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The Impact of Fintech Risk on Bank Performance in Africa: The PVAR Approach

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Abstract

This paper presents an empirical investigation into the role of Fintech risk, measured by the Fintech Financial Stress Indicator (FFSI), in shaping the dynamic behavior of bank performance by employing a panel vector autoregressive (PVAR) methodology on a dataset comprising 41 banks across 11 African economies over the semi-annual period from June 2004 to December 2020. The findings reveal that bank performance, measured by return on equity (ROE), exhibits a negative and short-lived response to FFSI shock, while the effects on bank stability, cost efficiency, and return on assets (ROA) are statistically insignificant. In addition, an increase in FFSI significantly enhances both ROA and ROE, with negligible impacts on cost efficiency and stability. In contrast, a decline in FFSI has a significant negative effect on ROE and stability but remains insignificant for ROA and cost efficiency. These results indicate that FFSI shocks have asymmetric effects on ROA, cost efficiency, and bank stability but a symmetric effect on ROE. The findings suggest that engagement in financial innovation initiatives may yield performance benefits for banks, provided such strategies are pursued within a sound regulatory framework to mitigate potential excessive risk-taking.

Keywords: Fintech; bank performance; risk management; panel vector autoregressive (PVAR) approach

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1. Introduction

Recent technological innovations in the financial sector are increasingly affecting the provision of financial services through various streams, including but not limited to financial technology (Fintech) startups, an extension of the financial services and products domain, and digital innovation (Basel Committee on Banking Supervision, 2024). While financial innovation is good for banks and customers to enhance process efficiency, financial inclusion, and competition, it also challenges traditional banks. Thus, it has been determined that Fintech startups have increased competition in the banking sector (KPMG, 2022).

The term "Fintech" refers to rapid innovations in financial technology that lead to new models, applications, and products that can tremendously transform financial markets and services (Bu et al., 2023). The development of Fintech has experienced substantial momentum in China, driven by cultural aspects such as a high level of technological adoption, government support, and a rapidly growing Fintech market. It is noted that the United States (US) and the United Kingdom (UK) are characterized by mature financial markets with a robust regulatory framework, and a lot of financial innovation is embedded in the traditional banking system (Xu et al., 2025).

In contrast, Africa has historically lagged in the Fintech sector. However, recent years have witnessed an emergence of Fintech startups reshaping financial services, fostering financial inclusion, and driving economic growth. For example, Kenya has positioned itself as the global Fintech hub, home to 14 Fintech startups, including the iconic M-Pesa, which offers loans, MoMo services, and other microfinance services, followed by Tala, which offers loans to customers using SMS records and transaction histories to assess creditworthiness. Other Fintech companies in Kenya include Branch, Pesapal, Juma, Zoa, Cellulant, Kopo-Kopo, Pezesha, Bit Pesa, Lipa Later, Chipper Cash, Tanda, and Aspira Kenya (Walyaula, 2007). In South Africa, prominent Fintech companies include 22Seven, Bank Zero, and Yoco. In Egypt, Fawry stands out, while in Nigeria, notable companies such as Kuda and Opay are making significant strides. Many of these companies operate within the digital payment space, while others function as neobanks (Okapor, 2023).

The African banking sector is becoming more aware of these players, and a few African commercial banks are now partnering with Fintech startups. For example, the "big four" banks in South Africa are collaborating with Fintech firms to expand into previously underserved markets. Notably, one South African bank teamed up with a payment system targeting the informal market to better understand its unique needs (Timm, 2019). Similarly, an increasing number of Nigerian commercial banks are now collaborating with Fintech startups, highlighting that such partnerships encourage innovation, promote financial inclusion, and strengthen a country's financial system.[1] This strategic shift shows a change in traditional banks' approach—from competing with Fintech companies to actively working with them. By taking stakes in Fintech ventures, traditional banks position themselves to benefit from these innovative companies' success. Like Africa, Latin America is also experiencing a boom in Fintech. For instance, the volume of digital transactions in the country increased from $17 billion to $121 billion between 2017 and 2021, demonstrating a cultural shift from traditional banking to online banking (Xu et al., 2025).

Given Fintech's influence in the provision of financial services and the financial sector, some studies suggest that investment in Fintech may increase banks' performance by enhancing their business processes (Nekesa & Olweny, 2018; Ahmed & Wamugo, 2018). However, other studies suggest that the emergence of Fintech can be perceived as competition, thus deteriorating banks' performance (Jia et al., 2023; Bejar et al., 2022; Liu et al., 2024). It is further noted that banks partnering with Fintech startups to reinforce their Fintech capabilities may face reputational and data breach risks (Basel Committee on Banking Supervision, 2024). Conversely, profitable banks may bolster investment, particularly in Fintech, so that they are not left behind in the Fintech race (Emery et al., 2017). Such banks have investment strategies that consider changes in financial technologies, which, in turn, help them keep up with competitive pressures.

Despite extensive discussions on the relationship between Fintech and banks' performance (Nekesa & Olweny, 2018; Wang et al., 2021; Bejar et al., 2022; Jia et al., 2023; Anarigide et al., 2023; Liu et al., 2024; Benchimol & Bozou, 2024), the results of analyses remain inconsistent due to divergences in research contexts and time periods. One possible cause for this inconsistency may be attributed to discrepancies in banks' performance and Fintech metrics, including failure to account for other variables that may impact financial innovation's effect on banks' performance. In particular, numerous studies in Africa—Nekesa and Olweny (2018), Ahmed and Wamugo (2018), Ashiru et al. (2023) and Mhlongo et al. (2025)—emphasize the adoption of financial technologies while overlooking the associated risks that accompany Fintech adoption. The externalities associated with Fintech adoption have been identified to include systemic risk, operational risk, outsourcing risk, and cyber risk (Khalaf et al., 2023). These risks have been shown to exert adverse effects on banks' performance, particularly within developing economies (Khalaf et al.,

2023). Consequently, drawing on insights from the extant literature, the central research question guiding this study is as follows: *What is the impact of Fintech-related risk on the performance of banks operating in Africa?* In addressing this question, the study identifies three distinct marginal contributions aimed at supplementing the existing literature on banks' performance, competition, and Fintech.

First, unlike previous studies that emphasize the potential benefits of Fintech as measured by the number of mobile money (MoMo) transactions, the number of automated teller machines (ATMs), or new Fintech entrants, this study follows a different approach and develops a multidimensional Fintech Financial Stress Indicator (FFSI) following Bu et al. (2023) guidelines using actual features from African economies. Although existing measures have proven useful, they remain limited in their ability to capture the full complexity of the Fintech landscape. The proposed FFSI measure, by contrast, offers a more comprehensive approach, encompassing the multidimensional aspects of financial innovation-driven vulnerabilities. Additionally, research on Fintech's impact on bank performance remains underdeveloped within the African context (Xu et al., 2025). Given the region's substantial unbanked population, addressing this gap in knowledge is of critical importance for advancing financial inclusion and economic development.

Second, to account for competition in the relationship between bank performance and financial innovation, the study integrates the theory of oligopoly with collusion and a pair of Lotka–Volterra predator–prey models (Stigler, 1964; Berryman, 1992). By modeling the banking market within the theory of oligopoly, the model abstracts away from many factors, and relationships between bank performance and competition, competition and financial innovation, and bank performance and financial innovation are singled out.

Finally, to understand the impact of Fintech risk (measured by FFSI) on bank performance, this paper follows a multiple-equation framework, unlike previous studies that mostly rely on a single-country and single-equation model, which does not account for mutual influences. The multivariate approach helps account for the potential influence of competition in shaping the relationship between bank performance and Fintech while addressing possible endogeneity due to feedback effects. This is particularly important in the current financial landscape, where banks face competitive pressure from the emergence of Fintech startups. Accordingly, the panel vector autoregression (PVAR) model is used, which can also handle challenges associated with cross-country heterogeneity and two-way causality (Canova & Ciccarelli, 2013; Zribi et al., 2024). The study further investigates whether bank performance exhibits symmetric responses to positive and negative FFSI shocks. The rest of the study is organized as follows: the literature review is presented in the next section, followed by the research methodology, data and results, and finally, the conclusion.

2. Literature Review

2.1. Conceptual Framework

Financial innovation theories can be classified under the process innovation theory, adaptive innovation theory, and constrained induced financial innovation theory (Niehans, 1983). Process innovation involves technological breakthroughs or new business processes in delivering a service or product that leads to reduced costs of production and market expansion. Furthermore, the transaction cost innovation theory falls under the process innovation theory, as it identifies technological advancements in providing services in a cost-effective manner (Ahmed & Wamugo, 2018). Adaptive innovation theory is an advancement in bundling basic banking services. Central to adaptive innovation are entrepreneurial responses to changes in market conditions, which may involve a revolutionary development in banking (Niehans, 1983). As part of adaptive innovation, Fintech also has the power

to tremendously transform the banking industry and make it more inclusive through electronic banking channels (Niehans, 1983; Murinde et al., 2022; Ashiru et al., 2023).

Fintech is ultimately an advanced development in financial technology, or the interplay between finance and technology (Murinde et al., 2022). However, as part of innovative financial technologies, Fintech often moves in parallel with market disruption and is inherently accompanied by risk, primarily due to limited regulatory oversight. The absence of adequate supervision may, in turn, exaggerate vulnerabilities within the financial system, potentially leading to broader financial instability (Bu et al., 2023). Moreover, Fintech is more encompassing than broader financial innovations, as it involves innovation outside the banking sector. For instance, Fintech includes non-banking businesses that play into the banking space. These businesses are shadow banks, neobanks, digital banks, crowdfunding, cryptocurrencies, online payment systems, and co-operative financial institutions (CFIs).

In Africa, financial inclusion is reinforced through CFIs, credit unions, or deposit-taking financial institutions. CFIs form part of adaptive financial innovation, as they are entrepreneurial in nature, country-specific, and respond to market failure (Niehans, 1983; Mushonga et al., 2018). Banks often shun providing financial services to small and medium enterprises and marginalized communities, often citing information asymmetry (Mushonga et al., 2018; Zhu & Guo, 2024). In response to this market failure, communities often form CFIs to service the unbanked or markets that the banks cannot reach. However, it is argued that CFIs are highly regulated, which stifles their growth. Consequently, the constraint-induced theory hypothesizes that the high cost of adhering to regulation is central to the innovation of new financial products, thus making banks more profitable (Silber, 1983).

