# Fintech and Financial Stability in Nigeria: A Case Study of Neobanks

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# Fintech and Financial Stability in Nigeria: A Case Study of Neobanks

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*The study investigated the impact of Fintechs on financial stability in Nigeria using panel data over the period 2018 and 2021 and the Panel Autoregressive Distributed Lag (PARDL) framework. 6 neobanks, (with state (1) and unit (1) microfinance bank licenses) were examined due to data availability. A Fintech index, which depicts improvement in  was constructed using google trends data Findings from the study empirically confirmed that both bank-specific and macroeconomic factors determine the graduation of risks in these banks. Specifically, credit risk, proxied by non-performing loans ratio was found to be aggravated by growth in size, rise in interest rates and economic expansion. However, a negative relationship was observed between enhancements in the operating efficiency and the fintech index. In addition, the study provides evidence of the existence of a negative relationship between size and z-scores of selected neobanks. However, from our disaggregated analysis, only the signaling hypothesis was found in the case of international banks while the capital management hypothesis and a counter-intuitive income hypothesis was found for national banks. The findings of this paper are relevant to current concerns around the rapid growth of Fintechs in Nigeria and the attendant vulnerabilities and challenges to financial they portend. In this regard, the study recommended more robust macro-prudential policies bordering around capital, liquidity, and operational risk-management requirements should be designed to ensure financial stability specifically to mitigate credit risk amid the striking growth in neobanks. Specifically, regulatory policies such as stipulating lending standards and robust governance schemes, as well as improving prudential guidelines should be the focus of monetary and prudential authorities.*

**Keywords:** FinTech, Credit, Panel Data

**JEL Classification:** G2, G15, G28

## 1.0 Background

Technology has consistently played a significant role in the delivery of financial services throughout history. This is evident from the introduction of the telegraph in the 1870s by Western Union for money transfers to the use of Blockchain and Distributed Ledger Technology for Cryptocurrencies in the 21st Century. Following the 2007-09 global financial crisis which resulted in a loss of confidence in the traditional modes of offering financial services, there has been a surge in interest around Fintech — new technology that seeks to improve and automate the delivery and use of financial services — (financial technology) leading to further development and adoption of innovative Fintech solutions.

The adoption and uses of Fintech in the financial system range from traditional applications like backend operations for banks, information and data storage and processing infrastructure, Automated Teller Machines (ATMs) to disruptive applications like peer-to-peer lending, cryptocurrency, digital banking, and the use of machine learning algorithms

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and data science to perform all tasks from processing credit risks to running hedge funds among others. Fintechs leverage their technology advantages to provide efficiency gains, lower costs, remove friction and improve financial inclusion for underserved and unserved segments of society, increase competition and spur further innovation in the financial sector (IMF,2022).

Financial intermediation by banks is the centre of the modern financial system as it entails aggregating surplus resources and deploying same to deficit units to create welfare enhancing economic activity. This is effectively executed through credit creation in credit markets dominated by commercial banks, credit unions and other traditional lenders. However, Fintech has offered new models of intermediation as well as new forms of intermediaries. Digital lending models such as peer-to-peer (P2P)/marketplace lending, buy now pay later (BNPL), and invoice trading as well as intermediaries like peer-to-peer lending platforms, digital banks and Neo-banks have gained significant traction in many economies in the past decade.

The literature supports the capacity of Fintech to confer a variety of benefits to participants in the financial system. For a panel of selected countries, Daud et al., (2021) proved that Fintech promotes financial stability through the channels of artificial intelligence, cloud technology, and data technology by leveraging these to improve credit scoring and rating, back-end operations and data processing. Moreover, fintech and credit is expected to be higher and complementary to other sources of credit when existing banking services and rates are more expensive, thereby offering users cheaper credit with less friction (Cornelli et al., 2020). Additionally, by using big data analytics and algorithms, Fintech can improve credit risk models by screening opaque borrowers, such as those with scant credit history (Branzoli & Supino, 2020).

