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# FINANCIAL RESOURCE MANAGEMENT IN AI ERA: FINDING THE NEXUS BETWEEN NON-PERFORMING ASSETS (NPAs) AND FINANCIAL PERFORMANCE OF BANKING SECTOR IN NIGERIA

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## *ABSTRACT*

*Many prior studies in Nigeria examine NPAs at a general level, with limited focus on the Nigerian banking sector, and presents inconsistent and mixed empirical findings, especially on the study of connection between rising NPAs on performance of banks and other financial institutions (BOFIs). Thus, the objective of this study is to critically examine the effect of NPAs on the financial performance of five (5) randomly selected commercial banks in Nigeria, especially in this era where AI-driven financial management opportunities abound. Ex-Post facto and Descriptive designs were deployed for this study. NPAs was the independent variable for the study measured by NPAs ratios (incorporating non-performing loans and non-performing advances ratios), while the dependent variable, financial performance, was measured with ROA, ROE and NIM metrics. Data was analyzed with Autoregressive Distributed Lag (ARDL) and Bounds Test in E-Views (version 10). The study found that a rise in NPAs causes a negative impact and forces -0.19.5%, -0.79.7% and -0.70.1% decrease in NIM, ROE and ROA, respectively, in the long run. This is the finding that leads to the conclusion that rising*

NATIONAL BOARD FOR TECHNICAL EDUCATION
NIGERIAN JOURNAL FOR TECHNICAL EDUCATION
Volume 25 Nos. 1 2026
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*NPAs negatively affect the profitability, and overall financial performance, of BOFIs in Nigeria. Therefore, it was recommended that thorough corporate governance, loan exposures security validation, effective and flexible credit policy, and effective loan terms re-structuring with indicated red flags should be incorporated by BOFIs in Nigeria so to help bolster profitability and overall financial performance through guaranteed loan/asset recovery.*

*Keywords*: Non-Performing Assets/Loans, Financial Performance, Net Interest Margin, ROE, ROA

## *1.0 INTRODUCTION*

The banking sector around the world is known as the provider of balance between those with excess investment funds and those in need of loan funds (Pamuji, Supandi & Sa'diyah, 2022). According to Rajha (2017), this function of banking institutions leads to what they referred to as 'credit creation' – representing the major (85%) sources of assets and revenue for banks via the interest income it generates from loans. This therefore exposes banking sector to credit risks, including the experience of Non-Performing Loans/Assets (NPLs or NPAs). Vibhute, Jewargi & Haralayya (2021) concisely explained that NPLs/NPAs occur when interest income or principal, or a combination of both, are due but remain unpaid for 90 days or more. This explains why increasing NPLs leads to a decline in interest income and generally affects the profitability and overall financial performance of banks adversely. Saliba, Farmanesh & Athari (2023) opined that a high level of NPLs can threaten the stability and survival of banking sector, since it directly hit on their major revenue source – interest income.

In Nigeria's banking sector, discussions and concerns about NPAs have heightened, especially as it impacts bank profitability and systemic resilience. The Nigerian banking sector plays a crucial role in promoting economic growth by providing credit and mobilizing savings (Pamuji, Supandi & Sa'diyah, 2022). However, the persistent rise in Non-Performing Assets (NPAs) over the years poses a major threat to financial stability and bank performance. In recent years, Nigerian banks have experienced increasing loan defaults due to factors such as economic recession, oil price fluctuations, poor credit appraisal mechanisms, corruption, and weak regulatory enforcement (Umar, 2022). This has led to declining profitability, erosion of shareholders' funds, liquidity challenges, and in some cases, the collapse of banks.

Despite efforts by the Central Bank of Nigeria (CBN) and the Asset Management Corporation of Nigeria (AMCON) to mitigate the impact of bad loans, NPAs remain a significant problem (Idigbe, 2022). They reduce banks' lending capacity, increase provisioning requirements, and distort balance sheets, thereby weakening confidence in the financial system (Gjeçi, Marinč & Rant (2023). The persistence of NPAs raises fundamental questions about their actual effect on profitability, return on equity (ROE), return on assets (ROA), liquidity, and overall sustainability of Nigerian banks. Yet, many banks continue to report profits while simultaneously battling high NPA ratios, creating a paradox that needs empirical investigation.