Constraints are not the only source of innovation; competition also stimulates banks to innovate. Competition is best defined as the level of concentration of suppliers in the market. A lack of competition is characterized by a very concentrated market, featuring only a few suppliers. In highly competitive markets, suppliers and consumers are price takers facing infinitely elastic supply and demand functions at given market prices (Mas-Colell et al., 1995). A lack of competition signals market power. The most extreme case of market power is a monopoly, where a supplier notices that demand is less responsive to price changes. In this case, the supplier can increase the price above the competitive price and still make a profit. This case also arises in industries with few suppliers, like oligopolies (Mas-Colell et al., 1995). It is further argued that in an oligopoly market, oligopolists can maximize profits when they collude as monopolists (Stigler, 1964). Collusion is defined as an agreement between suppliers to gain market power and influence trade (Chassang & Ortner, 2023). However, there are costs associated with collusion, such as compromised quality standards and a lack of product innovation (Stigler, 1964).

It is reasonable to posit that the African banking sector exhibits oligopolistic characteristics, given its high level of concentration and documented instances of collusion. Evidence suggests that competition authorities have encountered challenges in addressing anti-competitive and dominant market power abuse practices within the sector. For example, regulatory bodies have investigated allegations of price-fixing among 28 banks involved in manipulating the rand–dollar exchange rate (Petersen, 2019). Such foreign exchange cartels can have significant adverse effects, as their influence extends beyond financial markets, impacting the broader real economy. In addition, the initial capital outlay required to establish a bank is very high in some African countries, promoting bank oligopolies (Browne, 2019). Moreover, African banks are highly profitable with relatively high net interest margins, which signals an oligopolistic market (Mabe & Simo-Kengne, 2023). As a result, oligopolists' use of Stigler (1964) price cut detection model to maximize profit offers an analytical framework to understand the FFSI's impact on bank performance while accounting for competition. Moreover, the adoption of Fintech is accompanied by a

range of risks, including inadequate consumer protection due to data breaches and fraud, regulatory arbitrage, contagion effects, and potential biases embedded in machine learning and artificial intelligence models, all of which may culminate in reputational risk (Oriji et al., 2023). Consequently, any breach of a collusion agreement through product differentiation or Fintech adaptation constitutes a bank's significant risk tolerance. Similarly, the breach of a collusion agreement enables the violating bank to gain a competitive advantage and subsequently capture a larger market share.

Following Stigler (1964) framework, it is assumed that each customer is pre-assigned to a specific bank. Furthermore, it is posited that a commercial bank engaging in product differentiation in violation of the collusion agreement does not actively advertise its differentiated product, either to potential customers or to competing banks. This strategic concealment makes the detection of product differentiation particularly challenging, as the violating bank seeks to avoid exclusion from the collusive arrangement. However, customers who have benefited from the innovative product or service may eventually disclose its existence to other potential customers. Over time, such dissemination of information can prompt competing banks to adopt and offer similar products, thereby diffusing the innovation throughout the market. Ultimately, a bank that breaches the collusion agreement is likely to be detected, as it will attract customers that it would not otherwise have obtained in the absence of its product innovation. The definition of perfect collusion states that no customer changes banks voluntarily; hence, it is necessary to detect secret product innovation.

Secret product innovation detection is investigated using a simple model in which all bank customers and banks are equal, and each customer is assigned to a bank. Secret product innovation may be detected by the behavior of old customers. If there are n_0 old customers, then new customers are represented by $n_n = \delta n_0$. Furthermore, suppose that there are n_s commercial banks. As a result, on average, a bank has $\frac{n_0}{n_s}$ customers and expects to sell $r = \pi.\frac{n_0}{n_s}$ in a given round of transactions, where π is the price, and r revenues.

Consequently, the objective is to construct a model of the bank's customer base. At this stage, this study diverges slightly from Stigler (1964) framework by employing the competitive Lotka–Volterra equations to characterize the dynamics of the evolving bank oligopoly market (Berryman, 1992). It is important to also emphasize that the assumption of a collusion violation still holds, that is, secret product innovation. This study assumes that there are N customers, and the customers are divided into two categories: the first category represents customers who are loyal to banks that adhere to the cartel agreement, denoted by N_c, and the second category represents customers who shift to banks that violate the cartel agreement as a result of product innovation, denoted by N_v. Subsequently, $N = N_c + N_v$. Hence, the number of customers in the oligopolistic bank market with collusion and violators changes over time according to a pair of equations:

$$\frac{dN_c}{dt} = \alpha N_c - \gamma N_c N_v - \rho \alpha N_c \quad (1)$$

$$\frac{dN_v}{dt} = -\omega N_v + \varphi N_v N_c + \rho \alpha N_c \quad (2)$$

The rest of the model's parameters are detailed in Table 1.

Table 1. Model parameters.

Model Parameters	Interpretations and Assumptions
α	The growth rate of cartel customers.
γ	The diminishing rate of cartel customers when they interact with the violator customers.

Table 1. *Cont.*

Model Parameters	Interpretations and Assumptions
ρ	The percentage rate of cartel customers who leave the cartel bank without any interaction with the violating banks' customers. The assumption is that customers who leave banks that conform to the cartel agreement become the violators' customers.
ω	The death rate of the violators' customers or customers who switch to mattress banking.
φ	The growth rate of the violators' customers when they interact with the cartels' customers.

To solve for the equilibrium number of customers who are loyal to banks that violate the collusion agreement through product innovation, the equation is

$$0 = \alpha N_c - \gamma N_c N_v - \rho\alpha N_c \tag{3}$$

$$0 = N_c(\alpha - \gamma N_v - \rho\alpha) \tag{4}$$

$$N_v = \frac{\alpha(1-\rho)}{\gamma} \tag{5}$$

Likewise, the equation to solve for the equilibrium number of customers who are loyal to the collusion agreement yields is

$$\mathbf{0} = -\boldsymbol{\omega N_v} + \boldsymbol{N_c}(\boldsymbol{\varphi N_v} + \boldsymbol{\rho\alpha}) \tag{6}$$

$$\boldsymbol{N_c} = \frac{\boldsymbol{\omega N_v}}{\boldsymbol{\varphi N_v} + \boldsymbol{\rho\alpha}} \tag{7}$$

$$\boldsymbol{N_c} = \frac{\boldsymbol{\omega(1-\rho)}}{\boldsymbol{\varphi}} \tag{8}$$

Further, note that $\boldsymbol{\omega \ll \alpha}$, so as $\boldsymbol{t \to \infty}$, $\boldsymbol{N_c < N_v}$. Consequently, the average number of customers loyal to banks that adhere to the collusion agreement is

$$\tilde{\boldsymbol{N}}_{\boldsymbol{c}} = \frac{\boldsymbol{\omega(1-\rho)}}{\boldsymbol{\varphi n_s}} \tag{9}$$

The average number of customers who are loyal to banks that violate the collusion agreement is

$$\tilde{\boldsymbol{N}}_{\boldsymbol{v}} = \frac{\boldsymbol{\alpha(1-\rho)}}{\boldsymbol{\gamma n_s}} \tag{10}$$

By imposing the probability on the model, it is further assumed that selecting a bank in every round of transactions follows a Bernoulli distribution, so $\boldsymbol{x = 0,1,2,3,\ldots\ldots,n}$. Moreover, success entails selecting a bank that conforms to a collusion agreement, denoted as $\boldsymbol{x}$. Conversely, failure is selecting a bank that violates the collusion agreement. The probability of choosing a bank that honors the collusion agreement in any round of transaction is thus $\boldsymbol{B(x) = \binom{n}{x} p^x (1-p)^{n-x}}$. Hence, the expected number of customers of the banks that collude is

$$\hat{\boldsymbol{N}}_{\boldsymbol{c}} = \frac{\boldsymbol{\omega(1-\rho)}}{\boldsymbol{\varphi n_s}} . \binom{\boldsymbol{n}}{\boldsymbol{x}} \boldsymbol{p^x (1-p)^{n-x}} \tag{11}$$

Likewise, the expected number of customers loyal to banks that violate the collusion agreement is

$$\hat{\boldsymbol{N}}_{\boldsymbol{v}} = \frac{\boldsymbol{\alpha(1-\rho)}}{\boldsymbol{\gamma n_s}} . (\mathbf{1} - \boldsymbol{B(x)}) \tag{12}$$

It is clear that in the limit or equilibrium, the probability of choosing a bank that violates the collusion agreement will increase as more banks violate the collusion agreement. This phenomenon is attributed to banks realizing that they gain a greater market share as they take the risk to innovate. The expected revenue of two categories of banks are $r_c = \pi.\hat{N}_c$ and $r_v = \pi\hat{N}_v$, respectively.

Additionally, if it is assumed that the cost of the violating bank granting banking services (c_v) is less than the cost of the bank that conforms to the collusion agreement (c_c) granting banking services, we have

$$p_c = r_c - c_c \tag{13}$$

$$p_v = r_v - c_v \tag{14}$$

Here, p_c and p_v are the profits of the colluding and violating banks, respectively. Finally, $p_c < p_v$, and it can be predicted that in an oligopolistic market consisting of banks that adhere to the collusion agreement and violators (risk-takers), banks that violate the collusion agreement through product innovation gain greater market share and profit. Several propositions can be made from this statement:

H1. *Bank product innovation (Fintech) negatively affects competition, enabling banks that innovate to gain market power.*

H1a. *Bank product innovation has no effect on competition.*

H2. *FFSI positively affects bank performance.*

H2a. *FFSI has no effect on bank performance.*

H3. *Market power (lack of competition) positively affects bank performance.*

H3a. *Market power has no effect on bank performance.*

H4. *Fintech innovation reduces competition, which, in turn, improves bank performance.*

H4a. *Fintech does not affect competition, consequently having a negligible impact on bank performance.*[2]

To operationalize the theoretical model, bank performance is captured based on return on assets (ROA), return on equity (ROE), cost-to-income ratio (CTI), and stability (Z-score). Fintech is an emerging form of finance, and FFSI is the indicator that signals financial risk.

