“Financial technology adoption and bank stability among African economies: Is the relationship monotonic?”

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FINANCIAL TECHNOLOGY ADOPTION AND BANK STABILITY AMONG AFRICAN ECONOMIES: IS THE RELATIONSHIP MONOTONIC?

Abstract

Many researchers attribute the vulnerability of African banks to financial frictions/crises to poor innovation/technology adoption on the continent. While many studies suggest that Fintech adoption can mitigate instabilities/risks, this study argues that adopting Fintech brings both challenges and opportunities. Consequently, the study examines a monotonic connection between Fintech and bank stability in a panel of 26 African economies from 2004 to 2021. After measuring bank stability with the bank Z-score, the Principal Component Analysis (PCA) was employed to generate an index of Fintech using various digital payment indicators. The results of the System Generalized Method of Moments (GMM) technique reveal that the relationship is U-shaped in the short run but monotonic in the long run with greater magnitude. Hence, an oscillatory divergent relationship was implied for the entire period. That is, Fintech improves and worsens bank stability intermittently over time. The result is still valid with the inclusion of bank-specific and macroeconomic variables but it was improved with the inclusion of institutional variables in the model. Furthermore, the U-test analysis employed as a second-order robustness check for the U-shaped relationship confirms that Fintech adoption will first worsen bank stability before improving it. The study concludes that Fintech's ability to improve bank stability depends on the extent and quality of institutional development/regulations in the region. The study therefore recommends institutional development and Fintech regulation to guarantee steady financial/bank stability through Fintech adoption.

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INTRODUCTION

Many researchers attribute the vulnerability of African banks to poor innovation and technology adoption in the continent. This could be due to its advantage in creating and delivering financial services as well as mitigating financial risk (Broby, 2021, p. 4). Hence, financial technology (Fintech) as used in this study refers to the integration of new technology that seeks to improve financial services and automate its creation and delivery. Although Fintech is associated with huge benefits, it comes with both problems and prospects (Ernest & Young, 2017, p. 8). The argument in the literature has been on whether Fintech will weaken policy response to financial volatilities and further aggravate the financial crisis. This concern is not only limited to its rapid adoption rate but also the way Fintech is evolving with better services than banks has become a matter of concern to traditional banks' stability.

There has not been a consensus in previous studies on whether Fintech adoption will ultimately promote or hamper the operations of traditional banks. Whereas some studies propose a positive impact (Meyer & Okoli, 2023; Azarenkova et al., 2018), others believe that it comes

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with greater challenges than opportunities (Azarenkova, et al., 2018; Lin & Dong, 2018; Decaro, 2017). It plays an important role in transforming and modernizing the financial system through improved financial service delivery, thereby raising the level of financial inclusion and improving the profitability of banks (Azarenkova et al., 2018, p. 12). This was sustained by Meyer and Okoli (2023, p. 17) who observed that Fintech is capable of promoting the operation and profitability of traditional banks if they collaborate. This is because its banking service style is characterized by modern payment systems, cost reduction, efficiency in service delivery, and speed. Although this could come with technological unemployment and by implication structural changes during the short run, its long-run benefits could be overwhelming.

Besides its benefits, Fintech's disruptive effects and its competitive advantage over bank financial institutions are capable of creating both financial and macroeconomic instability (Abadi & Brunnermeier, 2018, p. 12). Speaking on the economic implication of the advent of crypto-currency, the IMF asserts that it will lead to a reduction in the demand for central bank money in the future (Decaro, 2017, p. 227). This is capable of reducing government reserve and the ability of the central bank to control the financial system (Lin & Dong, 2018, p. 14). Azarenkova et al. (2018) added that the introduction of Fintech can increase cyber-risks and threaten the entire financial system. These have become policy issues, especially among African economies, given the underdeveloped nature of their financial system. Therefore, the inability of most financial authorities in Africa to regulate the financial system could be attributed to the disruptive effect of Fintech, given that the unregulated nature of crypto-currency is a potential financial risk (Foley et al., 2019, p. 21).

Given these two-edged sides of Fintech and the focus of previous studies on the advantages and potential limitations of Fintech, this study argues that the extent to which Fintech emits a positive or negative impact on bank stability is dependent on the level of regulations within the economy. Based on this assertion, in addition to generating an index of Fintech adoption rate among the economies of interest in this study, it also aims to identify the potential threshold point beyond which Fintech adoption emits a reverse effect on bank stability. Hence, a U-shaped or a monotonic/inverted U-shaped relationship between Fintech and bank stability becomes the focus of this study.

1. LITERATURE REVIEW

Despite concerted efforts by most central banks in Africa to cushion the spillover effects of the GFC, many financial institutions in the region have winded up. This has led to financial instability and high levels of unemployment in the region. Most economies in the region have embraced Fintech adoption to cushion the spread of financial volatilities, yet, financial frictions and instability still characterize the financial system in most African economies with no solution in view. Studies (Lestari & Rahmanto, 2023; Deng et al., 2021; Lee et al., 2021; Wang et al., 2021) have examined the impact of Fintech on bank efficiency, especially among developed and emerging economies. The general findings across these studies are that Fintech mitigates bank risk and promotes efficiency levels. They affirm that Fintech improves the technology of banks, especially under different ownership structures. However, there remained lots of gaps in the literature in areas such as structural transformation/institutional quality, nonlinear relationship, regulation, region of Africa, and different methodologies employed. Therefore, this study believes that a nonlinear relationship between Fintech and bank stability and the role of institutional quality might complement previous studies and promote stability in banks among African economies irrespective of shocks from Fintech.