Thus, the problem is the growing disconnect between regulatory interventions, the recurring incidence of NPAs, and their adverse implications on the financial performance of banks in Nigeria. If unchecked, this trend could undermine banking stability, discourage investment, and threaten long-term economic development. Thus, understanding their impact on financial performance is essential for strategic credit risk practices and informed policy and decision making.

This study represents the empirical efforts into the problem, as many prior studies in Nigeria presents inconsistent and mixed empirical findings on the effect of NPAs on bank performance—some find a strong negative effect, others report weak or no significant effect. This inconsistency highlights the need for further research using updated data and robust methodologies. Additionally, while many studies examine NPAs at a general level, there is limited focus on the Nigerian banking sector specifically, especially considering its unique challenges such as oil dependence, unstable macroeconomic conditions, and weak credit risk management frameworks. Finally, most prior research emphasizes profitability indicators (ROA and ROE), with limited exploration of how NPAs affect other financial performance metrics such as net income margin (interest-income ratio). Thus, this study would prove relevant and contribute to the constituted body of knowledge by narrowing these highlighted research gaps especially in this post-COVID-19 pandemic and post-AMCON intervention data era.

Thus, the objective of this study is to contribute to the update of literature on financial resource management by critically examining the effect of NPAs on the financial performance of top five (5) randomly selected commercial banks in Nigeria for era where AI-driven financial management opportunities abound, specifically for 2020 – 2024 financial years. These selected banks are Zenith Bank plc, Access Bank plc, First Bank plc, FCMB and UBA plc.

## *2.0 LITERATURE REVIEW*

### 2.1 Conceptual Review

#### 2.1.1 Non-Performing Assets (NPAs)

NPAs, also referred to as NPLs, has remained a vital subject in the field of financial management and corporate finance. According to Rahaman & Sur (2025), NPAs was defined as assets that have stopped income-generation and represent credits (including interest and/or principal) that have remained "past due" for a specified period, usually ninety (90) days and above. Many studies have qualified the increasing NPAs to be a 'virus' that threatens the credit risk management, performance and survival of banking sector (Mallik, Puri, Bhansali, Manikandan & Rahunathan (2024).

Hastuti, Wibowo & Nurcahyono (2024) also opined that NPAs refers to unexpired and default loans that banking institutions no longer profit from, and whose collection from borrowers has remained uncertain. Goldstein and Turner (1996) in their study, attributed this experience of banks to various factors, ranging from the volatility of macroeconomic indexes, high interest rate, economic downturn, moral concerns and insider borrowing, prevalence of inter-bank borrowings that are highly priced among others. More also, Mogaji (2024) suggested that the increase in NPAs is attributed to the increasing rate of diversion and misappropriation of funds, both in the public and private sectors, from their original purposes – which further drive the general economic hardship, especially in Nigeria.

According to Chun & Ardaaragchaa (2024), high NPAs in banks are argued to limit accessibility of financing and negatively impact their capital position. When this happens, it in return increases the lending rates of banks and impairs the growth of credit in most cases. This explains why high NPAs are used by most studies as an

NATIONAL BOARD FOR TECHNICAL EDUCATION
NIGERIAN JOURNAL FOR TECHNICAL EDUCATION
Volume 25 Nos. 1 2026
ISSN No. 2992 - 3522

indicator for poor performance of banks in a country, and vice versa (Rahaman & Sur, 2025). This was further corroborated when Tijani, Umar, Aliyu & Dantsoho (2024) posits that NPLs ratio is an efficient metric for measuring the assets-quality of banks. In that, a decline in NPLs ratio represents an improvement in assets-quality of a bank, and vice versa. Perhaps, various prior studies have ascertained a direct nexus between asset quality and NPLs, with the latter found to significantly affect the profitability, solvency and liquidity of banks (Visani & Patel, 2025). This relationship would be better reviewed in the next sub-head.

