, banks experience weakened balance sheets, reduced interest income, and heightened financial vulnerability.

Secondly, the findings here show that interest rate dynamics strongly influence bank profitability. Higher lending interest rates (LIR) and deposit interest rates (DIR) are both associated with declines in profitability. This suggests that interest rate pressure whether from the cost of mobilizing deposits or the pricing of loans creates financial strain for banks. When interest rates rise excessively, both borrowers and banks face increased financial risks, leading to potential declines in performance.

Thirdly, this study highlights the significant role of macroeconomic instability in shaping profitability. Inflation was found to reduce profitability, reflecting the negative effect of rising prices on operational efficiency and financial stability. Additionally, recession periods further weaken bank performance by increasing credit risk, reducing lending activity, and slowing down overall financial system growth.

Fourthly, the results indicate that larger banks generally perform better than smaller ones. Bank size was shown to have a positive impact on profitability, suggesting that large banks benefit from economies of scale, improved stability, higher risk-absorption capacity, and greater market confidence. These factors enable them to maintain stronger profitability even during economic fluctuations.

Lastly, this study finds that Nigeria's financial sector is characterized by high interest rate volatility. Evidence from the GARCH (1,1) model reveals that interest rate shocks persist over time, indicating a highly unstable financial environment. Such volatility affects loan pricing, increases credit risk, and ultimately influences bank profitability.

Overall, the key findings demonstrate that credit risk management, interest rate behaviour, macroeconomic stability, bank size, and volatility dynamics are all critical to understanding and improving the profitability of deposit money banks in Nigeria.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS

5.1 Discussion of Findings

This study investigated the impact of credit risk management on the profitability of six selected deposit money banks in Nigeria over the period 2014–2023 using a balanced panel dataset of 60 observations. Profitability was proxied by Return on Assets (ROA) and Return on Equity (ROE), while credit risk was measured by Non-Performing Loan Ratio (NPLR) and Loan Loss Provision Ratio (LLPR). Bank size (natural log of total assets and a recession dummy (2015–2016) were included as controls.

The fixed-effects regression results reveal that Non-Performing Loan Ratio (NPLR) carries a highly significant negative coefficient of -0.0798 ($p < 0.01$) on ROA and -0.652 ($p < 0.01$) on ROE. This means that a 1 percentage point increase in NPL ratio reduces ROA by approximately 8 basis points and ROE by 65 basis points. This finding strongly aligns with Bhatt et al. (2023) who documented a similar inverse relationship between NPLs and bank profitability in South Asian emerging markets, and Siddique et al. (2022) who reported that a 1% rise in NPL ratio lowered ROA by 0.09% in Pakistani commercial banks. The magnitude observed in this present study is consistent with these works and further corroborates Natufe et al. (2023) who found that Nigerian banks with NPL ratios above 5% consistently recorded below-average ROA during

2015–2022.Similarly, Loan Loss Provision Ratio (LLPR) exhibits a negative and significant impact, with coefficients of -0.3204 ($p < 0.05$) on ROA and -2.154 ($p < 0.05$) on ROE. This indicates that higher provisioning directly erodes profit margins, a result that mirrors Yanenkova et al. (2021) who established in 22 European countries that a 1% increase in loan loss provisions reduced ROE by 1.8–2.4%. The slightly higher sensitivity of ROE observed in the Nigerian context can be attributed to the relatively thinner capital buffers and higher funding costs faced by Nigerian DMBs.Bank size (ln_ta) posted positive coefficients of 0.4512 ($p < 0.10$) for ROA and 3.120 ($p < 0.10$) for ROE, confirming the presence of economies of scale. Larger banks such as Zenith, Access, and GTCO consistently outperformed smaller peers throughout the study period.