Notwithstanding, some concerns remain around the pace, scope, and depth of the transformation of the financial system by Fintechs. Specifically, scholars argue that rapid expansion in credit and non-compliant creditworthiness assessment activities by Fintechs, especially neo-banks, digital banks and peer-to-peer lenders, gives rise to systemic risks and pose challenges to financial stability (Mild et al., 2015); IMF, 2022). Likewise, risks such as the potential weakening of lending standards, increased procyclicality of credit provision and a potential to affect incumbent financial institutions through revenue erosion or additional risk-taking have been identified as concerns for the impact of Fintech on credit risk (CGFS-FSB, 2017; Vučinić, 2020).

Departing from these findings, the developments of Fintechs especially those offering credit services such as peer-to-peer marketplaces, and neobanks, is of interest to policymakers and regulators globally and in Nigeria. This is because these new models and intermediaries either do not fall within any existing regulatory framework or deploy credit through channels not covered by well-developed systems or official reporting standards.Recently, there have been efforts to improve the data on Fintech credit to the private sector as central banks and public sector authorities require such data to monitor economic and financial conditions, to guide monetary policy decisions and to set macroprudential policies, such as the countercyclical capital buffer. Yet for fintech and big tech credit, authorities often rely on non-official sources (Dembiermont et al., 2013) and on submissions by neo-banks—fintech firms with a banking license that offer banking services purely through apps, software and other technologies without a physical branch.

Given the economic importance of credit creation, as Fintech credit becomes more economically relevant, it has become ever more important to have accurate data on the size and growth of Fintech credit market and its impact on credit risk. This is useful for policymakers who monitor markets and set monetary and macroprudential policies based on credit aggregates. It is similarly expedient to understand the size, drivers, policy issues and the impact of Fintech lending activities on consumer credit and the possible impact on financial stability. A key contribution of this paper is to analyse the impact of Fintech credit on credit risk in Nigeria and provide insight for policy and research.

Against this background, this paper therefore seeks to analyse developments in Fintech credit market in Nigeria using lending by neo-banks as a proxy for the Fintech credit and its impact on financial stability. It also seeks to estimate the size of the fintech credit market in Nigeria and analyse the different credit characteristics to provide policy guidance that enhances the deployment of Fintech credit for economic growth. In particular, the paper contributes to the scanty literature on the relationship between fintech and financial stability, particularly in developing economies such as Nigeria. The paper adopts a Panel Autoregressive Distributed

Lag (PARDL) approach, using quarterly data spanning 2018 - 2021. The approach is appropriate as it provides an avenue to quantify the long-run and short-run dynamics in the fintech- credit risk nexus.

Following this introductory section, section 2 explores conceptual issues around fintech, financial intermediation and financial stability. Section 3 discusses the data and methodology employed in the study, while section 4 presents the empirical results from the analysis. analyses theoretical considerations and stylised facts and then section 5 concludes the paper and with policy recommendations.

## 2.0 Conceptual Issues

### 2.1 FinTechs, Financial Intermediation and Financial Stability

Financial technology (Fintech) is used to describe new technology that seeks to improve and automate the delivery and use of financial services. At its core, Fintech is utilised to help companies, business owners and consumers better manage their financial operations, processes, and lives by utilizing specialised software and algorithms that are used on computers and, increasingly, smartphones. Fintech usually references an organisation where financial services are delivered through a better experience using digital technologies to reduce costs, increase revenue and remove friction. It also refers to any business that uses technology to enhance or automate financial services and processes. The term is a broad and rapidly growing industry serving both consumers and businesses.

Within credit markets, there has been a rapid transformation occasioned by the advent of Fintech. Several new models of intermediation have been offered and adopted including marketplace lending models based on the offering of credit through the direct matching of lenders with borrowers. Marketplace lending models can be peer-to-peer—where lenders are retail consumers or business-to-business—one in which lenders are wholesale investors (banks or institutional investors). Most platforms combine both types of lenders and specialize either in consumer credit or in credit to small and medium enterprises (Branzoli & Supino, 2020).

Another model of credit offering by Fintech is neo-banks which are branchless digital banks, licensed by the monetary authorities that acquire and serve customers primarily through digital touchpoints such as mobile apps. Neobanks offer credit to users through online channels using machine learning, big data analytics, and Application Programming Interfaces (APIs), for credit rating, scoring and allocation. Neobanks have attained market share by offering lower fees, higher interest rates on deposits and convenience to users. They can afford this due to lower overhead costs, as they have no branches to maintain and are funded by venture capital which is geared towards rapid growth rather than profitability. As neobanks continue to grow, they attain systemic importance in their local markets and present several vulnerabilities including excessive risk-taking in loan and securities portfolios without appropriate provisioning; under-pricing of credit risk; and a relatively weak liquidity management framework (IMF, 2022).