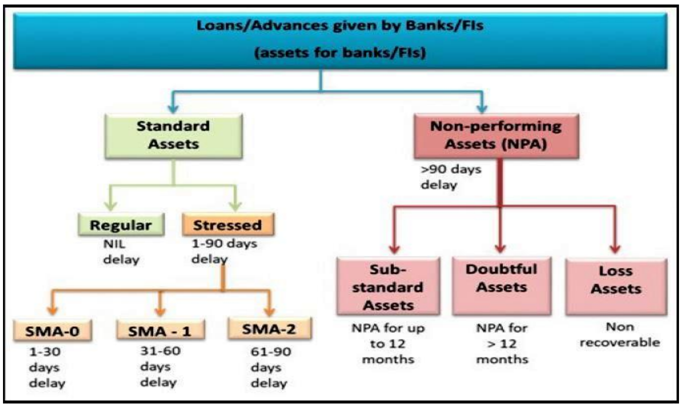



**Fig. 2.1.1.1.:** Assets/Loans Classification of Banks/Financial Institutions
**Source:** Wadhwa & Ramaswamy (2020)

### 2.1.2 NPAs and Financial Performance of Banks

Over the years, the study on the impact of NPAs specifically on the financial performance of banking institutions around the world has been met with mixed empirical results as would be highlighted here. Kumari, Singh & Sharma (2017) in their study, attempted to investigate the nexus between NPAs and financial performance (using ROA as a metric) of some selected Indian banking institutions from both private and public sector. In the study, it found a positive and significant connection between gross NPAs and the financial performance of the banks in India. However, in a similar study, Singh (2015) and Gnawali (2018) both made contrary findings – revealing that negative nexus exists among the NPAs and profitability of banks.

Mohd, Karim, Sok-Gee & Sallahundin (2010) argued that, not only do rising NPAs impair the performance of banks, it hampers their liquidity, cripples capital growth and distorts expansion of credit. And the cumulated negative impact of these could lead to general erosion of investors' confidence and collapse of banking system in a region (Somoye, 2010; Christaria & Kurnia, 2016). Mohd *et al.* (2010) also pointed out that the financial performance of banks is gravely deepened by the high operational costs associated with NPAs.

NATIONAL BOARD FOR TECHNICAL EDUCATION
NIGERIAN JOURNAL FOR TECHNICAL EDUCATION
Volume 25 Nos. 1 2026
ISSN No. 2992 - 3522

### 2.1.3 Financial Performance Metric

Financial performance is term that refers to the financial wellbeing and progress of companies (Kayani, Gan, Rabbani & Trichilli (2024). In this study, financial performance of selected banks is measured using indicators that have been deduced by many scholars to be good measures. These indicators are ROE, ROA, and NIM.

According to Kasie, Onyenwe & Rita (2023), ROE is a financial performance metric and a gauge of profitability of organizations that is obtained by dividing average shareholders' equity with their total income. A higher ROE of a bank implies increased efficiency and profitability in relation to its equity.

Additionally, ROA was defined by (Grzelak & Staniszewski (2025) as a financial ratio that assesses the profitability and financial performance of organizations in connection to their total assets. The ratio measures the ability of organizations in efficiently utilizing their assets to generate profit (Kasie, Onyenwe & Rita, 2023). A higher ROA of a bank implies its efficient operation and productive management of assets in generating more profit, and vice versa.

Finally, Obeid (2024) opined that NIM is a metric that measures the extent of net income generation from the credit products (such as loan, advances and mortgages) of banks and other financial institutions (BOFIs), against the interest they pay saving account and certificates of deposit (CoD) holders. According to Kasie, Onyenwe & Rita (2023), NIM represents a percentage expression of profitability that is particularly relevant for investors – giving them the vital information about the approximate propensity of banks to survive over a long haul. A positive NIM of a bank implies its efficient operation and financial wellbeing, and vice versa.

### 2.1.4 AI-Driven Financial Resource Management Tools

Artificial intelligence (AI) has been seen to reshape how both individuals and organizations manage financial resources and/or assets using various AI-powered tools. Chief of these tools are digital systems that apply machine learning, predictive analytics, and natural language processing to forecasting, budgeting, investment decisions, and reporting. According to Ocrolus (2025), their principal function is to automate routine financial functions/tasks, enhance accuracy, and generate actionable insights from datasets – be it large or complex.