In their study on the challenges of Fintech in the banking sector, Lestari and Rahmanto (2021, p. 11) argued that the rapid development of technology has shifted consumer behavior to a nonconventional traditional banking style. Consumers' banking behavior has become more digital, and this has been leveraged with the spread of the recent COVID-19 pandemic. Households and corporate bodies have embraced technology to ease the

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stress of banking. Likewise, most bank and nonbank financial institutions are beginning to diversify operations toward a Fintech-based compliant system of banking. Financial innovation/technology makes economies less vulnerable to crises by widening access to liquidity (Gai et al., 2008, p. 27). Although this process is capable of improving financial inclusion, it seems to have far-reaching long-run implications on the continual existence of the conventional banking system. This is because of the possibility of reducing bank profits since nonbank-Fintech companies provide services that banks previously provided at a reduced cost with higher efficiency. In addition to reducing profit, Fintech threatens bank stability and ultimate existence.

Although Fintech has a stabilizing effect and can help to promote financial liberalization and efficient financial service delivery, it can also introduce uncertainties in the system (Wang et al., 2021). Given this potential negative effect, especially among banks in Africa, Eyal (2017, p. 21) argued that it is not likely that Fintech will replace traditional banks. This is because Fintech companies still operate with existing bank accounts. Lee et al. 2021, p. 13 believe that Fintech adoption is capable of not only improving the cost efficiency of banks but also enhancing their technology compliance. This suggests that too much Fintech adoption, especially among banks, can improve their efficiency level. Given these dichotomies, this study argues that a condition of U-shaped or monotonic relationship between Fintech and bank stability could emerge. Although many studies examined a U-shaped relationship between Fintech and bank credit risk (Okoli, 2020, p. 18), Fintech and financial risks of banks in China (Chen et al., 2022, p. 15) and between Fintech and bank profitability/performance (Li et al., 2023; Huang & Zhang, 2022; Kayed et al., 2024, p. 20), studies on its nexus with bank stability have not been sufficiently explored in the literature.

Besides these, there have been some contradictory conclusions among these studies on whether the adoption of Fintech should be increased or reduced. For instance, whereas Chen et al. (2022) recommend a high adoption level to cushion financial risks, Okoli (2020, p. 18) found that too much Fintech adoption could be detrimental to banks' credit risk. This suggests that besides having a sparse study on the Fintech-bank stability nexus, there is huge evidence of wrong model specifications and methodological flaws among the previous studies. Hence, this study aims to circumvent these limitations by modeling a dynamic stochastic equation on the nexus between Fintech and bank stability, using the moment conditions estimation technique and moderating for high Fintech adoption by incorporating bank regulation as a control variable in the model.

In addition to these methodological flaws, previous studies also could not account for regions' peculiar attributes that are capable of defining the direction of the relationship. In Africa, inadequate financial structures and policies have impeded financial and bank development in the region (Benyah, 2010, p. 22). The strict digital regulatory policies in South Africa must have been the reason why M-Pesa (a mobile money transfer) could not thrive in the country (Alexander et al., 2017). Moreover, Africa's poor institutional quality makes it difficult to replicate similar progress recorded by their advanced counterparts in Asia and the Middle East even with similar income levels (Allen et al., 2014). This suggests that, in Africa, institutional factors are likely to explain changes in the financial sector more than the real sector or financial variables (Okoli & Tewari, 2020). Even with a stable economy and high institutional quality, historical experience has shown that a stable macroeconomic environment is not a sufficient condition to have a stable financial system. This is because financial imbalances were still built up in most of the advanced economies despite stable growth with low inflation during the 2008 global financial crisis (Unsal, 2011).

As most African economies struggle with financial and economic instabilities and a deteriorating exchange rate, large capital inflows into the continent from the advanced countries are capable of making the financial system more vulnerable and unstable (Unsal, 2011, p. 14). Apart from the inflow of capital from the advanced economies, the adoption of Fintech can worsen the status quo. Alexander et al. (2017) found that African bank's response to Fintech adoption has been very slow. However, they added that the outlook for mobile banking remains very impressive and that this is capable of improving the financial industry in the region (Alexander et al., 2017, p. 109). Moreover, with the advent of Fintech and its disruptive impacts, it is unlikely that this condition will ever emerge. This is because of the short-run policy conflicts in macroeconomic policy measures. Consequently, macroeconomic variables are less likely to promote bank stability, especially during the short run.

On the other hand, many studies (Danisman & Demirel, 2019; Shaddady & Moore, 2019; Laeven & Levine, 2009) examined the role of regulations on bank stability and found that regulations can enhance stability and limit risk. However, these studies could not account for the impact that institutional quality could have on bank stability. The extent to which regulations could impact stability depends on the quality of its institutions which is capable of improving the enforcement capacity of banks (Haldane & Neumann, 2016, p. 23). Recent insights by Sodokin et al. (2023) suggest that an encouraging institutional environment enhances rigorous enforcement of regulatory bottlenecks and robust supervision, thereby smoothening the rough edges and promoting bank efficacy. This affirmation implies that although regulation sets the standard for improvement, it is the quality institution that creates an enabling environment for policy pursuit to thrive.