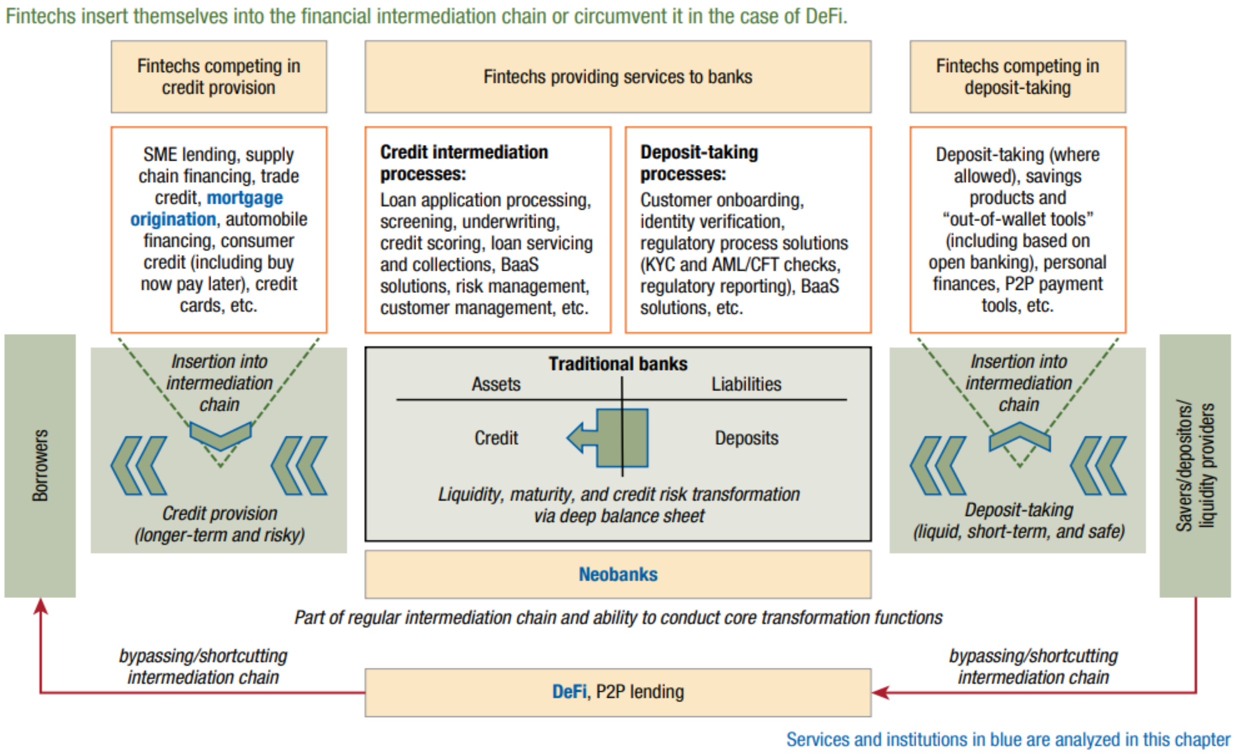
Over the years, Fintechs have integrated into the financial intermediation chain of traditional banks, through the provision of specialised services and competition. IMF (2022) identifies three (3) ways through which this could occur. For instance, Fintechs provide services related to loan application and collection such as provision of credit scores and debt collection. Secondly, they may also be involved in deposit-taking services such as customer identity verification, Bank as a Service solutions, regulatory process solutions (KYC and AML/CFT processes), e.t.c. Thirdly, Fintechs may also be engaged directly in credit allocation and deposit-taking processes, through provision of credit to SMEs, consumers (automobile and mortgage), supply chain financing and issuance of credit cards, on one hand, and the deployment of savings products and "out-of-wallet tools", P2P payment tools, personal finances, e.t.c, on the other[2].