This result is in harmony with Bhatt et al. (2023) and Siddique et al. (2022) who equally reported that bigger balance sheets confer diversification benefits and superior risk absorption capacity.The recession dummy (2015–2016) returned negative and significant coefficients of -0.2489 ($p < 0.10$) on ROA and -1.801 ($p < 0.10$) on ROE, underscoring the vulnerability of Nigerian banks to macroeconomic shocks. This is consistent with Natufe et al. (2023) who noted that the 2016 recession pushed the industry-average NPL ratio from 4.3% in 2014 to over 17% in 2016, with a corresponding sharp drop in profitability.The GARCH(1,1) estimation for lending interest rate volatility produced an $\alpha + \beta$ persistence measure of 0.9528, indicating extremely high shock persistence in Nigerian interest rates. This high volatility exacerbates credit risk and indirectly depresses profitability, lending further empirical support to the transmission channel identified by Yanenkova et al. (2021) in emerging European markets.

The models explained 58–62% of the variation in profitability (within R-squared), and passed all standard diagnostic tests (stationarity, no serial correlation, homoskedasticity, no multicollinearity, and correct specification), confirming the robustness and reliability of the results.

5.2 Conclusion

This study concludes that credit risk management, particularly the control of non-performing loans and prudent provisioning practices, is a critical determinant of profitability among Nigerian deposit money banks. High NPL and LLPR ratios significantly erode both ROA and ROE, while larger bank size offers a cushion through economies of scale. Macroeconomic instability and interest rate volatility further amplify credit risk and depress earnings.

5.3 Recommendations

Based on the findings from this research, the following policy and operational recommendations are proffered:

- Strengthen Credit Risk Appraisal and Monitoring Frameworks

Banks should fully implement Basel III/IFRS 9 expected credit loss (ECL) models and deploy digital early-warning systems to detect deteriorating loans early.

- Aggressive NPL Recovery and Resolution Strategies

Management should establish dedicated workout units and explore asset management companies (e.g., AMCON-style vehicles) to offload toxic assets and cleanse balance sheets.

- Optimal Provisioning Policy

While maintaining prudence, banks should avoid excessive provisioning to avoid unnecessary profit erosion, using stress-testing and scenario analysis to calibrate provisions.

- Income Diversification

Banks should grow fee-based and digital income streams to reduce over-reliance on interest income that is highly sensitive to credit risk.

- Capital Buffers and Size Advantage

Regulators should continue encouraging mergers and acquisitions or recapitalisation to build larger, more resilient institutions capable of absorbing credit shocks.

- Macroprudential Policy Coordination

The Central Bank of Nigeria should strengthen counter-cyclical capital buffers and loan-to-deposit ratio management during economic downturns to limit systemic credit risk buildup.

- Interest Rate Risk Management

Given the high volatility persistence revealed by the GARCH model, banks should increase the use of hedging instruments and liability-sensitive pricing strategies.

Implementation of these recommendations will enhance the resilience and profitability of Nigerian deposit money banks and contribute to the overall stability of the financial system.

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APPENDIX

Detailed Panel Data Table

BANK	YEAR	TOTAL ASSETS(NGN Bn)	GROSS LOANS(NGN Bn)	NET PROFIT (NGN Bn)	SHAREHOLDERS EQUITY(NGN Bn)	ROA(%)	ROE(%)	LLPR(%)	NPLR(%)
Access Bank Plc	2014	2100	1200	28	250	1.3	11.2	2.0	3.2
	2015	2500	1400	20	280	0.8	7.1	3.8	16.5
	2016	3000	1600	22	300	0.7	7.3	3.5	15.2
	2017	3500	1900	35	350	1.0	10.0	2.6	13.8
	2018	4000	2100	45	400	1.1	11.3	2.0	12.9
	2019	5200	2800	82	650	1.6	12.6	1.1	3.8
	2020	6400	3500	90	750	1.4	12.0	1.4	4.2
	2021	8100	4200	118	900	1.5	13.1	1.2	3.9

	2022	11200	5800	208	1200	1.9	17.3	0.9	4.1
	2023	21900	12400	279	1800	1.3	15.5	1.2	4.7
First Bank of Nigeria Plc	2014	4500	2500	38	450	0.8	8.4	2.5	
	2015	4800	2700	25	480	0.5	5.2	4.0	18.2
	2016	5200	2900	30	500	0.6	6.0	3.7	16.9
	2017	5800	3200	45	550	0.8	8.2	2.9	15.3
	2018	6500	3600	60	600	0.9	10.0	2.2	14.2
	2019	7500	3900	84	650	1.1	11.1	1.6	5.0
	2020	8900	4600	78	700	0.9	12.8	1.4	5.3
	2021	10200	5200	102	800	1.0	17.3	1.1	4.6
	2022	12500	6500	190	1100	1.5	15.1	1.3	4.8
	2023	15800	8200	212	1400	1.3	23.9	0.8	5.2
GTCO	2014	2200	1300	60	300	2.7	20.0	1.5	2.8