Competition is denoted by the Boone Indicator (BI), which measures efficiency's impact on performance in terms of profits. It is estimated as the marginal elasticity of profits to cost.[3] The main idea behind the BI is that reduced competition increases banks' efficiency, and the BI is less negative. The more negative the BI, the more competitive the market.[4]

2.2. Empirical Review

Empirical studies have investigated the relationship between financial innovation and bank competition (Bejar et al., 2022; Jia et al., 2023), and the results are mixed. On the one hand, financial innovation has a positive effect on large banks' competitiveness. On the other hand, financial innovation is detrimental to the competitiveness of small banks. The link between competition and bank performance has been widely documented, with the overall conclusion that competition makes banks more efficient (Allen & Gale, 2004;

Andries & Capraru, 2014; Fang et al., 2019; Wang et al., 2021). Moreover, the connection between financial innovation and bank performance has been extensively explored (Nekesa & Olweny, 2018; Ahmed & Wamugo, 2018; Zhao et al., 2022; Kulu et al., 2022; Ashiru et al., 2023; Liu et al., 2024), with the general finding that financial innovation enhances bank performance. A shortcoming of the previous studies is their failure to account for competition in the analysis of financial innovation's impact on bank performance. In contrast, this study attempts to account for competition in assessing the FFSI's impact on bank performance.

Fintech entities, CFIs, and MoMo platforms directly compete with traditional banks, presenting a significant challenge to the banking sector. In addition, these platforms may come with regulatory arbitrage and add to systemic risk (Chipeta & Mapela, 2024). For instance, large technology firms whose primary operations do not center on banking can pose significant regulatory challenges due to the complexity of their business models, often leading to conflicts of interest. These firms, commonly referred to as "Big Tech", are known for exhibiting anti-competitive behaviors, frequently operating under a "winner-takes-all" framework. Such market dominance can lead to substantial systemic risks within the financial sector (Zamil & Lawson, 2022). As a result, nations need to ensure that their regulatory frameworks keep up with Fintech developments to aid consumer protection and minimize risks (Oriji et al., 2023).

The body of research examining Fintech's impact on African banks' performance ultimately remains limited (Xu et al., 2025). Existing studies primarily focus on the process-related effects of Fintech, such as mobile banking, internet banking, and ATMs, ignoring Fintech's competitive and negative externalities on commercial banks' performance in Africa, despite the sector's growing influence in the region's banking landscape. A review of empirical literature that focuses on the relationship between financial innovation and competition follows.

2.2.1. Studies Related to Financial Innovation and Competition

Competition can drive banks that fail to innovate out of business. For instance, the negative relationship between technological advancement and operational efficiency has been investigated. It is predicted that the negative effect of technological advancement on the operational efficiency of small to medium banks operating in Western China is intensified by a high degree of competition, where competition is measured by the Lerner index (Liu et al., 2024). Competition can also be measured by bank profitability, where tight competition in the banking sector is reflected through low margins, whereas a lack of competition is reflected through high net interest rate margins.

Using a sample of 692 banks in Latin America and the Caribbean between 1988 and 2018, Fintech's effect on competition was analyzed using a difference-in-difference approach. It was revealed that banks situated in countries with high Fintech firm entry had low net interest rate margins relative to banks in countries where Fintech firm entry was less prevalent (Bejar et al., 2022). In parallel, the impact of financial innovation on bank competition was investigated for a sample of banks that operate in South Africa, where financial innovation was measured by the volume of MoMo transactions. It was revealed that MoMo transactions significantly reduced market power (Mhlongo et al., 2025).

In another instance, the Quadratic Assignment Procedure was used to study the impact of digital finance on competition for a sample of 16 listed banks in China. It is acknowledged that a consensus on the relationship between financial innovation and competition has not been reached as a result of different measures of competition and financial innovation. Banking competition is measured by a market commonality network, and it has been revealed that digital finance changes the landscape of bank competition.

Digital finance has a positive effect on large banks' level of competitiveness, whereas it increases the competitive pressure for small and medium banks. Overall, digital finance increases the level of competition, which is favorable to consumers in terms of promoting financial inclusiveness and decreasing the price of financial products (Jia et al., 2023).

Using a sample of 46 countries across sub-Saharan Africa for the period between 1978 and 2017, the drivers of financial innovation were investigated. It was revealed that competition, among other factors, has a meaningful impact on stimulating financial innovation. Competition was captured by the BI, whereas the measure of financial innovation constituted ATMs and branchless banking (Anarigide et al., 2023). Competition not only affects financial innovation but also has consequences on bank performance and stability.

2.2.2. Studies Related to Competition and Bank Performance/Stability

The degree of competition, to some extent, can affect the stability of the banking system (Claessens, 2009). It is noted that competition in the banking sector should lead to lower costs and improved efficiency in financial intermediation and product innovation (Berger & Mester, 2003). This notion was established after an examination of a sample of Chinese banks between 2003 and 2017, which revealed that the positive effect of cost efficiency on bank performance is high under high levels of competition (Fang et al., 2019). The competition efficiency hypothesis was also confirmed in a study using a sample of 27 European Union (EU) members between 2004 and 2010, where competition was measured by the H-Statistic. Overall, it was established that an increase in the level of competition improves both cost and profit efficiencies (Andries & Capraru, 2014). However, in some cases, competition has been revealed to have detrimental effects on banking efficiency and thus stability.

For instance, in a model setup, it was predicted that a more competitive market reduces banks' markups, which hampers financial stability (Benchimol & Bozou, 2024). Based on a sample of 48 rural banks operating in China between 2012 and 2018, competition's effect on banks' operating profit was investigated, and competition was indicated by the Lerner index. It was revealed that increased market competition is associated with reduced bank operating profit (Wang et al., 2021). Based on the reviewed literature, the relationship between competition and bank performance thus emerges as ambiguous, with empirical findings yielding conflicting outcomes. Notably, competition has been found to stimulate both performance and financial innovation. Therefore, to ensure a comprehensive analysis, it is imperative to also examine the link between financial innovation and bank performance.

2.2.3. Studies Related to Financial Innovation and Bank Performance

With a sample of 16 commercial banks in Kenya, researchers established that financial innovation factors, such as agency banking, mobile banking, ATM banking, and internet banking, have a meaningful impact on bank performance. The channels through which financial innovation affects banking were found to be increased profitability, reduced costs of banking, increased productivity and efficiency, increased customer outreach, customer relationship management, increased accessibility, and quality of services (Ahmed & Wamugo, 2018). A similar study was carried out, where financial innovation's effect on performance was investigated on a sample of Savings and Credit Co-operative Societies (SACCOS) in Kajiado County, Kenya. Performance was measured by ROA and ROE, whereas financial innovation was constrained to product, process, and organization innovation. Product innovation was proxied by electronic banking, mobile banking, and the introduction of new products. Process innovation was proxied by office automation, the use of real-time gross settlements, and loan tracking systems. Organizational innovation was proxied by

the expansion of institutions and organizational restructuring. The regression analysis revealed a significant positive relationship between all forms of innovation and performance (Nekesa & Olweny, 2018).

A similar outcome was observed with a sample of Nigerian deposit money banks, where performance was measured based on ROA and equity, and financial innovation was proxied by ATMs, point of sales, internet banking, MoMo banking, the National Electronic Fund Transfer (NEFT) system, and instant payment (Ashiru et al., 2023). Using monthly country-level data between 2015 and 2020, MoMo banking's effect on banks' performance in Ghana was studied. A performance index was constructed by principal component analysis, comprising three components, namely private sector credit, ROA, and capital adequacy ratio. The findings revealed that, in the long run, MoMo banking has a negative significant effect on the banking sector's efficiency, whereas it has an insignificant effect on credit extended to the private sector and capital adequacy (Kulu et al., 2022). In a sample of South African banks, performance was measured based on the capital adequacy ratio, and it was established that financial innovation developments, such as MoMo platforms and ATMs, have no significant impact on performance (Mhlongo et al., 2025).

Outside Africa, a dynamic threshold regression analysis was used in studying the relationship between bank performance and financial innovation for a sample of 120 banks operating in China between the years 2003 and 2018. Financial innovation was captured by the development of a Fintech index, which involved enterprise-level data of China's Fintech companies. The Fintech companies were digital banks, online brokerages, online insurance, online fund sales, online asset management, online microfinance, online consumer finance, peer-to-peer (P-2-P) lending, financial information services, crowdfunding, digital currency, financial infrastructure, payments, credit assessment, and credit scoring. To reduce the complexity of the analysis, a Fintech index was constructed out of factors such as total established companies, registered capital, number of financing events, and amount of financing. Performance was captured by capital adequacy, asset quality, earnings power, and liquidity (CAMEL) ratio indicators. It was revealed that Fintech development significantly improved management efficiency, capital protection, and liquidity but reduced asset quality and profitability (Zhao et al., 2022). Using a sample of 130 banks operating in Western China between 2008 and 2021, digital financial development was also deemed detrimental to the banks' operational efficiency (Liu et al., 2024).

Therefore, this study reconciles three strands of prior research by examining competition's role in driving the impact of FFSI on bank performance within a unified theoretical and empirical framework. Accordingly, it seeks to investigate whether and how quickly Fintech development creates competition and risk that may hamper bank stability. Unlike previous studies that mainly focused on Fintech's potential benefits, this study considers the negative externalities of Fintech (FFSI) resulting from a combination of factors from various sources. These sources include Fintech companies, financial institutions, non-bank institutions offering financial services, economic environments, financial environments, science and technology, and network environments (Bu et al., 2023). Thus, the study employs the panel vector autoregression approach to quantify the dynamic responses in banks' performance to changes in the FFSI through the impulse response functions. This approach reviews the transmission mechanism through which FFSI affects bank performance while addressing endogeneity due to feedback effects. In addition, the shock response among the three variables is investigated. The PVAR methodology is particularly well suited for this analysis, as it treats all three variables as endogenous and allows us to study the response of bank performance to shocks in FFSI (Canova & Ciccarelli, 2013). Moreover, the impulse response functions provide a quantitative measure of the temporal dynamics.