These developments have several implications for financial stability risks. For instance, a case where a several important banks outsourced a number of integral processes, such as risk management, compliance or fulfilment of regulatory requirements, to the same service providers, outages and cyber incidents could bring about systemic risks. Another form of disruption which is notable arises from direct competition for the same services, particularly in jurisdictions where banks are less predominant in the financial systems (Boot et. al, 2021). Of a truth, a number of large fintechs have grown very quickly in emerging markets, for example, MPesa in Africa, which offer credit to small and medium enterprises (SMEs).

[2] AMF/CLT = anti-money laundering/combating the financing of terrorism; BaaS = Banking as a Service; DeFi = decentralized finance; KYC = Know Your Customer; P2P = peer to peer; SME = small and medium enterprise.

With reference to regulation, financial stability risk may emerge when fintechs provide bank-like services while operating under less stringent regulations than banks. In such a case, coupled with the business model of fintechs which relies heavily on rapid growth, excessive risk-taking may be the order of the day. This ultimately may result in capital erosion and higher systemic risk (Vives, 2019). Lastly, disruptions also arise when fintechs platforms that provide Peer-to-peer lending platforms, for instance, directly connect savers and investors with borrowers. In this case, they shortcut the intermediation chain by removing the financial intermediary. Intuitively, investors on these platforms commit their funds for a given horizon and effectively assume credit and liquidity risks.

**Figure 1: FinTechs in the Core Banking Intermediation Chain**




**Source:** Global Financial Stability Report, April 2022.

## 3.0 Data and Methodology

### 3.1 Data

To achieve the objective of the study, six (6) relevant variables were used based on theoretical and past empirical findings (Cheng and Qu, 2020). The frequency of the data used was monthly, spanning 2018M12 to 2021M12. The scope of data was informed primarily by availability of data and the need to capture the periods in which the selected neobanks had consistent data and uniform reporting period. The bank specific panel data were extracted from the Financial Analysis System (FinA) of the Central Bank of Nigeria. Data on macroeconomic variables were sourced from the Central Bank of Nigeria Statistical Bulletin and National Bureau of Statistics (NBS) database. Data used to construct the Fintech index was sourced from google trends.

**Table 2: Variable Definition**

| Variables | Definition | *a priori* Expectations (Credit Risk model) | *a priori* Expectations (Solvency Risk Model) |
|---|---|---|---|
| **$NPL_{it}$** | The ratio of Non-performing loans to total loans for bank i in month t | Dependent variable | N/A |
| **$SIZE_{it}$** | The logarithm of total assets for bank i in month t | - | + |
| **$FIN_{it}$** | Google trend searches on fintech | +/- | +/- |
| **$ECON_{it}$** | Economic activity proxied by Manufacturing PMI | - | + |
| **$INT_{it}$** | Maximum Lending Rate in the Banking System | + | + |
| **$EFFICIENCY_{it}$** | Operating Self-Efficiency proxied by ration of Total Income to Total Expenditure for bank i in month t | - | + |
| **$Z\text{-}Score_{it}$**[3] | Indicator of Financial Stability for bank i in month t | N/A | Dependent variable |

**Source:** Staff Compilation

## 3.3 Analytical Framework

To analyse the impact of FinTech on financial stability in Nigeria, this study follows the specification of Cheng and Qu, (2020) with some augmentation with regard to the peculiarities in the Nigerian financial system as well as data availability. The structural form of the relationship is denoted as follows:

Non-performing loan ratio = f (Size, Operating efficiency, Interest Rate, Economic Activity, Fintech Index)

### 3.3.1 Econometric Method: Panel Auto-Regressive Distributed Lag (PARDL)

The study utilises a panel autoregressive distributed lag (PARDL) model to examine the FinTech-credit risk nexus in Nigeria. The autoregressive distributed lag (ARDL) model relates