The challenge with studies on Fintech is that Fintech has not been globally pinned down to a common indicator. Therefore, most of the studies on Fintech innovation employed digital payment systems (Lestari & Rahmanto, 2023; Chen et al., 2022; Deng et al., 2021), while other employed the financial inclusion index constructed by Peking University (Lee et al., 2021, p. 14). However, the challenge with these indices is that they either focus on the actual use of financial services by the users (Guo et al., 2020), or they are constructed from the demand perspective, rather than the perspective of industry supply (Lee et al., 2021) and yet others are limited in scope. Therefore, given that the technological transition of the industry is mainly promoted by financial innovations, internet banking, and mobile digital payment, this study constructs an index for Fintech from the perspective of demand, supply, and financial innovation channels using the principal component analysis (PCA).

2. METHODOLOGY

This section starts with the presentation and the description of the various data used in this study as they provide information on the different components of the model specifications. Next in this section are the techniques employed to analyze the data. Three unique techniques were employed. They are the principal component analysis (PCA), the generalized method of moments (GMM), and the Lind and Mehlum (2010) U-shaped analysis. The PCA was used to generate an index for Fintech using four components (see Table 1), whereas the GMM was employed as the main estimation technique of this study and the U-test was used as a robustness check for monotonicity.

2.1. Data description, sources and measurement

The analysis is for twenty-six African economies for the period 2004–2021. The data are sourced from the World Bank database (WBD). The variables comprise internal/bank-specific, macroeco-

Table 1. Data description, sources and measurement

Source: Author's compilation.

Data	Definition	Expected Sign	Sources	Measurement
BS	Bank Stability	Positive	World Bank database https://databank.worldbank.org/source/world-development-indicators#	Bank Z-scores
BRA	Banks efficiency level	Positive	World Bank database	Bank return on assets
BLL	Banks' liquidity	Positive	World Bank database	Bank liquid liability
BNII	Bank diversification	Positive	World Bank database	Bank non-interest income to total income
Ftch	Index of Fintech	Pos/Neg	Generated	Principal component analysis
Ftchsq	Turning point of Ftch	Pos/Neg	Generated	The squared of Fintech
GDPG	Economic growth	Positive	World Bank database	GDP Growth Rate
BREG	Institutional Quality	Positive	World Bank database	Bank Regulation

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nomic, institutional, and Fintech variables. The study used four variables such as ATM, internet banking proxy with individuals using the internet, mobile banking proxy with mobile cellular subscription, and ICT import to generate an index of Fintech using the PCA.

2.2. Principal Component Analysis

The Principal Component Analysis was employed to aggregate four different variables into a single component called Fintech. This technique is preferred to other index generation techniques such as the variance equal weight because it does not account for the biasedness associated with possible co-movement between indicators. This study, therefore, calculates an index of Fintech using the following formula:

$$Fintech = \left(\delta^0 Z_t\right) \cdot \beta_t \cdot \left(\delta^0 Z_t\right)^T, \qquad (1)$$

where $\Delta = (\delta_1, \ldots, \delta_s)$ is the vector of the sub-index weights, $Z = (z_1, \ldots, z_s)$ the vector of sub-indexes of four components comprising of ATM, mobile banking/payment proxy with mobile cellular subscription, internet banking proxy with individuals using internet and ICT import, and $(\delta^0 Z_t)$ the Hadamard-product of the vector sub-index weight and the vector of sub-indices in time t. $(\delta^0 Z_t)^T$ is the transpose of this matrix. β_t is a matrix of time-varying cross-correlation coefficients between sub-indices *i and j*. The rationale behind the selection of these indexes is that they are financial innovations upon which Fintech is built.

The generated index is then normalized and put on a scale of between zero and one (0, 1). This procedure transforms the indicator to their zero mean and standard deviation of one to avoid aggregation distortion which may arise if the means of the indicators are different (Sere-Ejembi et al., 2014). The formula is as follows:

$$Fintech_{it} = \frac{x_{it} - \min x_{it}}{\mathrm{Max}(x_{it}) - \mathrm{Min}(x_{it})}, \qquad (2)$$

where Fintech is the generated index, x_{it} is the individual observations, $\min(x)_{it}$ is the minimum observation, while $\max(x)_{it}$ is the maximum observation.