3. Methodology

3.1. Fintech Financial Stress Indicator Development

The FFSI is a latent variable; therefore, it requires the use of a proxy indicator to gauge its dynamics. The FFSI serves this role by capturing the multifaceted nature of Fintech-related risks as detailed in Table 2. This study follows the FFSI as proposed by Bu et al. (2023)[5] while tailoring it to the specific characteristics of African economies.

Table 2. Detailed index system of FFSI.

Metric Type	Level 1 Indicators	Secondary Indicators
Fintech companies	Market risk	MoMo growth rate Stoxx Global Fintech volatility Internet use Deposits and loans with credit unions
Banking-financial institutions	Digital operational risk	ATM growth rate Branch growth rate
	Operational risk	Non-performing loan ratio Capital adequacy ratio Provision for loan loss reserves
	Market risk	Liquidity ratio Net interest margin Financial market volatility
Non-banking financial institutions	Securities market cycle risk	Treasury bill rates
Peripheral services	Economic environment	Year-on-year CPI GDP growth rate
Finance	Financial environment	Net loans-to-total deposits of financial institutions
External environment	Technological environment	Secured internet servers R&D growth rate
	Network environment/cyber crime	Crime rate

In the African context, community-based financial intermediaries, or CFIs, play a significant role in promoting financial inclusion. The CFIs are formalized versions of traditional "stokvels", demonstrating a unique model of financial intermediation where members access financing based on their savings behavior as opposed to credit history. As such, the growth rates of loans and deposits within CFIs are utilized as indicators within the FFSI to reflect Fintech-driven financial activities.

Additionally, the proliferation of internet usage is employed as a proxy for public awareness and potential adoption of digital financial services, including P-2-P lending platforms and online banking. MoMo platforms have emerged as a dominant financial service channel in remote regions, allowing unbanked individuals to engage in financial transactions without the need for a conventional bank account.

Furthermore, the growth rate of ATMs is used to measure the extent to which banks are automating services through technological innovations. Similarly, an increase in the number of bank branches also reflects technological adaptation. As digital banking gains traction, banks invest less in physical branches. In sum, the FFSI, as applied to the African setting, integrates various indicators that capture multi-factor aspects of Fintech development, thereby providing a comprehensive measure of Fintech-related financial stress in the region. The rest of the indicators are detailed in Table 2.

The overall FFSI index is computed by principal component analysis (PCA) using all 19 secondary indicators. The notion behind PCA is to construct a variance–covariance matrix (A) out of the indicators and then solve for the eigenvalues so that $\mathbf{det}(A - \lambda I) = 0$.[6] Every estimated λ has an associated eigenvector, v. Then, v remains to be solved so that $(A - \lambda I)v = 0$.[7] The principal component is the eigenvector that is associated with the highest eigenvalue. The highest eigenvalue is the one that explains much of the variation in the data. The eigenvectors are the factor loadings. The factor loadings are then used as the linear combination of the 19 secondary indicators to estimate the FFSI index.

3.1.1. Pretest Requirements

To obtain consistent parameter estimates, the model's variables, which are initially non-stationary, are differenced to achieve stationarity. Moreover, failing to account for potential correlations in regression disturbances over time and across units may result in biased statistical inferences (De Hoyos & Sarafidis, 2006). Consequently, the Pesaran (2004) cross-sectional dependence test is conducted to address this issue.

Cross-Sectional Dependence Test

The cross-sectional dependence test that will be applied is the one proposed by Pesaran (2004). Pesaran (2004) has no substantial measurement error when N is asymptotically large and T is finite. The test is appropriate in the current study where there are 41 banks and 34 time units; that is, $N > T$. The cross-sectional dependence (CD) test is given as

$$CD = \left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)\sqrt{\frac{2T}{N(N-1)}} \tag{15}$$

where $\hat{\rho}_{ij}$ is the estimate of the pairwise correlation of the residuals. Under the null hypothesis of no cross-sectional dependence, $CD \xrightarrow{d} N(0,1)$ for $N \to \infty$ and T is sufficiently large. The CD statistic has a mean at exactly zero for given values of N and T under a variety of panel data models (De Hoyos & Sarafidis, 2006). The step that follows tests the model's variables for unit roots.

Panel Unit Root Test

To ensure that a VAR representation of any vector exists, the assumption of stationarity must be met. Moreover, if the stationarity condition is satisfied, it ensures that the variance of a VAR representation is bounded and greater than zero (Greene, 2002).

The panel unit root test that is followed is the Im–Pesaran–Shin (IPS) unit root test. This unit root test is well suited for heterogeneous panels, making it an appropriate choice for this study, given that the banks operate across different countries (Im et al., 2003). Based on a sample of N cross sections of banks observed over time, it is assumed that the stochastic process, y_{it}, is generated by the first-order autoregressive process:

$$y_{it} = (1 - \theta_i)u_i + \theta_i y_{i,t-1} + \varepsilon_{it}\ i = 1, \ldots\ldots\ldots, N \text{ and } t = 1, \ldots\ldots, T \tag{16}$$

The objective is to test for the null hypothesis of unit roots, that is, $\theta_i = 1$, for all the banks. Alternatively, Equation (16) can be written as[8]

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \varepsilon_{it}. \tag{17}$$

where the null hypothesis of a unit root becomes

$$H_0 : \beta_i = 0 \text{ for all } i.$$

Against the alternatives

$$H_1 : \beta_i < 0, i = 1, 2, \ldots\ldots, N_1 \; i = N_1 + 1, N_1 + 2, \; \ldots\ldots, N.$$

The formulation of the alternative hypothesis allows for the β_i to differ across groups. It further allows for some, but not all, of the individual series to have unit roots. The test statistic is derived for Equation (16) under the assumption that errors are serially uncorrelated and T is fixed. More assumptions are made, and the t-statistics are computed based on the pooled log-likelihood function. Hence,

$$t_{iT} = \frac{\hat{\beta}_{iT}\left(y'_{i,-1} M_\tau y_{i,-1}\right)^{\frac{1}{2}}}{\hat{\sigma}_{iT}} \tag{18}$$

where $\hat{\sigma}^2_{iT} = \frac{\Delta y'_i M_{X_i} \Delta y_i}{T-2}$ and $M_{X_i} = I_T - X_i \left(X'_i X_i\right)^{-1} X'_i$.

The simplified version of the t-statistic is

$$\tilde{t}_{iT} = \frac{\Delta y_i M_\tau y_{i,-1}}{\tilde{\sigma}_{iT}\left(y'_{i,-1} M_\tau y_{i,-1}\right)^{\frac{1}{2}}} \tag{19}$$

Therefore, the average t-statistic is

$$\bar{t}_{NT} = \frac{1}{N} \sum_{i=1}^{N} \tilde{t}_{iT} \tag{20}$$

The test is well suited for our data, as the study is based on a panel of banks that operate across different nations; hence, there is heterogeneity across panels. Once stationarity is achieved, the PVAR model is estimated.

3.1.2. PVAR Model

The structural PVAR model that is estimated is

$$y_{it} = A_0(t) + A_i(l) y_{t-1} + u_{it} \;\; i = 1, \ldots, n, \; t = 1, \ldots\ldots, T \tag{21}$$

where $y_{it} \equiv [P_{it}, C_{it}, F_{it}]^T$ is a stacked three-dimensional vector of endogenous variables, and P_{it}, C_{it}, and F_{it} denote bank performance, competition, and financial innovation for bank i at time t, respectively. Financial innovation is captured by FFSI. Moreover, $A(l)$ is the matrix of coefficients of the lag variables. The model is estimated with one lag. Restrictions are placed on the polynomial coefficients, $A(l)$, to ensure that the polynomial is invertible and the variance of the VAR representation is finite. This ensures the moving average representation of the structural VAR model, which allows one to assess the response of one variable to the shock in the residual of another variable. The error term in Equation (21) can be decomposed into a linear combination of the residuals of the three variables so that

$$u_{i,1t} = b_{11} e_{i,1t} + b_{12} e_{i,2t} + b_{13} e_{i,3t} \tag{22}$$

$$u_{i,2t} = b_{21} e_{i,1t} + b_{22} e_{i,2t} + b_{23} e_{i,3t} \tag{23}$$

$$u_{i,3t} = b_{31} e_{i,1t} + b_{32} e_{i,2t} + b_{33} e_{i,3t} \tag{24}$$

The structural PVAR process allows shocks in the residuals of each variable. Where $u_{i,kt} = (u_{i,1t}, u_{i,2t}, \ldots\ldots.., u_{i,Nt})' \sim iid(0, \Sigma)$ (or zero means white noise process). More-

over, the error terms are unobservable. To model the impacts of $e_{i,1t}$, $e_{i,2t}$, and $e_{i,3t}$ on $P_{i,t}$, $C_{i,t}$, and $F_{i,t}$, the matrix is formed out of Equations (22)–(24) so that

$$\begin{pmatrix} u_{i,1t} \\ u_{i,2t} \\ u_{i,3t} \end{pmatrix} = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} \begin{pmatrix} e_{i,1t} \\ e_{i,2t} \\ e_{i,3t} \end{pmatrix} \tag{25}$$

Alternatively, $U_{i,kt} = Be_{i,kt}$. Central to the identification of structural PVAR is the identity, $\Sigma_u = BB^T$, which is the variance–covariance matrix of a reduced form of residuals given in Equations (22)–(24).

Since the variance–covariance matrix is symmetric, there are six unique equations and nine unknowns. Thus, the model is under-identified, which is the identification problem presented by structural VAR equations. To solve the identification problem, the structural VAR needs to be restricted. The restrictions considered in the study are the Cholesky zero short-run restrictions, which decompose the variance–covariance matrix into a product of the lower triangular matrix and its conjugate transpose.