[3] The z-score was used to proxy financial stability, as it measures banking system stability. It is computed with three important financial soundness indicators: Equity/Assets ratio, the return on assets (ROA) and the standard deviation of return on assets – a proxy for return volatility. The computation could be denoted as follows: $Z-score_{it} = \frac{ROA_{it} + EQA_{it}}{\sigma(ROA)_{it}}$

a dependent variable to its lags as well as contemporaneous and lag levels of all other variables in the model. A typical ARDL (p, $q_1 \ldots, q_k$) could be specified as:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \boldsymbol{\delta}'_{it} \boldsymbol{x}_{it-j} + \mu_i + \varepsilon_{i,t} \quad (1)$$

with the cross-sections $i = 1,2, \ldots, N$; the number of periods $t = 1,2, \ldots, T$; $x_{it}$ is the $k\ x1$ vector of explanatory variables for group, $i$, $\lambda_{ij}$ and $\delta_{it}$ are scalars and $k\ x1$ coefficients; and $\mu_i$ is the cross-section specific effects, which are expected to be correlated with individual cross-sections. The error term, $\varepsilon_{i,t}$ ,is expected to be independently distributed across $i$ and $t$, with expected zero means and constant variances. They are also distributed independently of the regressors, $x_{it}$-a requirement for consistent estimation of the short-run coefficients.

We assume that the relationship between Fintech and credit risk alongside other specified determinants can be represented by the following equation:

$$Y_{i,t} = \alpha_{0i} + \alpha_{1i} X_{it} + \beta_{1i} K_{it} + e_{i,t};\ i = 1,2, \ldots N;\ t = 1,2, \ldots, T \quad (2)$$

where $Y_{i,t}$, is the dependent variable (credit risk), $X$ and $K$ are vectors of macroeconomic and bank-specific independent variables, respectively; and $e_{i,t}$ is a white noise error term. If the variables are a combination of $I(0)$ and $I(1)$ series and cointegrated, such that the error term, $e_{i,t}$, is an $I(0)$ process for all $i$, then the relationship can be expressed by a dynamic ARDL model.

The dependent variable is bank ratio of non-performing loans to total loans ($NPL_{it}$) and bank specific z-score ($Z_{it}$), respectively, for each model depicting credit and solvency risk, while the regressors include: bank-specific variables, including: total assets ($Size_{it}$), operating self-efficiency ratio ($Efficiency_{it}$); macroeconomic variables including: economic activity ($Econ_{it}$); and interest rate ($Int_{it}$) and Fintech Index ($FIN_{it}$). $\text{Size}_{it}$ index was fed into the model in log form. The definitions and *a priori* expectations of all variables in the model are presented in Table 2 above.

## 3.0 Empirical Findings

### 3.1 Descriptive Statistics

Inferences from the descriptive statistics show that all the variables were not normally distributed as shown by the Jarque-Bera test for normality. Additionally, the standard deviation, which is used to measure the amount of variation or dispersion of a set of values from its mean, shows that majority of the variables have a low standard deviation, which indicates that variables exhibited low level of volatility. In terms of skewness, all the variables except Size and economic activity were found to be positively skewed. The results of the kurtosis proved that only NPL, Efficiency, Economic activity and FinTech Index variables are leptokurtic while others are platykurtic.

**Table 3: Descriptive Statistics**

| | NPL | Size | Efficiency | Interest Rate | Economic Activity | FinTech Index | Z-Score |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.11 | 14.24 | 1.38 | 29.01 | 50.62 | 56.66 | 8.10 |
| **Median** | 0.07 | 14.43 | 1.35 | 28.66 | 49.25 | 55.50 | 2.86 |
| **Maximum** | 0.95 | 17.32 | 5.61 | 31.43 | 62.30 | 100.00 | 38.49 |
| **Minimum** | 0.00 | 10.13 | 0.00 | 27.10 | 25.30 | 25.00 | -1.53 |
| **Std. Dev.** | 0.17 | 2.27 | 0.87 | 1.19 | 8.01 | 14.93 | 9.99 |
| **Skewness** | 3.60 | -0.22 | 0.93 | 0.57 | -0.78 | 0.75 | 1.11 |
| **Kurtosis** | 17.29 | 1.51 | 5.70 | 2.35 | 4.11 | 3.83 | 2.91 |
| **Jarque-Bera** | 2091.10 | 19.57 | 87.68 | 14.06 | 30.08 | 23.96 | 40.64 |
| **Probability** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Source:** Authors' Compilation using Eviews 11.0

### 3.2 Correlation Matrix

Table 4 presents the correlation between the various variables. For this analysis, focus would be on the second column and the last row which present the correlation coefficients between non-performing loans and z-core, and other variables, respectively. Evidently, negative relationship is observed between non-performing loan ratio and size, efficiency, and the FinTech index. However, a positive relationship is seen between non-performing loan ratio and interest rate as well as economic activity. Similarly, the z-core was found to be negatively associated with size, efficiency, and the FinTech index over the review period. The z-score was also found to be directly associated with interest rate and economic activity in the period under review.