2.3. Estimation technique: System Generalized Method of Moments (GMM)

This technique is informed both by theory and empirical evidence (Yen & Huy, 2023; Okoli & Tewari, 2021; Okoli, 2020), which affirms that previous states of bank stability affect its present stability level. Besides this, the GMM technique is most appropriate when the number of groups/countries in the panel (26) is above or equal to the time observations (18). The rationale for adopting a system GMM as against the difference GMM is due to gaps in the data series. The system GMM estimate is considered superior to the difference GMM when there are gaps in data series (Bond et al., 2001) Hence, the orthogonality command was employed since it subtracts the averages of the entire series from its successive values thereby closing gaps in the series. The standard form of a GMM is expressed in normal terms thus:

$$\begin{gathered} BS_{it} = C + \beta BS_{it-1} + \alpha X'_{it} \\ +\lambda Z'_{it} + \left(e_i + \varepsilon_{it}\right), \end{gathered} \qquad (3)$$

where BS_{it} and ε_{it} are the bank stability index/dependent variable and its unexplained components of N x 1 vectors, respectively. BS_{it-1} and $X`_{it}$ are N x K matrixes of the first lag of bank stability and a vector of independent variables, which includes an index of Fintech, respectively. α*'s* is vector K x 1 of unknown parameters. In the GMM estimation technique, given that the first lag of the dependent variable is part of the regressors, the problem of endogeneity becomes inevitable. Hence, another matrix $Z`_{it} = (z_1, \ldots, z_m)$ of instrumental variables of the order $N$ x $M$ is assumed to circumvent the endogeneity problem. Therefore, $M$ must be greater than or equal to $K$ ($M \geq K$), which is the number of groups. Moreover, the Z matrix must be exogenous {i.e. $E(Z` \varepsilon_{it}) = 0$} and it must also be highly correlated with the explanatory variables but orthogonal[1] to the error term. β and λ are also K x 1 vectors of the parameters to be estimated on lagged dependent variables and instrumental variables respectively, and e_i *and* ε_{it} are the countries' fixed effect and the unexplained portion of the dependent variable, hence $\varepsilon_{it} \sim IID\ (0, \sigma_\varepsilon^2)$. However,

1 Orthogonality in this sense means that the Z matrix comprises variables that are not correlated with the residuals.

since the countries' fixed effect does not vary with time, it disappears when the first difference of equation (3) is taken thus:

$$\Delta BS_{it} = C + \beta \Delta BS_{it-1} + \alpha \Delta X_{it}^{'} + \lambda \Delta Z_{it}^{'} + \Delta \mu_{it}. \tag{4}$$

Equation (4) expresses the relative stability of commercial banks in Africa as a function of an arbitrary constant (C), changes in banks' stability level in the previous period, changes in other explanatory variables (including the Fintech index) and changes in instrumental variables and the year dummies. The problem with estimating this model is that of over-identification of instrumental variables such that $M > K$. The solution to this problem is to collapse the endogenous variables in the GMM command window. That is $E_N(Z` \varepsilon_{it})$.

The GMM technique uses two estimators of difference GMM and the System GMM techniques. The latter was employed in this study because of its ability to reduce potential bias and imprecision especially when the model is wrongly specified or there are gaps in the model (Arellano & Bover, 1995; Blundell & Bond, 1998).

2.3.1. Model specification

The empirical model to be employed to achieve the objective of this study is therefore specified in equation (5), which expresses the real variables in the model thus:

$$\Delta BS_{it} = \beta_0 + \beta_1 \Delta BS_{it-1} + \beta_2 \Delta BRA_{it} + \beta_3 \Delta BLL_{it} + \beta_4 \Delta BNII_{it} + \beta_5 \Delta Ftch_{it} + \beta_6 \Delta Ftch_{it}^2 + \beta_7 \Delta GDPG_{it} + \beta_8 \Delta BREG_{it} + \Delta \mu_{it}. \tag{5}$$

The variables, their definitions, and measurements are reported in Table 1.

2.3.2. U-shaped test

Having examined the first-order condition for a nonlinear relationship between Fintech and bank stability with equation (5), its second-order sufficient condition is investigated using the Lind and Mehlum (2010) U-test approach. This is necessary to ascertain whether the relationship is U-shaped or monotonic. Studies like Chen et al. (2022) and Okoli (2020) employed this test to examine the non-linear relationship between Fintech and financial risk and credit risks, respectively. Therefore, to do this, this study first sets the first partial derivative of equation (5) with respect to Fintech overtime equal to zero, i.e.:

$$\frac{\partial BS_{it}}{\partial Ftch_{it}} = \beta_5 + 2\beta_6 Ftch_{it} = 0. \tag{6}$$

The variables remain as defined above and under Table 1. The relationship is confirmed to be U-shaped if at the lower bound of the interval, the relationship is decreasing but increases at the upper bound, otherwise the relationship is to be monotonic. According to Lind and Mehlum (2010), the null and the alternative hypotheses for the test is presented thus:

H_0:

$$(\beta_5 + 2\beta_6 Ftch_{it} lower\ bound) \geq 0) \text{ and/or } (\beta_5 + 2\beta_6 Ftch_{it} upper\ bound) \leq 0. \tag{7}$$

This can be rejected in favor of the alternative hypothesis:

H_1:

$$(\beta_5 + 2\beta_6 Ftch_{it} lower\ bound) < 0) \text{ and/or } (\beta_5 + 2\beta_6 Ftch_{it} upper\ bound) < 0, \tag{8}$$

where $\beta_5 + 2\beta_6 Ftch_{it}$ *lower bound* and $\beta_5 + 2\beta_6 Ftch_{it}$ *upper bound* represent the minimum and maximum values of Fintech changing with time and in relation to bank stability, respectively. The rejection of the null hypothesis confirms the existence of a U-shaped rather than a monotonic relationship between Fintech and bank stability, otherwise a monotonic relationship is implied.