The assumption behind zero short-run restrictions is that the innovations of the FFSI index have no short-run effects on performance and competition. This assumption aligns with the prevailing technological paradigm, which posits that innovation occurs cumulatively and incrementally rather than instantaneously. Technological advancements, typically built upon prior developments, progress gradually over time. However, in cases of radical innovation, this pattern may not hold, as such innovations introduce unpredictable outcomes that may not be anticipated by industry experts (Werker, 2003). The generalized method of moments (GMM) technique is thus used to estimate the PVAR model.

The primary advantage of the GMM lies in its flexibility, as it does not require the assumption that the data-generating process belongs to a specific family of distributions. Instead, parameter estimation is achieved by aligning sample moments with their corresponding population moments. However, a key challenge associated with GMM is the precise specification of moment conditions, which is crucial for obtaining reliable estimates. To address this issue, Andrews and Lu (2001) propose a moment selection criterion based on the J-statistic. The J-statistic tests for over-identifying restrictions in GMM estimation under the null hypothesis that all moment conditions are correct. Consequently, the J-test statistic based on the model selected by b and the moment selected by c is defined as

$$J_n(b,c) = n\, inf_{\theta_{[b]} \in \Theta_{[b]}} G_{nc}\left(\theta_{[b]}\right)' W_n(b,c) G_{nc}(\theta_b) \tag{26}$$

Here, $(b,c) \in R^p \times R^r$ denote an ordered pair of model and moment selection vectors. By definition, b and c are vectors made up of zeros and ones. If the k^{th} element of b is one, then the k^{th} element of the parameter vector θ is the one to be estimated. If the k^{th} element is zero, then such a parameter is not to be estimated. Likewise, if the j^{th} element of c is one, then the j^{th} moment condition is included in the GMM function specification; otherwise, it is not included if it is zero, where $W_n(b,c)$ is the $|c| \times |c|$ matrix employed with the moments $G_{nc}\left(\theta_{[b]}\right)$ and the model selected by b. It is noted that $W_n(b,c)$ is defined so that it is an optimal weight matrix as $n \to \infty$ when the moments selected by c are correct (Andrews & Lu, 2001). Upon estimating the PVAR model, diagnostic tests are carried out to ensure that the model is stable.

The eigenvalues of the matrix $A(l)$ should lie inside the unit circle for a structural PVAR to be stable or for a dynamic system to have a PVAR representation. Once a model has a stable dynamic process, impulse response functions (IRFs) can be obtained (Stata Corp, 2023). The IRFs measure the response of one variable to the shock in the residuals of another variable in a dynamic system at a given point in time. If there is a response

in one variable to a shock in another variable, we may conclude that the latter variable causes the former (Lütkepohl, 2005). Technically, $A_1^m = B_m$ is the m^{th} coefficient matrix of the moving average (MA) representation of a VAR(1) process. Consequently, the MA coefficient matrices contain the impulse response system. The results can be generalized to a VAR(p) process. Given that $Y_m = A^m Y_0$, the impulse responses are the upper left-hand $K \times K$ block of A^m. The matrix A^m can be shown to be the m^{th} coefficient of the matrix B_m, the MA representation of y_t. Hence, $B_m = JA^m J^T$ with $J = [I_K : 0 \ldots\ldots\ldots\ldots : 0]$, a $(K \times Kp)$ process. In other words, $b_{jk,m}$ is the jk^{th} element of B_m, representing the reaction of the j^{th} variable of the system to a unit shock in variable k, m periods ago. The response variable j to a unit shock in variable k is generally illustrated graphically to get an image representation of dynamic inter-relationships within the system (Lütkepohl, 2005). Moreover, a formal causality test is implemented to identify the causal direction between the variables.

The Granger causality test followed in this study is the one proposed by Dumitrescu and Hurlin (the DH test). This test is suited to this study as the data are macro panels. Macro panels involve large units and time periods where issues of non-stationarity and causality creep in (Lopez & Weber, 2017). The DH test is an extension of the test developed by Granger (1969). Dumitrescu and Hurlin (2012) provide an extension designed to detect causality in panel data, where the regression is given as

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_{ik} y_{i,t-k} + \sum_{k=1}^{K} \beta_{ik} x_{i,t-k} + \varepsilon_{i,t} \text{ with } i = 1, \ldots, N \text{ and } t = 1, \ldots, T \quad (27)$$

where $x_{i,t}$ and $y_{i,t}$ are the observations of two stationary variables for individual units and periods. Causality exists if the past values of x have a significant effect on the current values of y. The null hypothesis is

$$H_0 : \beta_{i1} = \beta_{i2} = \cdots = \beta_{ik} = 0 \text{ for all } i = 1, 2, \ldots, N \quad (28)$$

Which is equivalent to the absence of causality.

The alternative hypothesis is

$$\begin{gathered} H_1 : \beta_{i1} = \beta_{i2} = \cdots = \beta_{ik} = 0 \text{ for all } i = 1, 2, \ldots, N_1 \\ \beta_{i1} \neq 0 \ldots \beta_{ik} \neq 0 \text{ for all } i = N_1 + 1, \ldots, N \end{gathered} \quad (29)$$

Which means there is causality for some individual units, and N_1 is strictly less than N.

To compute the test statistic N, regressions are run as detailed in Equation (27), then the F test is performed on K linear hypothesis to compute individual Wald statistic W_i, and subsequently, the average Wald statistic is computed so that

$$\overline{W} = \frac{1}{N} \sum_{i=1}^{N} W_i \quad (30)$$

4. Empirical Analysis

4.1. Data

Semi-annual data spanning from June 2004 to December 2020 are utilized in the study. This period is selected in part due to the completeness of the data, as many economic datasets prior to 2004 have missing data points. Furthermore, this timeframe includes several notable events that have had a profound impact on the banking sector, like the global financial crisis and the first stage of the COVID-19 pandemic. The analysis focuses on a sample of 41 banks from 11 African economies. These 11 economies include Botswana, Egypt, Ghana, Namibia, Nigeria, Kenya, Uganda, Rwanda, South Africa, Zambia, and Zimbabwe. This sample encompasses both economies that have made substantial investments in financial innovation and those that are transitioning towards making Fintech

investments. The data resources and measurement of the variables are detailed in Table 3. According to Table 4, the data of the variables are clustered around the mean, as indicated by the small standard deviation. However, the data of CTIs and the FFSI are widely spread around the mean. Of particular interest is the FFSI, which is derived by PCA (Bu et al., 2023). The eigenvalue that is associated with the principal component is estimated at 4.724 and explains 22.50% of the variation in the data. The eigenvector of the first component is detailed in Table 5. The factor loadings of the first component are then used to compute the FFSI index. The FFSI index is the linear combination of the factor loadings and the factors. The market and Fintech's volatility is computed in two steps. First, the GARCH (1, 1) model is estimated from S&P Fintech stock returns and financial market returns. Second, the variance from the GARCH (1, 1) model is predicted, followed by estimation of the standard deviation, which is the volatility. The volatility is estimated using daily returns; upon estimating daily volatility, the data are then averaged semi-annually using E-Views 8.

Table 3. Data resources and measurements.

Description	Variable	Source
The ratio of net income to equity	ROE	Thomson Reuters
The ratio of net income to total assets	ROA	Thomson Reuters
Cost-to-income ratio	CTI	Thomson Reuters
The difference between ROA and its mean over the standard deviation of ROA	Z-score	Derived by the author
Fintech Financial Stress Index	FFSI	Derived by the author

Table 4. Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	1394	0.009	0.054	−1.310	0.623
ROE	1394	0.188	0.412	−10.000	1.392
CTI	1394	−2.167	61.257	−1379.000	327.528
Z-score	1394	0.000	0.986	−5.066	4.902
FFSI	1394	0.387	19.072	−26.753	67.461
BI	1394	−0.205	0.366	−2.578	0.240

Table 5. Factor loadings of the principal component.

Factors	Component 1
Loan to deposit ratio	0.3589
Leverage ratio	0.2129
Liquidity (current liability: current assets)	0.2652
Non-performing loans	−0.2713
Net interest margin	0.0741
Tier 1 capital ratio	−0.299
Loan loss reserves	−0.0029
Market volatility	−0.0022
Fin tech volatility	0.0164
Rate of change of MoMo transactions	−0.0833
Rate of change in the number of bank branches	0.2643
Rate of change in the number of ATMs	0.3254
Internet use per 100 individuals	−0.3095
Treasury bill rates	−0.2165
Consumer price index (CPI)	0.2552
GDP	0.2223
Rate of change in the number of secured internet servers	−0.0939
Crime rate	−0.2709
Research and development	0.0219
Deposits in credit unions	0.2308
Loans issued by credit unions	−0.1046

The dynamics of the FFSI risk index are illustrated in Figure 1. The correlation matrix is detailed in Table 6 to assess the degree of association. Moreover, in Figure 2, a regression line is fitted on the scatter plots to assess the degree of linear relationship between performance and FFSIs. Similarly, a regression line is fitted to assess the degree of linear relationship between competition and FFSIs, as illustrated in Figure 3. Panel data techniques remain to be used for meaningful analysis.

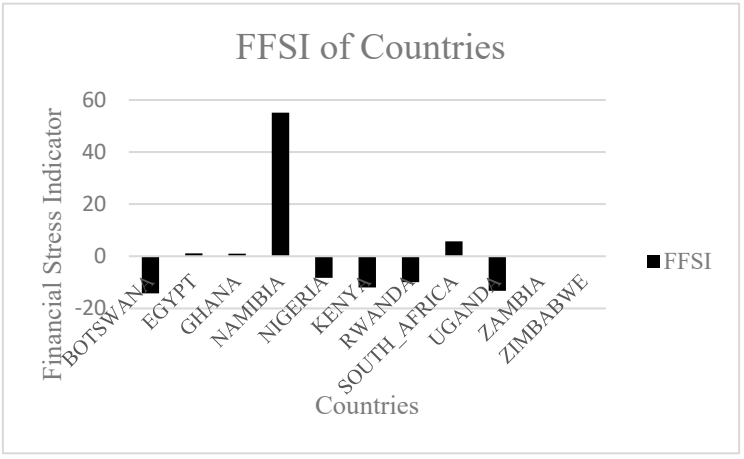


Figure 1. Average FFSI. Note: PCA is used to compute the FFSI. Namibia has the highest FFSI. Overall, countries with many banks tend to have the smallest FFSI, as positive and negative FFSIs cancel each other out. Namibia is characterized by a few banks that contribute positively to FFSI; thus, the FFSI is high.