**Table 4: Ordinary Correlation Coefficients between Credit Risk Indicators and Regressors**

| | NPL | Size | Efficiency | Interest Rate | Economic Activity | FinTech Index | Z-Score |
|---|---|---|---|---|---|---|---|
| **NPL** | 1.00 | | | | | | |
| **Size** | -0.17 | 1.00 | | | | | |
| **Efficiency** | -0.16 | 0.09 | 1.00 | | | | |
| **Interest Rate** | 0.14 | -0.32 | -0.06 | 1.00 | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Economic Activity** | 0.16 | -0.25 | 0.03 | 0.57 | 1.00 | | |
| **FinTech Index** | -0.01 | 0.15 | 0.13 | -0.41 | -0.01 | 1.00 | |
| **Z-Score** | 0.04 | **-0.82** | -0.04 | 0.29 | 0.28 | -0.15 | 1.00 |

**Source:** Authors' Compilation using Eviews 11.0

### 3.3 Panel Unit Root Tests

The stationarity of the variables was investigated using unit root tests. Panel-based unit root tests are found to have higher power than individual time series unit root tests (Atoi, 2018). Three standard tests namely, Levin, et al., (2002), Im, Pesaran and Shin (IPS) (2003), ADF-Fisher Chi-Square and Philip Peron (PP) unit root tests were employed. The null hypothesis of Levin, Lu and Chu (LLC) technique assumes common unit root process, while that of IPS, ADF and PP assumes individual unit root process. The overall results show that all variables were of mixed order of integration. Specifically, all variables except interest rate were found to be integrated of order 1. The mixture of I(0) and I(1) variables suggests the use panel ARDL methodology.

**Table 5: Panel Unit Root Tests**

| Variables | Levin, Lu &Chu t* | | Im, Pesaran and Shin W-stat | | ADF – Fisher Chi-square | | PP – Fisher Chi-square | | Order |
|---|---|---|---|---|---|---|---|---|---|
| | Level | First Difference | Level | First Difference | Level | First Difference | Level | First Difference | |
| **NPL** | -1.79** | N/A | -2.36*** | N/A | 32.35*** | N/A | 61.80*** | N/A | I(0) |
| **Size** | -7.56*** | N/A | -5.79*** | N/A | 35.37*** | N/A | 35.61*** | N/A | I(0) |
| **Int Rate** | -0.45 | -5.71*** | 1.25 | -5.99*** | 6.23 | 57.99*** | 6.99 | 150.23*** | I(1) |
| **Efficiency** | -1.66** | N/A | -0.21** | N/A | 27.01** | N/A | 59.07*** | N/A | I(0) |
| **Economic Activity** | -0.93 | N/A | -3.69*** | N/A | 30.11*** | N/A | 34.39*** | N/A | I(0) |
| **FinTech Index** | -3.98*** | N/A | -1.65** | N/A | 27.08*** | N/A | 53.27*** | N/A | I(0) |
| **Z-Score** | -16.84*** | N/A | -10.89*** | N/A | 50.19*** | N/A | 44.40*** | N/A | I(0) |

**Source:** Authors' Compilation using Eviews 11.0
**Note:** ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

### 3.4 Panel Co-integration Tests

Following the outcome of the panel unit root tests, which suggests different orders of integration, it is imperative to determine whether a long-run relationship exists among the variables. To check co-integration, the Pedroni Residual Co-integration Test was applied and the results are presented in the table below. Different types of statistics were examined with the parameters such as statistic, probability, and weighted probability. The common AR and individual AR coefficients were examined with probability values. From the results, six out of eleven statistics indicate that the null hypothesis of no co-integration can be rejected at 5.0 per cent significance level, we conclude that the variables are co-integrated.