The banking, and at large, financial sector, are found to be increasingly deployed these tools for their various financial routine functions, such as for expense tracking, fraud prevention and detection, portfolio optimization, automated reporting, and financial planning. Fringe Global (2024), for example, opined that predictive analytics models assist BOFIs forecast cash flows and detect anomalies in spending trend or pattern. More also, robo-advisors have been argued to utilize AI algorithms to tailor investment strategies to the risk profiles of clients, thereby offering personalized financial advice and direction (Gupta et al., 2025). In the banking sector, generative AI agents have been integrated into Enterprise Resource Planning (ERP) platforms to support streamlining of compliance reporting and budget planning, reducing both error rates and processing times (Wang *et al.*, 2024).

The benefits of these tools are significant. According to Ocrolus (2025), they foster efficiency by automating repetitive functions, improving decision-making through advanced data analysis, and offer scalability for managing large transaction volumes. Furthermore, they enable proactive risk management by identifying credit and market risks before they escalate (Fringe Global, 2024). However, these are not without some observed challenges in their adoptions. Gauss (2025) posits that, such concerns and challenges range to the question of data quality, regulatory compliance, algorithmic transparency, and widespread integration bottleneck. Notwithstanding, AI-driven financial resource management tools epitomize a paradigm shift in financial operations and resources/assets management, whose effective implementation are anchored on robust transparency, governance, and human oversight to manage risks of misuse, bias, or over-reliance (Forbes, 2025).

## 2.2 Theoretical Framework

Information Asymmetry Theory is the framework that underpins this study. This framework was first used in a seminar and work of Akerlof (1970) titled “The Market for Lemons” – where it the theory was used to demonstrate or entail an uneven dissemination of information between parties to a transaction that can breed an imperfect market (Kulkarni, Cristofaro & Ramamoorthy, 2024). Stiglitz (1981) further argued that information is imperfect, and access to information can prove costly. This could be the reason Pagaon & Jappelli (1993) recommend the adequate dissemination of credit application-related information can help reduce adverse borrowers' selection, and by extension, lower the NPLs for banks.

This theory therefore aligns with this study with the argument that banks' lack of customer-related information can be attributed to the increasing non-performing loans. (Arhinful, Gyamfi, Mensah & Obeng (2025) exacerbated this argument when opined that when banks are made to access credible information that reveals the creditworthiness of borrowers, many deserving and credit-worthy borrowers would have gotten credit facilities, thereby helping to reduce NPLs and defaults.

However, Kulkarni, Cristofaro & Ramamoorthy (2024) pointed that Information Asymmetry Theory have been criticized over the years mainly because of the morality concern in adverse choosing and segregating between two types of borrowers – the bad and good borrowers. Notwithstanding, this theory was effectively adopted in this study to demonstrate how increased customers-related information sharing can help to minimize the aggregation of poorly and NPLs – that have negatively affected the performance of BOFIs (Bofondi & Gobbi, 2003).

## *3.0 DATA AND METHODOLOGY*

*Ex-Post* facto was the research design for this study. This is justified with the utilization of quantitative data, retrieved from already published and credible public sources – such as published and respective annual report and accounts of selected banks and relevant years, among other data from their corporate websites. Descriptive research was also deployed to support the study with further evidence from descriptive statistics.

NPAs ratio (incorporating non-performing loans and non-performing advances ratios) represents the independent variable of this study, while the financial performance measures (ROA, ROE and NIM) represent the dependent variables. The data retrieved for period 2020 - 2024 were utilized for the study's data analysis – that was conducted using Autoregressive Distributed Lag (ARDL) in *E-Views* (version 10) to help reveal statistical evidence on the relationship between NPAs and the financial performing metrics early highlighted. Bounds test was also run to further reveal further statistical evidence, particularly on the long-run nexus among the highlighted study's variables.

NATIONAL BOARD FOR TECHNICAL EDUCATION
NIGERIAN JOURNAL FOR TECHNICAL EDUCATION
Volume 25 Nos. 1 2026
ISSN No. 2992 - 3522

## *4.0 RESULTS AND DISCUSSION*

This section analyzes the datasets retrieved to gain some statistical evidence and further interpreted to give greater insights into the investigation of this study.