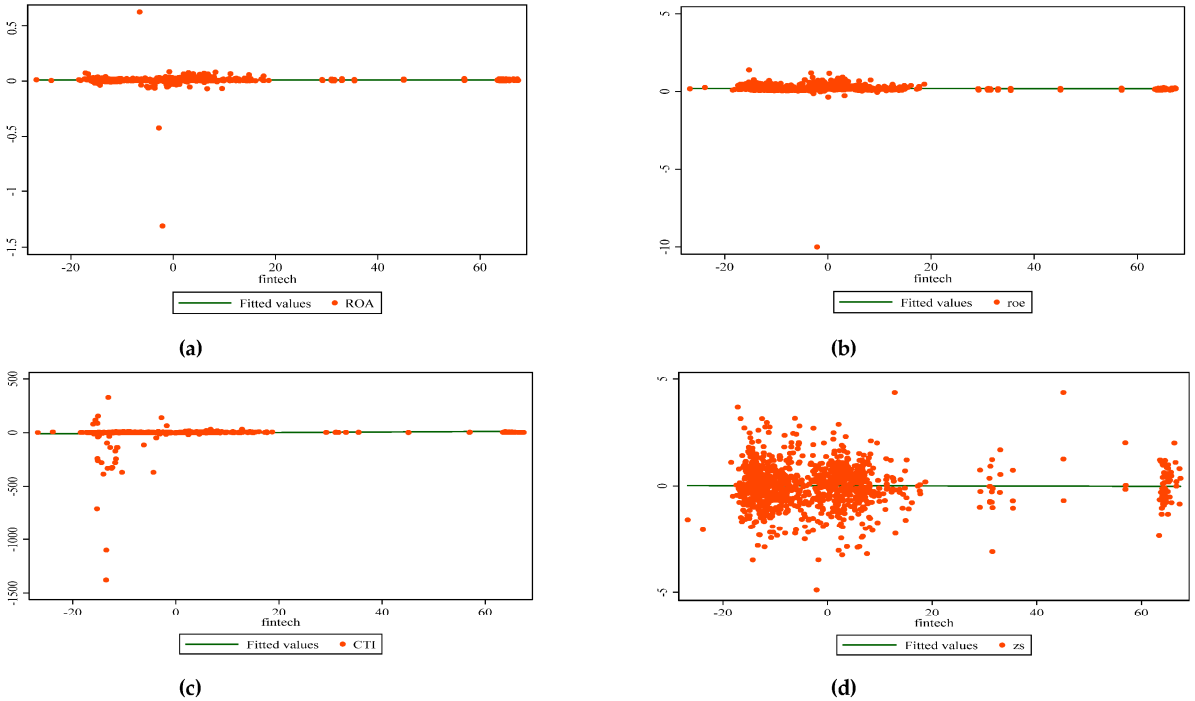


Figure 2. The linear relationship between performance metrics and FFSI across countries. (**a**) ROA vs. FFSI; (**b**) ROE vs. FFSI; (**c**) CTI vs. FFSI; (**d**) Z-score vs. FFSI. Note: The linear relationship between all the performance metrics and FFSI is less obvious, as scatter plots are clustered around zero with a flat fitted line. However, a robust panel statistical analysis should be undertaken.

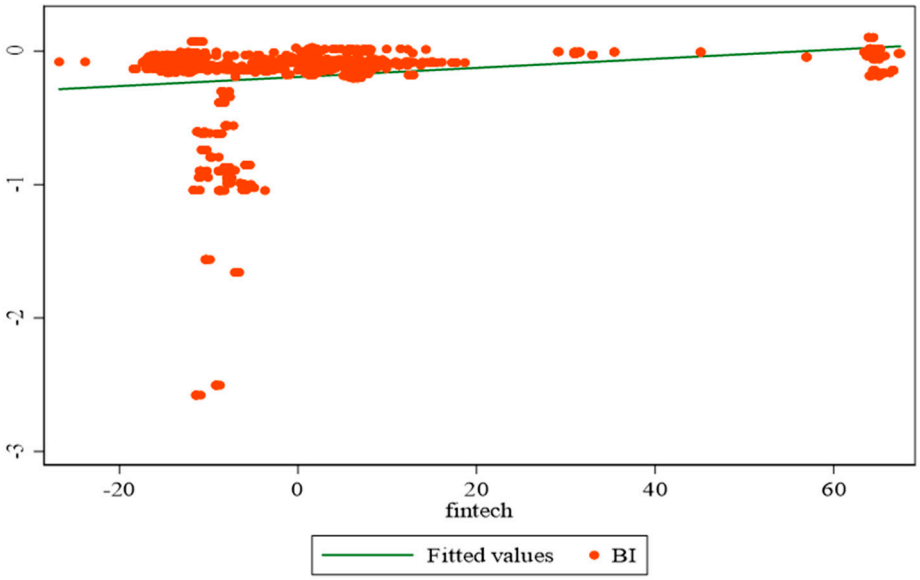


Figure 3. The linear relationship between competition (BI) and FFSI. Note: There is a slight positive relationship between FFSI and BI, indicating that when banks take on more FFSIs, they can neutralize competition.

Table 6. Correlation matrix.

	ROA	ROE	CTI	Z-Score	FFSI	BI
ROA	1.000					
ROE	0.8165 *	1.000				
CTI	0.019	−0.012	1.000			
Z-score	0.3214 *	0.2259 *	−0.039	1.000		
FFSI	0.003	−0.011	0.0704 *	−0.008	1.000	
BI	0.018	0.0713 *	−0.036	−0.006	0.1910 *	1.000

Note. * <less than 10% level of significance.

The panel data used in this paper may come with the problem of cross-sectional dependence (De Hoyos & Sarafidis, 2006; Dong et al., 2024). Therefore, a cross-sectional dependence test is performed according to Pesaran (2004); the results of the cross-sectional dependence test are shown in Table 7. According to the results for all variables, the null hypothesis is significantly rejected, indicating the existence of cross-sectional dependence in the data. Consequently, the unit root test is performed (Bu et al., 2023). Furthermore, due to the presence of dependence across different units, the variables are demeaned when conducting the unit root tests. The results are shown in Table 8, and all the variables are stationary at level.

Table 7. Cross-sectional dependence test.

Models	Pesaran Test Statistic	Probability
ROA	3.535 ***	0.0004
ROE	3.973 ***	0.0001
CTI	9.649 ***	0.0000
Z-Score	3.135 ***	0.0017
BI	21.212 ***	0.0000

Note. *** <1% level of significance.

Table 8. Panel Im–Pesaran–Shin test for unit roots.

Variables	Statistics	*p*-Value	Order of Integration
ROA	−21.65 ***	0.0000	I(0)
ROE	−17.037 ***	0.0000	I(0)
CTI	−22.29 ***	0.0000	I(0)
Z-score	−12.11 ***	0.0000	I(0)
FFSI	−10.03 ***	0.0300	I(0)
BI	−9.71 ***	0.0000	I(0)

Note: *** <less than 1% level of significance.

4.2. Results and Discussion

As previously mentioned, the IRFs measure the response of one variable to the shock in the residuals of another variable in a dynamic system at a given point in time. Thus, they can be used to assess the spillover effects of FFSI on bank performance (Simo-Kengne et al., 2013). Moreover, panel VAR models have been widely used to study relationships among various economic variables and transmission mechanisms (Zribi et al., 2024). The estimated panel VAR models (Tables A1–A3) are used to construct IRFs.[9] Overall, FFSI has a negative effect on performance, albeit insignificant, and the results are consistent across all performance measures. According to Table A1 in Appendix A, aggregate FFSI has a significant negative effect on ROE, and the results are consistent with the findings of Zhao et al. (2022), where financial innovation had negative profitability outcomes in a sample of banks that operate in China. Our results refute a portion of the African literature claiming financial innovation has positive effects on performance. However, the shortcoming of these studies is that they assumed that financial innovation is one-dimensional. The findings lend support to the notion that Fintech may not always yield profitable outcomes (Xu et al., 2025). It is argued that unfavorable outcomes may be attributed to organizational adaptability, social disparity, and gender diversity (Shehadeh et al., 2024). The results indicate that the relationship between financial innovation and bank performance is somewhat more complex than we think, warranting deeper analysis (Shehadeh et al., 2024).

However, a positive shock in FFSI has a positive and significant effect on ROA and ROE at the conventional level of significance (Nekesa & Olweny, 2018; Ahmed & Wamugo, 2018; Ashiru et al., 2023). This pattern aligns with our main research hypothesis (H4), which posits that as banks take on more FFSI, they are able to bolster performance by driving competition out of the market. The results further solidify the notion that the benefits associated with Fintech substantially outweigh its potential risks (Oriji et al., 2023). Moreover, an increase in FFSI has a negative effect on BI, indicating that FFSI makes the banking market more competitive, although the impact is insignificant. Conversely, a decline in FFSI has a significant positive effect on BI, indicating that competition is neutralized when there are fewer Fintech players. The findings are also in line with the observation that banks in the selected African countries are increasingly forming strategic partnerships with Fintech firms to enhance their technological capabilities, thereby enabling them to consolidate market power. In addition, a negative shock in FFSI has a negative effect on performance, supporting the notion that banks will be left behind if they do not take on Fintech investment initiatives (Zhao et al., 2022; Liu et al., 2024).

Nonetheless, the results confirm that the emergence of Fintech startups poses a challenge for the banking sector. As mentioned earlier, competition is measured by the BI, which measures the level of market concentration. The higher the BI, the higher the market concentration. Market concentration is inversely related to competition; when the market is concentrated with few banks, it is less competitive. Consequently, and consistent with

our H1, a positive response in the BI to negative FFSI implies that, as banks take on more Fintech-related risk, they are able to capture their competitors' market.