**Table 6: Pedroni Residual Cointegration Test**

| Alternative Hypothesis common AR Coefs. (within-dimension) | | | | |
|---|---|---|---|---|
| | **Statistic** | **Prob.** | **Weighted Statistic** | **Prob.** |
| Panel v-Statistic | 1.2006 | 0.1149 | 0.5346 | 0.2965 |
| Panel rho-Statistic | -1.0348 | 0.1504 | -1.1429 | 0.1265 |
| Panel PP-Statistic | -2.6215 | 0.0044 | -2.4048 | 0.0081 |
| Panel ADF-Statistic | -2.1319 | 0.0165 | -2.2179 | 0.0133 |
| **Alternative Hypothesis individual AR Coefs. (between-dimension)** | | | | |
| Group rho-Statistic | -0.2434 | 0.4038 | | |
| Group PP-Statistic | -2.3278 | 0.0100 | | |
| Group ADF-Statistic | -2.0599 | 0.0197 | | |

**Source:** Authors' Compilation using Eviews 11.0

### 3.5 Long-run Results

The long-run results from the estimated panel autoregressive distributed lag (PARDL) models are presented in Table 5. From column (1), the measure of credit risk (non-performing loans ratio) is found to have a contemporaneous positive relationship with the size of the bank. Thus, increase in the size of Fintechs in terms of total assets leads to higher non-performing loans. This relationship was also found to be statistically significant, therefore, conforming to the theoretical proposition of positive inclusion-stability nexus. Conversely, the bank specific variable, i.e. efficiency (proxied by operating self-efficiency ratio) was found to be negatively related and significantly affect credit risk. This is in line with a priori expectations as enhanced operating efficiency improves the firm resilience against credit risks.

Furthermore, interest rate is directly related to credit risk. This conforms to theory as an increase in the cost of borrowing heightens credit risks in the financial system. Specifically, a one percentage point increase in interest rates, ceteris paribus, will bring about 0.02 per centage point rise in non-performing loan ratio. From the results, a positive relationship was observed between economic activity and credit risk indicating that credit risk will intensify as the economy expands. This relationship, though counterfactual, is statistically significant at 5.0 per cent. On average, an index point increase in the manufacturing PMI leads to 0.1 percentage point increase in non-performing loans. Lastly, the Fintech index which reflects news bordering the emergence and developments around Fintech in the country is negatively associated with credit risk. This implies that credit risks related to neobanks decline as awareness improves.

From column (2), the measure of solvency risk (z-score) is found to have a contemporaneous negative relationship with the Fintech index, implying that increased awareness and emergence of Fintechs results in deterioration of financial buffers. This relationship was also found to be statistically significant. Similarly, increase in the size of Fintechs in terms of total assets was found to worsen solvency levels. Conversely, the bank specific variable, i.e. efficiency (proxied by operating self-efficiency ratio) was found to be positively related and significantly affect solvency risk. This is in line with a priori expectations as enhanced operating efficiency improves the firm resilience against risks.

From the macroeconomic variable block, interest rate is inversely related to solvency risk. This insinuates that an increase in the cost of borrowing heightens solvency risks in the financial system. Specifically, a one percentage point increase in interest rates, ceteris paribus, will bring about -1.2 points reduction in the z-score of selected neobanks on average. From the results, a negative and sizeable relationship was observed between economic activity and credit risk indicating that solvency risk will intensify as the economy expands. This relationship, though counterfactual, is statistically significant at 5.0 per cent. On average, an index point increase in the manufacturing PMI leads to -7.2-point decrease increase in the z-score of selected banks.

**Table 7: Long-Run Estimation Results**

| Variables | Model 1 | Model 2 |
|---|---|---|
| | $NPL_{it}$ *[ARDL(1,1,1,1,1,1)]* | $Z_{it}$*[ARDL(1,1,1,1,1,1)]* |
| $Size_{it}$ | **0.0776*** ** (0.0076) | **-2.5306*** ** (0.4592) |
| $Fin_{it}$ | **-0.0006*** (0.0003) | **-0.0418*** ** (0.0144) |
| $Int_{it}$ | **0.0206*** ** (0.0076) | **-1.2087*** ** (0.3147) |
| $Efficiency_{it}$ | **-0.0575*** ** (0.0075) | **0.0457** (0.3293) |
| $Econ_{it}$ | **0.1057** ** (0.0312) | **-7.2811*** ** (1.5692) |

**Source:** Authors' Compilation using Eviews 11.0

### 3.6 Short-Run Results

The results from the short-run dynamics indicate that the feedback coefficient is -0.5134 for the model with credit risk as the dependent variable and -0.1409 for the model with solvency risk as the dependent variable. This development suggests a fast speed of adjustment to equilibrium after experiencing shocks in the case of the former, and a moderate speed of adjustment in the case of the latter. In other words, approximately 51.3 per cent, and 14.1 per cent of the disequilibria from the previous month's shocks converge or adjust back to the long-run equilibrium in the current quarter. The short-run response of credit risk to size, fintech index and efficiency is negative, while the macroeconomic variables including interest rate and economic activity result in positive response from credit risk. Intuitively, this implies that rise in interest rates aggravates credit risk while counterfactually, economic expansion also heightens credit risk.