3. RESULTS AND DISCUSSION

The analysis began with the presentation and discussion of the descriptive analysis and the correlation test as presented in Tables 2 and 3, respectively. These are necessary as they reveal the nature, basic characteristics, and degree of connection between bank stability (BS) and its various determinants. First, the descriptive statistics show

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that eight variables were sampled with a total of three hundred and thirty-six observations. The result shows that except for the Fintech index (ftch) which reported a negative median value, the rest of the series had positive mean and median values. This suggests that the variables are increasing over time, which further suggests a non-mean reverting series. Their positive skewness and high kurtosis values (above 3) are an indication that the series is not normally distributed. Moreover, the fact that the probability values of the Jarque-Bera statistics are less than 5 percent for almost all the series (except bank regulation (BREG)) accentuates this fact. Therefore, estimating the model with techniques that allow for normal Z-curve assumptions such as the pooled mean group estimator could be misleading.

Furthermore, high standard deviations, particularly for bank stability (BS), bank liquid liability (BLL), and bank non-interest income to total income (BNII) at 8.11, 18.32, and 8.87 per cents, respectively, imply that banking system among African economies is prone to risks. This is because a high standard deviation is an unconditional measure of risk.

On the other hand, the correlation test as reported in Table 3 is necessary to ensure that the model is free from the problem of multicollinearity. Although there is a high correlation between ftch and ftchsq; however, the adoption of the dynamic system GMM estimation technique helps to circumvent this by taking an orthogonal distribution approach of all the variables (Bond et al., 2001). With an emphasis on the dependent variable BS, the result reveals that both bank-specific and macroeconomic variables were negatively associated with bank stability. While this does not necessarily imply that they impact negatively bank stability, it does signify that they move in the opposite direction ceteris paribus. Furthermore, the correlation result reveals that Fintech and its squared value are positively associated with bank stability, while all other indicators of bank stability are negatively related to it. The implication of this is that the internal structures of banks and macroeconomic variables among African economies are capable of reducing their stability. Further tests were employed to justify this assertion.

Next to the correlation result is the PCA result used to generate an index for Fintech. The result

Table 2. Descriptive statistics

Source: Author's compilation.

	BS	BRA	BLL	BNII	FTCH	FTCHSQ	GDPG	BREG
Mean	17.32676	2.015776	21.81215	37.09154	0.154722	0.167519	3.953654	16.84582
Median	16.10382	1.808288	18.14893	37.33569	–0.250586	0.075192	4.184657	17.01489
Maximum	44.51421	5.197715	115.7186	78.19537	4.549169	1.000000	14.04712	26.97256
Minimum	3.713162	–0.326630	2.088046	10.05221	–1.957168	0.000261	–14.54654	5.472325
Std. Dev.	8.108622	1.019334	18.32063	8.874756	1.552713	0.207395	3.549402	4.252833
Skewness	1.181028	0.431826	1.908568	0.032224	0.757450	1.676443	–1.449608	–0.082487
Kurtosis	4.551243	2.423032	8.004074	4.239275	2.668354	5.348771	8.153581	2.689730
Jarque–Bera	111.7993	15.10302	554.5580	21.55940	33.66877	234.6200	489.5079	1.728773
Probability	0.000000	0.000525	0.000000	0.000021	0.000000	0.000000	0.000000	0.421310
Sum	5821.790	677.3008	7328.882	12462.76	51.98652	56.28624	1328.428	5660.196
Sum Sq. Dev	22026.16	348.0790	112441.3	26385.04	807.6577	14.40918	4220.414	6059.006
Observations	336	336	336	336	336	336	336	336

Table 3. Pairwise correlation result

Source: Author's compilation.

	BS	BRA	BNII	BLR	GDPG	BREG	Ftch	Ftchsq
BS	1.0000							
BRA	–0.1566*	1.0000						
BNII	–0.1440*	–0.0679	1.0000					
BLR	–0.4090*	0.0826	–0.1866*	1.0000				
GDPG	–0.1639*	0.1283*	0.0804	0.0284	1.0000			
BREG	–0.2425*	0.2250*	–0.3085*	0.2395*	–0.0069	1.0000		
Ftch	0.3726*	–0.2582*	0.0338	–0.2783*	–0.3896*	–0.1554*	1.0000	
Ftchsq	0.3112*	–0.2248*	0.1018*	–0.3151*	–0.3589*	–0.1581*	0.9568*	1.0000

Note: * Significance at 5%.

reveals that Fintech adoption among African economies is more susceptible to mobile payment systems[2]. Again, it shows that on average, emerging African economies (South Africa, Morocco, Egypt) reported the highest adoption rate in the recent past, which ranges between 70% to 95%. This suggests that emerging economies might be more prone to Fintech's prospects and problems. The percentage rate of Fintech adoption among other African economies in the study ranges between 21% to 55% on average. This implies that banks in African economies are gradually growing in the adoption of Fintech and diversification to a technology-enabled financial solution. However, this also suggests that African markets are still at their developing stages in Fintech adoption. Consequently, they might not be so much exposed to financial volatilities and risks that are associated with the adoption of Fintech.