The performance metrics and competition responses to aggregate FFSI shock are displayed in Figure 4. In Figure 4b, we observe that an aggregate FFSI shock of one standard deviation results in an initial ROE decline by 0.03%, staying significant for about 2.5 years, and gradually reverting to the baseline over 10 years. This observation aligns with the findings of Kulu et al. (2022), who reported that a rise in MoMo transactions adversely affected traditional bank performance. Moreover, their results underscore the presence of externalities associated with Fintech-related risks, including insufficient consumer protection due to regulatory shortcomings and increased vulnerability to data breaches. These challenges may contribute to stakeholder hesitancy in adopting financial innovation technologies, particularly within the studied African regions. Consequently, it is imperative that governments collaborate closely with financial institutions, Fintech firms, and legal entities to develop and implement robust regulatory frameworks aimed at enhancing consumer protection and safeguarding institutional integrity. Striking an appropriate balance between fostering financial innovation and ensuring customer protection is essential for realizing the full potential of Fintech in these contexts.

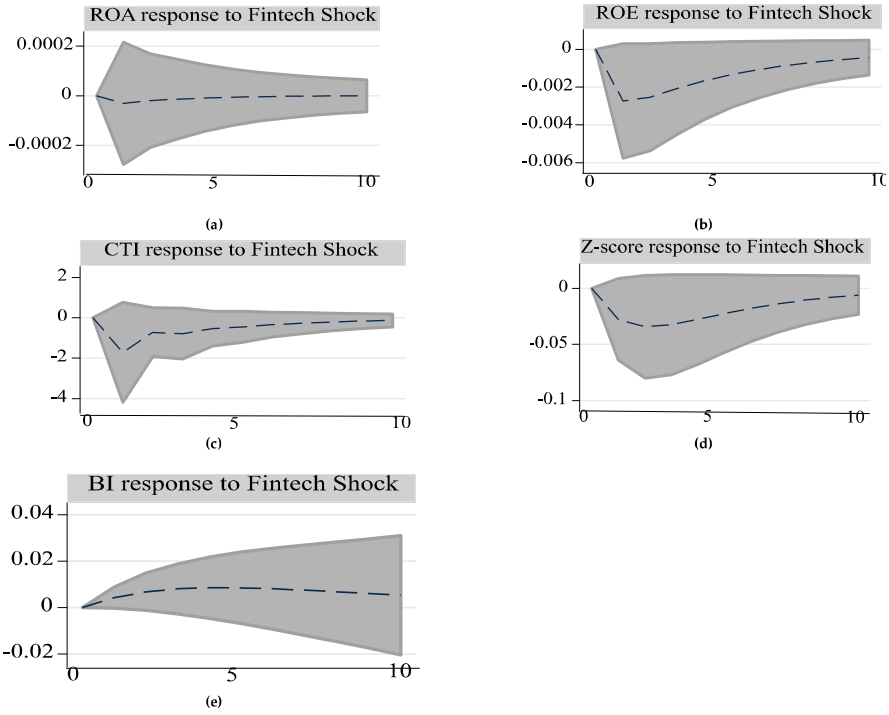


Figure 4. Impulse responses to orthogonalized one-unit FFSI shock. (**a**) ROA response to FFSI shock; (**b**) ROE response to FFSI shock; (**c**) CTI response to FFSI shock; (**d**) Z-score response to FFSI shock; (**e**) market power response to FFSI shock. Note: Dotted lines show the impulse response of a specific variable following an FFSI shock. The shaded area represents a 95% confidence band generated by 200 Monte Carlo replications.

Likewise, in Figure 4d, a joint FFSI shock leads to a 0.3% decline in financial stability (Z-score), remaining significant for a short while and reducing to zero after three years. This pattern aligns with the emergence of competitive Fintech technologies such as MoMo and P-2-P lending platforms that may erode traditional banking markets, which, in turn, hamper banking profits and stability. The findings are consistent with Allen and Gale (2004) conclusion that competition is good for banking efficiency but bad for financial stability. In Figure 4e, a delayed positive response to competition takes place following the FFSI

shock, peaks after three years, and subsides to zero over a 10-year period. Surprisingly, in Figure 4a, ROA does not respond to an FFSI shock, consistent with the findings of Mhlongo et al. (2025). Market power (BI) responds positively to a shock in FFSI. This result is consistent with H1, which posits that when banks take on more risk through financial innovation, they are in a better position to gain market power.

4.2.1. Asymmetric Effects of FFSI on Bank Performance

In Figure 4a, an increase in FFSI has a positive and significant effect on ROA, whereas an FFSI deceleration is not significant, confirming that FFSI changes exhibit an asymmetric effect on ROA. Likewise, the FFSI's effect on the Z-score, or bank stability, is asymmetric, with the positive FFSI shock exerting an insignificant positive effect on stability, whereas the negative shock exerts a significant negative effect. The negative response to the decrease in FFSI dies out after 2.5 years, suggesting that decreases in technological development affect bank stability in the short term.

In Figure 5b, the ROE response to positive shocks in FFSI is positive and significant. This indicates that Fintech projects are profitable, consequently improving equity. Likewise, in Figure 6b, ROE responds negatively to a negative shock in FFSI, establishing FFSI's symmetric effect on ROE. The evidence lends support to H4, where it is conjectured that when banks take on risk in the form of Fintech investments, they gain market power, in turn increasing performance.

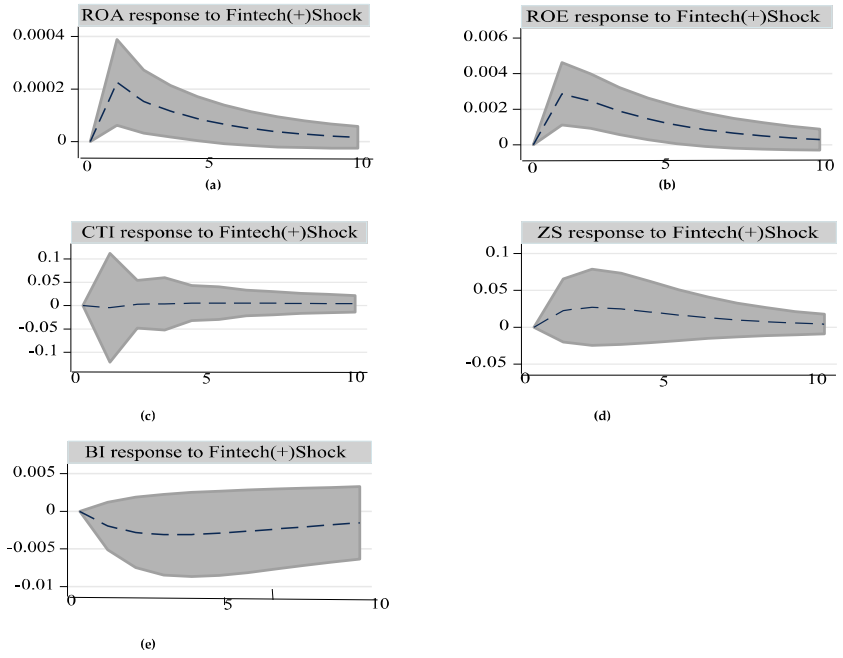


Figure 5. Impulse responses to orthogonalized one-unit positive FFSI shock. (**a**) ROA response to positive FFSI shock; (**b**) ROE response to positive FFSI shock; (**c**) CTI response to positive FFSI shock; (**d**) Z-score response to positive FFSI shock; (**e**) market power response to positive FFSI shock. Note: Dotted lines show the impulse response of a specific variable following an FFSI shock. The shaded area represents a 95% confidence band generated by 200 Monte Carlo replications.

CTI does not respond to a positive FFSI shock, but the response to a negative shock is negative and short-lived. This indicates that the benefits that come with Fintech projects far outweigh their costs. This is a clear indication that Fintech projects have a positive net present value, subsequently enhancing banks' equity (Emery et al., 2017). Moreover, the results are in part owed to the process innovation theory, which posits that technological breakthroughs in banking service provision minimize business costs (Niehans, 1983). In

Figure 6e, a negative shock in FFSI increases market power, whereas in Figure 5e, an increase in FFSI reduces market power. This indicates that when non-banking firms play into the banking space, it reduces banks' market power.

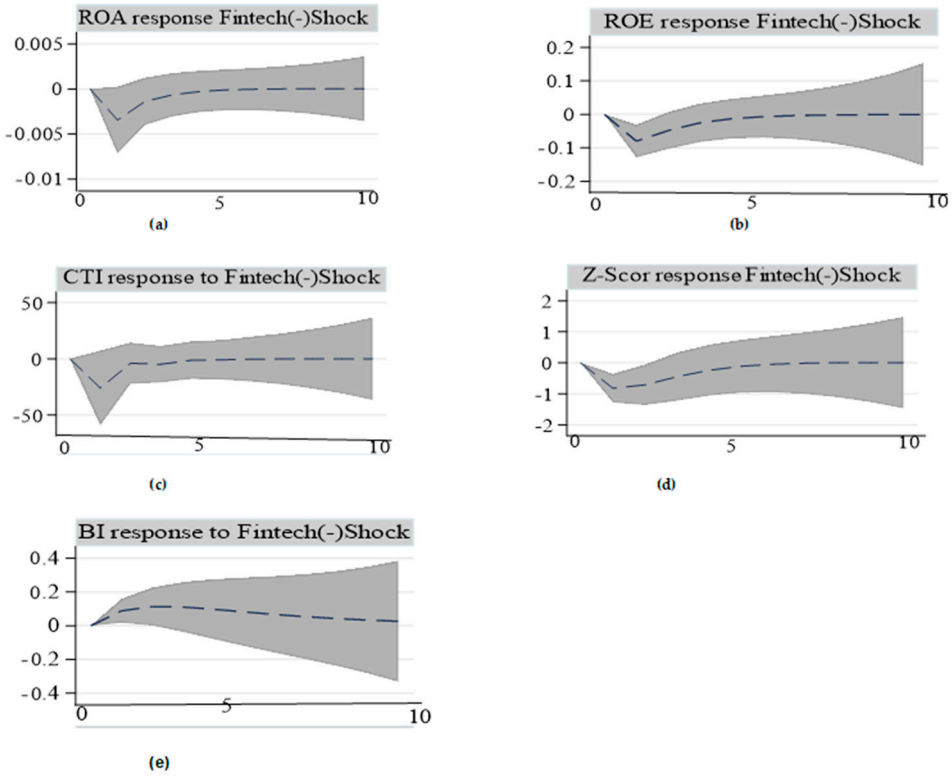


Figure 6. Impulse responses to orthogonalized one-unit positive FFSI shock. (**a**) ROA response to a negative FFSI shock; (**b**) ROE response to a negative FFSI shock; (**c**) CTI response to a negative FFSI shock; (**d**) Z-score response to a negative FFSI shock; (**e**) market power response to a negative FFSI shock. Note: Dotted lines show the impulse response of a specific variable following an FFSI shock. The shaded area represents a 95% confidence band generated by 200 Monte Carlo replications.