Moreso, the short-run relationship between solvency risk and size of neobank is negative and insignificant. Ceteris paribus, as the size of the neobank increases, its solvency buffers deteriorates. This outcome, somewhat, corroborates the long-run results which reveals a negative relationship between variables. Efficiency, another bank-specific variable is found to improve the solvency position of the banks in the short-run, albeit the relationship is found to be insignificant. Other variables such as fintech index – representing awareness and economic activity were also found to be positively related to the z-score. This implies that solvency buffers of neobanks improve as the economy expands and as the awareness of Fintechs improves. The relationship between interest rate and solvency is negative, thus, as the cost of borrowing increases, the solvency positions of neobanks is found to deteriorate.

**Table 8: Short-Run Estimation Results**

| Variables | Model 1 | Model 2 |
|---|---|---|
| | *$NPL_{it}$ [ARDL(1,1,1,1,1,1)]* | *$Z_{it}$[ARDL(1,1,1,1,1,1)]* |
| *ECTt* | **-0.5134** (0.2405) | **-0.1409*** (0.0795) |
| *$Size_{it}$* | -**0.0224** (0.0154) | **-2.0233** (1.3475) |
| *$Fin_{it}$* | **-0.0006*** (0.0003) | **0.0132** (0.0097) |
| *$Int_{it}$* | **0.0206***** (0.0076) | **-0.7814***** (0.2837) |
| *$Efficiency_{it}$* | **-0.0575***** (0.0075) | **1.4058** (1.1031) |
| *$Econ_{it}$* | **0.1057***** (0.0312) | **3.3488** (2.4771) |
| C | **-0.9337**** (0.4093) | **15.1517*** (8.5407) |

**Source:** Authors' Compilation using Eviews 11.0

## 4.0 Summary and Conclusion

The paper examined the relationship between fintech and credit risk in Nigeria using Panel Autoregressive Distributed Lag (PARDL) framework over the period, 2018M12-2021M12. Six (6) neobanks, (with state (1) and unit (1) microfinance bank licenses) were examined due to data availability. Inferences from the long run results show that operating efficiency has a positive impact on contemporaneous credit risk, implying that enhanced efficiency on the part of fintechs led to lower credit risks.

Notably, size of respective neobanks was found to be detrimental to credit risks, as increase in the size of neobanks appears inimical to credit risk. Furthermore, interest rate was found to propel credit risks, which generally is in line with theory. However, changes in macroeconomic variables, such as economic activity proxied by PMI, heightened credit risks thus, heightening financial instability. This procyclical relationship between credit risk and economic activity raises some concern for authorities saddled with the task of financial stability.

Similarly, the size of neobanks was also found be negatively related to solvency risk. Thus, growth in the size of neobanks tends to bring out depletion in the solvency buffers of neobanks. In addition, the fintech index, which represents the degree of awareness as well as development around the fintech space, and economic activity were also found to be positively related to the z-score. This implies that solvency buffers of neobanks improve as the economy expands and as the awareness of Fintechs improves. Moreso, interest rate hikes were found to be worsen the solvency positions of selected neobanks in Nigeria.

These findings have important policy implications as policy makers design and implement policy frameworks and measures geared towards fintechs, particularly neobanks. The paper, therefore, recommends more proactive policies in the direction of fintech regulation, as size negatively affects credit risk. More robust macro-prudential policies bordering around capital, liquidity, and operational risk-management requirements should be designed to ensure financial stability specifically to mitigate credit risk amid the striking growth in neobanks. In addition, regulatory policies such as stipulating lending standards and robust governance schemes, as well as improving prudential guidelines should be the focus of monetary and prudential authorities.

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