Results from the system generalized method of moments (GMM) are presented in Table 4 and Table 4 of this study, each with four unique models. While the short-run variables were presented in Table 4, the long-run results (for only the short-run significant variables) are the focus of Table 4. The first model in Table 4 presents results for only banks' specific variables. Models 2 and 3 focused on including Fintech and macroeconomic variables, respectively, to model 1. In addition to Model 3, Model 4 addressed the roles regulatory quality/institutional development[3] and the non-linear effect of Fintech could have on bank stability.

First, in Model 1, the result reveals that most bank-specific indicators significantly dampen bank stability during the short and long run (Table 5, model 5). The result shows that a unit increase in bank return on assets (BRA) on average and ceteris paribus is associated with 1.715 units and 5.814 units decrease in bank stability (BS) during the short run and long run, respectively, at a one percent significance level. Likewise, a unit increase in bank liquid liability is on average and ceteris paribus associated with 0.048 and 0.163 unit decrease in bank stability during the short run and long run6 respectively, at 5 percent significance levels. Moreover, the study also found that banks' diversification also detracts from their stability levels both during the short and long run. These ambiguous results could be attributed to excessive regulations of banks by the monetary authorities, poor capital base, and poor innovations and technology adoption among banks in the region. Although these findings are consistent with those of Ali and Puah (2019) and Ozili (2018), they observed that the direction of impact depends on the type of banking stability proxy employed by the researcher and on whether the period of study is a pre-crisis, during-crisis or post-crisis period. Bank-specific factors will ultimately detract from their efficiency and stability during financial stress periods (Ozili, 2018). This could worsen especially in regions with sluggish growth, poor institutional quality, and technology adoption (Okoli, 2020).

Models 2 and 3 aim to circumvent the poor technology adoption and the absence of macroeconomic variables by including Fintech and GDPG in Models 2 and 3, respectively. Aside from obtaining a consistent result that bank-specific factors detract from bank stability as in Model 1, results from Model 2 show that adopting Fintech among African banks could worsen the status quo. That is, apart from its (Fintech's) negative significant impact on bank stability at 4.524 units during the short run at a 5 percent significance level, it increased the negative effect of bank-specific variables on stability. However, results from Model 3 suggest that including GDPG can raise bank stability by 22.9 percent ceteris paribus at a 1 percent significance level. Results from Model 3 further found that the inclusion of GDPG in the model reduces the negative impact of bank-specific variables and corrects the negative effect of Fintech adoption. This implies that the impact of Fintech on banks' stability is strengthened by macroeconomic aggregates but it can be weakened by internal factors.

Furthermore, as Fintech significantly weakens bank stability but improves the impact of bank-specific variables (Model 2), it is an indication that Fintech adoption could have a monotonic effect on bank stability. Therefore, this study argues that Fintech's deteriorating effect on bank

2 See Table 1A in the appendix section.

3 Note that institutional development is measure with regulatory quality in this study.

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Table 4. Short-run system GMM results based on equation (3)

Source: Author's compilation.

Variables	Model (1)	Model (2)	Model (3)	Model (4)
	ΔBS	ΔBS	ΔBS	ΔBS
Constant	14.488	13.701	8.150	7.818
	(3.00) ***	(2.70) **	(1.68)	(1.00)
First Lag of Bank Stability (ΔBSit-1)	0.705	0.983	1.033	1.386
	(5.96) ***	(10.14) ***	(11.00) ***	(6.72) ***
Bank Return on Assets (ΔBRA_{it})	–1.715	–2.630	–2.249	–3.247
	(3.56) ***	(2.98) ***	(2.71) **	(3.22) ***
Bank Liquid Liability (ΔBLR_{it})	–0.048	–0.028	–0.002	0.030
	(1.89) *	(1.09)	(0.09)	(0.81)
Bank Non-interest Income ($\Delta BNII_{it}$)	–0.128	–0.157	–0.107	–0.129
	(1.92) *	(2.45) **	(1.73) *	(1.53)
Fintech ($\Delta Ftch_{it}$)		–4.524	–2.322	–22.053
		(2.53) **	(1.18)	(2.69) **
Growth Rate ($\Delta GDPG_{it}$)			0.229	
			(3.55) ***	
Regulatory Quality ($\Delta BREG_{it}$)				0.079
				(0.50)
Fintech^2 (ΔFtch $Squared_{it}$)				14.257
				(2.37) **
Year Dummies	No	No	No	Yes
Observations	363	318	318	307
No of group/Instruments	25/10	22/10	22/13	22/13
AR2	0.786	0.184	0.305	0.217
Sargan Test of Instrument Validity	0.051	0.752	0.737	0.466
Hansen Test of Overid. Restrictions	0.146	0.366	0.764	0.683

Note: Absolute value of t statistics in parentheses. *** significant at 1%; ** significant at 5%; * significant at 10%.