Thus, the statistical and descriptive results of such data analysis were as presented as follows:

**Table 4.1:** Outcome of ARDL Analysis

Dependent Variable: NIM_
Method: ARDL
Date: 08/27/25 Time: 15:27
Sample (adjusted): 5 25
Included observations: 21 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Hannan-Quinn criterion (HQ)
Dynamic regressors (4 lags, automatic): NPAS__ ROE_ ROA_
Fixed regressors: C
Number of models evalulated: 500
Selected Model: ARDL(4, 4, 4, 4)

| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
|---|---|---|---|---|
| NIM_(-1) | -5.841859 | 2.631089 | -2.220320 | 0.2694 |
| NIM_(-2) | -6.143328 | 2.572714 | -2.387878 | 0.2525 |
| NIM_(-3) | -1.645280 | 0.900982 | -1.826095 | 0.3190 |
| NIM_(-4) | 3.726501 | 1.728113 | 2.156399 | 0.2764 |
| NPAS__ | -6.032252 | 2.583601 | -2.334823 | 0.2576 |
| NPAS__(-1) | -5.206455 | 2.690025 | -1.935468 | 0.3036 |
| NPAS__(-2) | -0.623416 | 0.616408 | -1.011369 | 0.4964 |
| NPAS__(-3) | 4.819444 | 1.680055 | 2.868622 | 0.2135 |
| NPAS__(-4) | 4.916161 | 2.340566 | 2.100415 | 0.2829 |
| ROE_ | 1.342051 | 0.757707 | 1.771202 | 0.3272 |
| ROE_(-1) | -3.769276 | 1.766243 | -2.134065 | 0.2790 |
| ROE_(-2) | 1.196921 | 0.520939 | 2.297625 | 0.2613 |
| ROE_(-3) | 2.998679 | 1.208060 | 2.482228 | 0.2438 |
| ROE_(-4) | 6.925957 | 2.898641 | 2.389381 | 0.2523 |
| ROA_ | -6.163992 | 6.575855 | -0.937367 | 0.5206 |
| ROA_(-1) | 67.20061 | 29.55172 | 2.274000 | 0.2638 |
| ROA_(-2) | 25.54623 | 12.86694 | 1.985416 | 0.2970 |
| ROA_(-3) | -3.600309 | 4.801162 | -0.749883 | 0.5904 |
| ROA_(-4) | -75.33678 | 31.63607 | -2.381357 | 0.2531 |
| C | -60.25204 | 22.85216 | -2.636602 | 0.2308 |

| | | | |
|---|---|---|---|
| R-squared | 0.993180 | Mean dependent var | 9.386667 |
| Adjusted R-squared | 0.863610 | S.D. dependent var | 5.406359 |
| S.E. of regression | 1.996625 | Akaike info criterion | 3.081033 |
| Sum squared resid | 3.986510 | Schwarz criterion | 4.075816 |
| Log likelihood | -12.35084 | Hannan-Quinn criter. | 3.296926 |
| F-statistic | 7.665164 | Durbin-Watson stat | 1.293093 |
| Prob(F-statistic) | 0.278060 | | |

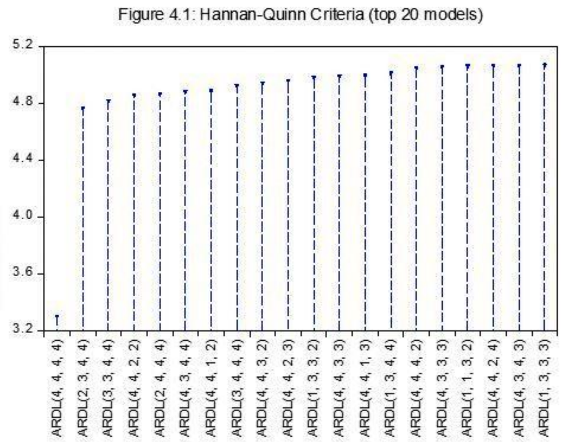
*Note: p-values and any subsequent tests do not account for model selection.

**Source:** Authors' Analysis based on *E-Views* (version 10).

Table 4.1 above is the outcome of ARDL analysis displaying short-run relationship and descriptive results. In the table, NPAs coefficient revealed that a 1% rise in NPAs would lead to a negative impact on the income (NIM), and by extension financial performance, of banks by approximately -6.03% (see the ARDL coefficient between NPAs and NIM) in the short run. However, of importance to this study is the relationship between NPAs and the combined dependent variables (NIM, ROE and ROA) in the long-run – which would better be estimated using co-integration measure of Bounds test in the subsequent tables.