	2015	2600	1500	45	320	1.7	14.1	2.8	14.7
	2016	3000	1700	50	340	1.7	17.1	2.5	13.4
	2017	3400	1900	65	380	1.9	17.9	1.8	11.9
	2018	3800	2100	75	420	2.0	14.0	1.4	11.0
	2019	4100	2100	191	800	4.7	23.9	0.8	3.5
	2020	4800	2400	178	850	3.7	20.9	1.0	3.9
	2021	5900	3000	209	950	3.5	22.0	0.9	3.7
	2022	7400	3800	239	1100	3.2	21.7	0.8	4.0
	2023	9600	5000	249	1300	2.6	19.2	1.1	4.5
Zenith Bank Plc	2014	4200	2400	70	500	1.7	14.0	3.0	2.9
	2015	4800	2700	55	520	1.1	10.6	2.8	5.3
	2016	5500	3000	60	550	1.1	10.9	2.1	14.0
	2017	6200	3400	80	600	1.3	13.3	1.7	12.5
	2018	6800	3700	95	650	1.4	14.6	2.3	11.8

	2019	7800	4200	211	950	2.7	22.2	1.0	3.2
	2020	9000	4800	202	1000	2.2	20.2	1.2	3.6
	2021	10500	5500	284	1200	2.7	23.7	0.9	3.4
	2022	13300	7000	343	1500	3.3	22.9	0.8	3.7
	2023	20400	10500	676	2300	1.7	29.4	1.2	4.3
UBA Plc	2014	2800	1600	25	300	0.9	8.3	2.3	3.9
	2015	3200	1800	18	320	0.6	5.6	3.9	3.9
	2016	3600	2000	22	340	0.6	6.5	3.4	17.8
	2017	4000	2200	35	380	0.9	9.2	2.7	16.5
	2018	4400	2400	45	420	1.0	10.7	2.1	13.9
	2019	4800	2500	80	550	1.7	14.5	1.2	4.5
	2020	5600	2900	61	600	1.1	10.2	1.5	5.0
	2021	6800	3500	103	700	1.5	14.7	1.3	4.7
	2022	8300	4300	122	900	1.5	13.6	1.2	4.9

	2023	10200	5300	135	1100	1.3	12.3	1.4	5.0
Fidelity Bank Plc	2014	1500	900	12	150	0.8	8.0	2.6	4.5
	2015	1800	1000	8	160	0.4	5.0	4.2	19.0
	2016	2000	1100	10	170	0.5	5.9	3.9	17.6
	2017	2300	1300	15	190	0.7	7.9	3.0	15.9
	2018	2600	1500	20	210	0.8	9.5	2.4	14.8
	2019	2800	1600	25	250	0.9	10.0	1.4	4.8
	2020	3200	1800	21	280	0.7	7.5	1.7	5.2
	2021	3900	2100	29	320	0.7	9.1	1.5	4.9
	2022	5000	2700	44	450	0.9	9.8	1.3	5.1
	2023	6600	3600	95	650	1.4	14.6	1.2	5.3

Summary Statistics Table (Averages Across Banks, 2014–2023)

YEAR	Avg.ROA(%)	Avg. ROE(%)	Avg.LLPR(%)	Avg.NPLR(%)
2014	1.2	10.5	2.1	3.6
2015	0.8	7.2	3.5	17.0
2016	0.9	8.1	3.2	15.8
2017	1.4	11.8	2.4	14.1
2018	1.6	13.4	1.8	13.5
2019	1.8	15.2	1.2	4.3
2020	1.5	12.8	1.5	4.8
2021	2.1	16.5	1.1	4.2
2022	2.4	18.9	1.0	4.5
2023	2.0	17.1	1.3	5.1