stability during the short run could be attributed to knowledge gaps and adaptive issues usually associated with early technology adoption. However, as people become increasingly aware of Fintech in the long run, its adoption begins to positively affect bank stability. This claim was strengthened by Jugurnath, et al. (2018) who asserted that Fintech adoption, especially among African economies, comes with both problems and prospects. This monotonic/nonlinear relationship between Fintech and bank stability becomes the focus of Model 4. Therefore, empirical evidence based on Model 4 reveals that a U-shape relationship is implied between Fintech and bank stability during the short run. This is because a unit increase in Fintech on average and ceteris paribus detracts from bank stability by 22.053 units but beyond a certain threshold, further adoptions of Fintech improve bank stability by 14.257 units at 5 percent significance levels in the short run. This means that during the short run, adopting Fintech will first worsen a bank's stability; however, beyond a certain threshold, it will significantly improve its stability. This finding is supported by Okoli (2020), who employed the panel ARDL technique to examine the impact of Fintech on credit risk among the BRICS economies. However, findings from Chen et al. (2022) suggest that the relationship is monotonic/inverted U-shaped for the entire period. These inconsistent results necessitated the estimation of its long-run output of the short-run significant variables. Equation (9) is used to estimate the log-run coefficients:

$$Long\text{ - }Run\,Coefficients = \frac{\beta}{1-\delta}, \tag{9}$$

where β's are the short-run parameters and δ is the coefficient of the first lag of the dependent variable (BS_{it-1}). The results as presented in Table 5 reveal that consistent short-run results were obtained during the long run (see Models 5-7). This long-run estimate is supported by empirical evidence (Reed & Zhu, 2017; Saini & Singhania, 2018; Albulescu, 2015). However, Model 8 shows that the relationship is monotonic during the long run rather than a U-shaped relationship found in the

Table 5. Long-run results based on the short-rum system GMM outputs in Models 1-4

Source: Author's compilation.

Variables	Model 5	Model 6	Model 7	Model 8
Constant	49.108	827.750	–249.766	–20.241
	(9.851)***	(4689.454)	(797.196)	(28.182)
First Lag of Bank Stability (BS_{it-1})	2.390	59.416	–31.645	–3.589
	(1.360)*	(354.039)	(88.174)	(1.382)***
Bank Return to Assets (BRA_{it})	–5.814	–158.913	68.932	8.407
	(2.651)**	(927.843)	(198.810)	(4.118)**
Bank Liquid Liability (BLR_{it})	–0.163	NSLS	NSLS	NSLS
	(0.045)***			
Bank Non–interest Income ($BNII_{it}$)	–0.435	–9.510	3.270	NSLS
	(0.169)***	(54.228)	(10.194)	
Fintech ($Ftch_{it}$)	NSLS	–273.312	NSLS	57.098
		(1659.107)		(17.638)***
Growth Rate $GDPG_{it}$)	NSLS	NSLS	–7.007	
			(20.448)	
Fintech^2 (Ftch $Squared_{it}$)	NSLS	NSLS	NSLS	–36.912
				(13.041)***

Note: *** significant at 1%; ** significant at 5%; * significant at 10%. NSLS = No Short-run and Long-run Significance.

short run. That is, a unit increase in the adoption of Fintech will on average and ceteris paribus raise bank stability by 57.098 units but as the adoption level reaches a particular threshold point, further adoption of Fintech among African economies will significantly reduce bank stability by 36.912 units.

This reverse relationship from U-shaped to inverted U-shaped in the long run with higher magnitude suggests that the relationship is a cyclical oscillatory divergent model. This can best be modeled with a polynomial rather than a quadratic function with multiple thresholds.

This assertion is strengthened by the growth pattern of bank stability as presented in Figure 1. Coefficients of the year dummies as obtained in Model 4 were employed to plot the graph of the growth process of bank stability among African economies with particular reference to Fintech adoption. The graph shows that bank stability among African economies ranges between 0.75 and -1.89. The closer the growth pattern is to zero, the better the system's stability. The result shows that African banks were highly unstable/volatile between 2004 and 2009. This was attributed to the negative impact of the global financial crisis. Again, an oscillatory divergent time path was also

Source: Estimation

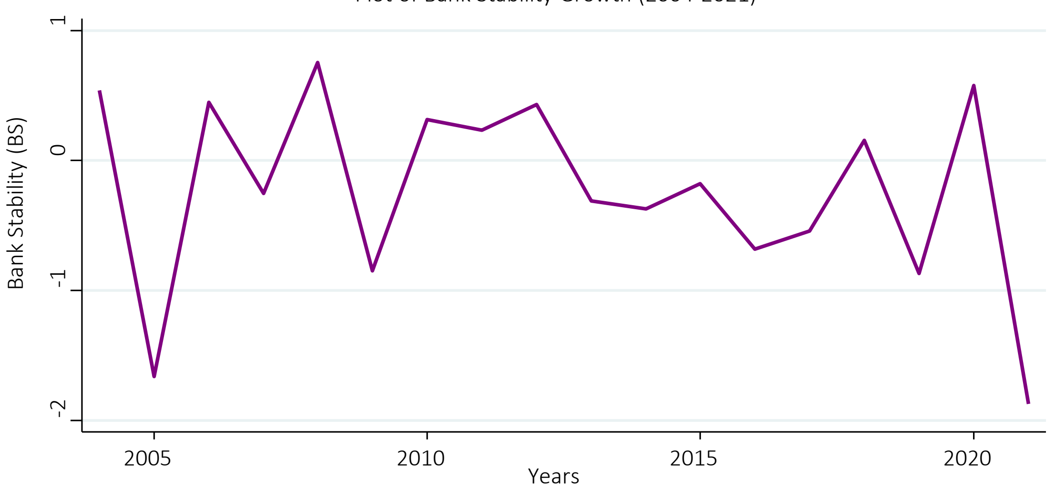

Figure 1. Growth pattern of bank stability among African economies 2004–2021

Table 6. Results of the Lind & Mehlum test for the U-shaped relationship

Source: Author's compilation.