Additionally, from the table above, some insight was gained about the best-fit and significance of the model deployed for the analysis. R-square was reported highly (0.998536 ≈ 99.9%), likewise adjusted R-square with a high coefficient of 0.970725 (≈ 97.1%). Both revealed that the model is best-fit because both coefficients were greater than 0.5 (50%). The probability of F-statistics (of 0.130780 ≈ 1.3%) being less than 5% further implies that the model is significant. It is worthy of note that the model for this analysis was selected in *E-Views* using Hannan-Quinn criterion (as was shown in the figure 4.1 below).

NATIONAL BOARD FOR TECHNICAL EDUCATION
NIGERIAN JOURNAL FOR TECHNICAL EDUCATION
Volume 25 Nos. 1 2026
ISSN No. 2992 - 3522




**Source:** Authors' Analysis based on *E-Views* (version 10).

Figure 4.1 is a criteria graph that demonstrates how the ARDL model used in the regression analysis was selected using Hannan-Quinn criterion. From the graph, it is evident that ARDL (4, 4, 4, 4) is the least among all others, thus selected for the ARDL analysis.

**Table 4.2:** Conditional Error Correction Regression

ARDL Long Run Form and Bounds Test
Dependent Variable: D(NIM_)
Selected Model: ARDL(4, 4, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 08/27/25 Time: 15:30
Sample: 1 25
Included observations: 21

| Conditional Error Correction Regression | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** | **t-Statistic** | **Prob.** |
| C | -60.25204 | 22.85216 | -2.636602 | 0.2308 |
| NIM_(-1)* | -10.90397 | 4.289748 | -2.541866 | 0.2386 |
| NPAS__(-1) | -2.126518 | 1.775199 | -1.197904 | 0.4428 |
| ROE_(-1) | 8.694333 | 3.401102 | 2.556328 | 0.2374 |
| ROA_(-1) | 7.645755 | 4.867547 | 1.570762 | 0.3609 |
| D(NIM_(-1)) | 4.062107 | 1.700927 | 2.388172 | 0.2525 |
| D(NIM_(-2)) | -2.081221 | 0.944821 | -2.202767 | 0.2713 |
| D(NIM_(-3)) | -3.726501 | 1.728113 | -2.156399 | 0.2764 |
| D(NPAS__) | -6.032252 | 2.583601 | -2.334823 | 0.2576 |
| D(NPAS__(-1)) | -9.112189 | 3.811622 | -2.390633 | 0.2522 |
| D(NPAS__(-2)) | -9.735605 | 3.908722 | -2.490739 | |
| D(NPAS__(-3)) | -4.916161 | 2.340566 | -2.100415 | |
| D(ROE_) | 1.342051 | 0.757707 | 1.771202 | |
| D(ROE_(-1)) | -11.12156 | 4.444643 | -2.502239 | |
| D(ROE_(-2)) | -9.924636 | 4.042146 | -2.455289 | |
| D(ROE_(-3)) | -6.925957 | 2.898641 | -2.389381 | |
| D(ROA_) | -6.163992 | 6.575855 | -0.937367 | |
| D(ROA_(-1)) | 53.39086 | 20.05744 | 2.661898 | |
| D(ROA_(-2)) | 78.93709 | 32.18908 | 2.452294 | |
| D(ROA_(-3)) | 75.33678 | 31.63607 | 2.381357 | |

* p-value incompatible with t-Bounds distribution.

**Source:** Authors' Analysis based on *E-Views* (version 10).

Table 4.2 reveals descriptive statistics on the Conditional Error Correction Regression of the study's test-variables from the long-run relationship test, including the coefficients, standard errors, t-statistics and probability descriptive statistics for each variable. However, for detailed bounds test's long-run relationship outcome can be obtained from table 4.3 and 4.4 below.

**Table 4.3:** Levels Equation
Case 2: Restricted Constant and No Trend

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| NIM__ | -0.195022 | 0.108564 | 3.796386 | 0.0234 |
| ROE_ | -0.797355 | 0.036219 | 22.01454 | 0.0289 |
| ROA_ | -0.701190 | 0.268688 | 2.609685 | 0.0330 |
| C | -5.525700 | 0.660837 | -8.361668 | 0.0758 |

EC = NPAs_ - (-0.1950*NIM__ + 0.7974*ROE_ + 0.7012*ROA_ -5.5257 )

**Source:** Authors' Analysis based on *E-Views* (version 10).

*Table 4.3* above is also a result of the long-run relationship. From the table, the expression applied in the determination of long-run relationship between NPAs and the dependent variables is given as:

**EC = NPAs_** - (-0.1950*NIM__ + 0.7974*ROE_ + 0.7012*ROA_ -5.5257 )

From the coefficient column, it was revealed an increase in NPAs would cause a negative impact and force a -0.19.5%, -.0.79.7% and -0.70.1% decrease in NIM, ROE and ROA respectively in the long-run. Therefore, the extent or severity of this negative impact was also revealed by the t-

NATIONAL BOARD FOR TECHNICAL EDUCATION
NIGERIAN JOURNAL FOR TECHNICAL EDUCATION
Volume 25 Nos. 1 2026
ISSN No. 2992 - 3522

statistics. The t-statistics outcome for NIM (3.796386), ROE (22.01454) and ROA (2.609685) show that they are above 2, implying that the negative effects of NPAs rise on NIM, ROE and ROA are significant. The probabilities of each of the three dependent variables (where each prob. Was found to be less than 5%) corroborates this.

**Table 4.4:** F-Bounds Test

| Test Statistic | Value | Signif. | I(0) | I(1) |
|---|---|---|---|---|
| | | Null Hypothesis: No levels relationship | | |
| | | | Asymptotic: n=1000 | |
| F-statistic | 4.357578 | 10% | 2.37 | 3.2 |
| K | 3 | 5% | 2.79 | 2.67 |
| | | 2.5% | 3.15 | 4.08 |
| | | 1% | 3.65 | 4.66 |
| | | | Finite Sample: n=35 | |
| Actual Sample Size | 21 | | | |
| | | 10% | 2.618 | 3.532 |
| | | 5% | 3.164 | 4.194 |
| | | 1% | 4.428 | 5.816 |
| | | | Finite Sample: n=30 | |
| | | 10% | 2.676 | 3.586 |
| | | 5% | 3.272 | 4.306 |
| | | 1% | 4.614 | 5.966 |

**Source:** Authors' Analysis based on *E-Views* (version 10).

*Table 4.4* is the results of Bounds test. In the table, the significance was checked through 5% level. Thus, the criteria for decision making are specifically based on F-statistics consideration, whether it is greater or less than the value of upper-bound at 5% significant level. Going by this, the table revealed that the value of F-statistics (4.357578) is greater than the value of upper-bound (2.67) at 5% level of significance. This test summarily revealed that the rise in NPAs negatively affects the financial performance (estimated by NIM, ROE and ROA) of BOFIs in the long run.

## *5.0 CONCLUSION*

The findings of this research indicate that there is a negative nexus between rising NPAs and the study's financial performance measures (NIM, ROE and ROA) among BOFIs in Nigeria, both in the short-run and long-run, even in this era where AI-driven financial resources management tools abound. This can be evident when a rise in NPAs was found to cause a negative impact and force a -0.19.5%, -0.79.7% and -0.70.1% decrease in NIM, ROE and ROA respectively. This is the finding that leads to the conclusion that rising NPAs negatively affect the profitability, and overall financial performance, of BOFIs in Nigeria, even with the prevalence of AI-driven financial resource management tools.

Therefore, this study recommends that thorough corporate governance, loan exposures security validation, effective and flexible credit policy, and effective loan terms re-structuring with indicated red flags should be incorporated by BOFIs in Nigeria so to help bolster profitability and overall

NATIONAL BOARD FOR TECHNICAL EDUCATION
NIGERIAN JOURNAL FOR TECHNICAL EDUCATION
Volume 25 Nos. 1 2026
ISSN No. 2992 - 3522

financial performance through guaranteed loan/asset recovery.

This study was undertaken mainly by reliance on quantitative data from annual financial reports and financial data published in selected banks' respective corporate websites. However, other qualitative factors may affect the financial performance of the banks, that should have necessitated the tinge of primary data sources by the study. Notwithstanding, this represents research opportunities for future research – where both quantitative and qualitative factors impacting the financial performance of the BOFIs could be considered.

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