H_0: Monotone or Inverse U shape vs H_1: U shape		
Particulars	**Lower bound**	**Upper bound**
Interval	0	1
Slope	–22.05321	6.46067
t-value	–2.691323	1.458576
P-Value	0.0068351	0.0097387
Overall test of the presence of a U shape: t-value = 1.46 P-Value = .0097 Extreme point: 0.7734202		

implied after the year 2020. This could be attributed to the global lockdown following the outbreak of the COVID-19 pandemic.

Given that a U-shaped relationship was found in the short run, and a monotonic relationship was found in the long run, the Lind and Mehlum (2010) U-test analysis was employed as a second-order sufficient check to either refute or affirm the direction of the relationship. The results from the U-test as presented in Table 6 suggest that we can reject the null hypothesis of monotone and accept the alternative hypothesis of the U-shaped relationship between Fintech and bank stability.

This is because, at the lower bound of the series, the slope of the curve is downward sloping, that is, it is significantly negative, and at the upper bound, it is significantly positive thereby suggesting that Fintech adoption within the financial system among African banks will first worsen the state of art before improving it. Moreover, the results show that on average Fintech adoption will not fall below the 77.3 threshold point before Fintech adoption begins to improve bank stability in Africa.

CONCLUSION

This study explored the dynamic impact of Fintech on bank stability among twenty-six African economies for the period 2004 to 2021. The study is motivated by the controversial debate in the economic literature on the prospects and problems of Fintech, especially as it concerns bank stability in Africa. The study hypothesized that Fintech adoption can deteriorate bank stability in the short run, however, as its adoption grows beyond a certain threshold, it will promote bank stability. The findings show that this hypothesis is true as Fintech first worsens bank stability before improving it. Hence, the study concludes that a short-run U-shaped relationship exists between Fintech and bank stability among African economies. This was confirmed by the second-order U-test. However, the long-run analysis reveals an inconsistent conclusion as the relationship turns out to be monotonic with a greater magnitude of impact. Consequently, the study concludes that the impact of Fintech on bank stability can best be described as an oscillatory/cyclical divergent time path that can threaten future financial crises if not regulated by financial authorities.

With a clear precision to this conclusion, findings from the plot of bank stability over time affirm the cyclical divergent relationship between Fintech and bank stability with the greater explosion between 2007 to 2009 and beyond 2020. The study attributed the high fluctuations within these two periods to the cyclical fluctuations of the 2007/2008 global financial crisis and the economic downturns following the 2020 global shutdown of the COVID-19 pandemic. Further studies can investigate the role of such structural breaks in bank stability in the context of Fintech adoption.

In addition to the cyclical divergent relationship between Fintech and bank stability, results from Models 1 to 3 show that bank internal variables significantly detract from their stability level, while the macroeconomic variable (GDPG) significantly promotes it. This implies that the stability of most

African banks was hindered by poor and incompetent managerial networks within the banking system, whereas external factors/policies can promote it. Moreover, findings based on Model 4 show that institutional quality, a proxy for bank regulatory quality (BREG), could not significantly explain the variations in bank stability among African banks. Therefore, the ability of Fintech to improve or worsen bank stability is not strengthened or weakened by poor institutions. However, the role of institutional quality is dependent on the type of measure for institutional quality employed by the researcher and the model specification (Haldane & Neumann, 2016). Based on the foregoing findings, conclusions, and policy implications, the study recommends bank collaboration with Fintech companies to harness and maintain a consistent and growing impact on their stability and efficiency.

AUTHOR CONTRIBUTIONS

Conceptualization: Tochukwu Okoli.
Data curation: Tochukwu Okoli.
Formal analysis: Tochukwu Okoli.
Funding acquisition: Tochukwu Okoli.
Investigation: Tochukwu Okoli.
Methodology: Tochukwu Okoli.
Project administration: Tochukwu Okoli.
Resources: Tochukwu Okoli.
Software: Tochukwu Okoli.
Supervision: Tochukwu Okoli.
Validation: Tochukwu Okoli.
Visualization: Tochukwu Okoli.
Writing – original draft: Tochukwu Okoli.
Writing – review & editing: Tochukwu Okoli.

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APPENDIX A

Table A1. Results of the principal component analysis for Fintech index

Source: Author's estimation.

Number of obs = 468
Number of comp. = 4; Trace = 4
Rotation: (unrotated = principal); Rho = 1.0000

Principal components/correlation					Principal components (eigenvectors)				
Compt.	E.value	Diff.	Proport.	Cumul.	Variable	Comp1	Comp2	Comp3	Comp4
Comp1	2.39413	1.35418	0.5985	0.5985	ATM	0.5431	0.1822	–0.8022	–0.1681
Comp2	1.03995	0.644653	0.2600	0.8585	INTU	0.5843	–0.1295	0.4977	–0.6278
Comp3	0.395299	0.224684	0.0988	0.9573	ICT	0.0946	0.9558	0.2607	0.0976
Comp4	0.170615	.	0.0427	1.0000	MB	0.5955	–0.1910	0.2019	0.7537