Overall, disaggregating FFSI shock into its positive and negative components leads to further insights that aggregate shock cannot uncover. Finally, it is important to note that the constructed FFSI measure is multidimensional in nature, capturing both the negative and positive aspects of Fintech. The evidence suggests that banks' investments in financial innovation technologies serve as a strategic response to mitigate the adverse effects associated with Fintech developments, including heightened competitive pressures.

For the sake of completeness, the PVAR model is also estimated for the period encompassing the global financial crisis. The results indicate that none of the bank performance measures exhibited a significant response to shocks in FFSI during this period, with the exception of the Z-score. Specifically, the Z-score responded positively and significantly to a negative shock in FFSI, suggesting that a sudden decline in technological advancement heightened return variability during the crisis period. Furthermore, a positive and aggregated shock to FFSI was found to enhance market power during the global financial crisis, whereas market power does not exhibit a significant response to negative Fintech shocks within the same period.[10]

4.2.2. Diagnostic Tests: Stability of the Panel VAR Model

It is crucial to assess the stability of the panel VAR model. The panel VAR must have an infinite-order moving average representation and be invertible in order to meet the stability condition. The stability of the panel VAR is established using the modulus of

each estimated model eigenvalue. The model is said to be stable if each modulus in the companion matrices is strictly less than one (Lütkepohl, 2005). The graphs in Figure 7 illustrate that the estimated panel VAR models are stable, as every eigenvalue modulus is strictly less than one.[11]

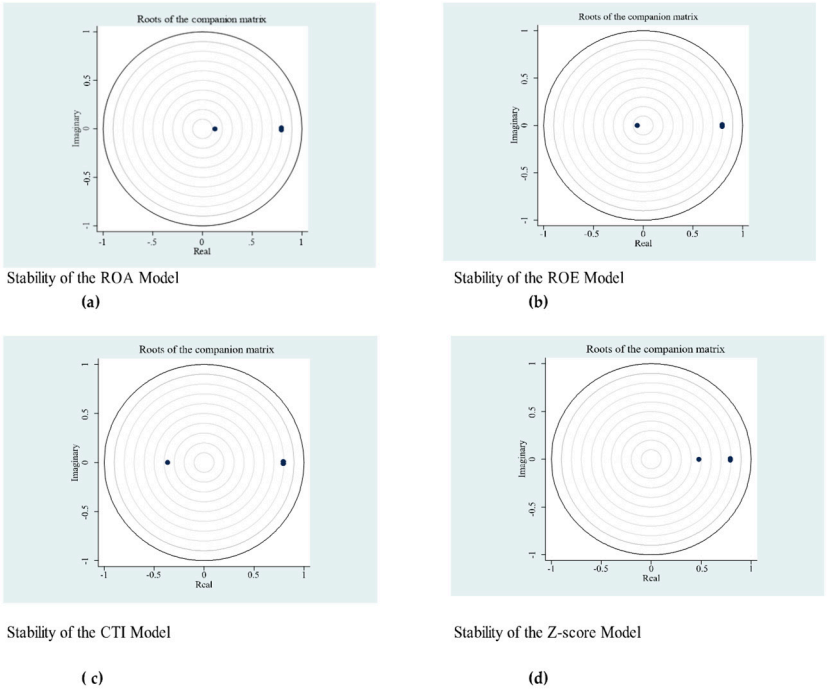


Figure 7. Stability of the performance metrics models for FFSI shock. (**a**–**d**) The roots of the characteristic equation lie inside a unit circle, which indicates that the models are stable. Furthermore, the dots represent the eigenvalues, since the model has three variables and one lag, there are three (3×1) roots. If the model had two lags, there would have been six roots (3×2) or six dots inside a unit circle.

4.2.3. Robustness Check: Granger Non-Causality Test

As reported in Table 9, the results indicate that aggregate FFSI significantly predict variations in ROE and market competition. These findings support H2, which posits that FFSI exerts a positive influence on bank performance. Similarly, the observed relationship between Fintech and competition is consistent with H1, which suggests that financial innovation contributes to the diffusion of competitive pressures within the banking sector. The results are consistent with the notion that banks can use their vast resources to acquire Fintech companies and outstrip them (Bejar et al., 2022). Furthermore, in the CTI model, competition is found to be a significant predictor of cost-to-income ratios. Positive shocks to FFSIs are also found to be predictive of ROA and ROE, while negative shocks explain variations in both performance and competition indicators. Notably, reverse causality is not supported in any of the models estimated—whether for aggregate, positive, or negative Fintech shocks—implying that neither competition nor performance metrics Granger-cause FFSI. Additionally, aggregate FFSI does not explain much of the variation in ROA, CTI, and Z-scores. The results support evidence from Mhlongo et al. (2025) study, likely attributed to some Fintech developments not yet having filtered through some bank performance measures. CTI's lack of sensitivity to changes in FFSI indicates that the benefits of Fintech far outweigh its cost.

Table 9. DH Granger non-causality test.

ROA		**ROE**		**CTI**		**Z-Score**	
Hypothesis		Hypothesis		Hypothesis		Hypothesis	
BI ⇏ ROA	0.074	BI ⇏ ROE	1.65	BI ⇏ CTI	3.37 *	BI ⇏ Z-score	0.302
Fintech ⇏ ROA	0.051	Fintech ⇏ ROE	3.537 *	Fintech ⇏ CTI	2.118	Fintech ⇏ Z-score	1.729
ROA ⇏ BI	0.416	ROE ⇏ BI	0.733	CTI ⇏ BI	0.035	Z-score ⇏ BI	0.133
Fintech ⇏ BI	3.44 *	Fintech ⇏ BI	3.389 *	Fintech ⇏ BI	3.427	Fintech ⇏ BI	3.427 *
ROA ⇏ Fintech	0.089	ROE ⇏ Fintech	0.201	CTI ⇏ Fintech	0.165	Z-score ⇏ Fintech	0.512
BI ⇏ Fintech	0.93	BI ⇏ Fintech	0.916	BI ⇏ Fintech	0.932	BI ⇏ Fintech	1.23
Positive Fintech		Positive Fintech		Positive Fintech		Positive Fintech	
BI ⇏ ROA	0.009	BI ⇏ ROE	2.497	BI ⇏ CTI	1.936	BI ⇏ Z-score	0.002
Fintech ⇏ ROA	6.394 ***	Fintech ⇏ ROE	9.542 **	Fintech ⇏ CTI	0.006	Fintech ⇏ Z-score	1.255
ROA ⇏ BI	0.068	ROE ⇏ BI	1.049	CTI ⇏ BI	0.338	Z-score ⇏ BI	1.515
Fintech ⇏ BI	1.074	Fintech ⇏ BI	1.041	Fintech ⇏ BI	1.075	Fintech ⇏ BI	1.522
ROA ⇏ Fintech	1.507	ROE ⇏ Fintech	1.661	CTI ⇏ Fintech	2.165	Z-score ⇏ Fintech	0.042
BI ⇏ Fintech	0.215	BI ⇏ Fintech	0.292	BI ⇏ Fintech	0.243	BI ⇏ Fintech	0.042
Negative Fintech		Negative Fintech		Negative Fintech		Negative Fintech	
BI ⇏ ROA	0.082	BI ⇏ ROE	3.367 *	BI ⇏ CTI	1.578	BI ⇏ Z-score	0.639
Fintech ⇏ ROA	3.527 *	Fintech ⇏ ROE	10.664 **	Fintech ⇏ CTI	2.038	Fintech ⇏ Z-score	11.297 ***
ROA ⇏ BI	0.378	ROE ⇏ BI	1.195	CTI ⇏ BI	1.386	Z-score ⇏ BI	3.367 *
Fintech ⇏ BI	6.262 ***	Fintech ⇏ BI	6.271 **	Fintech ⇏ BI	6.28 **	Fintech ⇏ BI	6.591 ***
ROA ⇏ Fintech	0.24	ROE ⇏ Fintech	0.105	CTI ⇏ Fintech	0.041	Z-score ⇏ Fintech	0.113
BI ⇏ Fintech	1.193	BI ⇏ Fintech	1.25	BI ⇏ Fintech	1.235	BI ⇏ Fintech	1.174

* <10% level of significance, ** <5% level of significance, and *** <1% level of significance.

5. Conclusions

This study employs a PVAR approach using bank-level data from 11 African economies over a semi-annual period spanning 2004 to 2020. The analysis reveals that Fintech-related risk exerts a marginal influence on various bank performance indicators across the countries included in the study. However, when decomposing the aggregate FFSI shock into its positive and negative components, the results indicate that positive Fintech shocks are associated with improvements in ROA, ROE, and bank stability (Z-score), with asymmetric effects observed particularly on ROA and Z-scores. This suggests that disaggregating FFSI

shocks provides deeper insight, as the aggregated measure may obscure the complex effects on the response variables.

Furthermore, the findings imply that for the sampled countries, the benefits of financial innovation outweigh the associated investment costs. Specifically, Fintech-related financial risk shocks appear to have minimal discernible effects on the CTI ratio, suggesting that Fintech investments do not substantially compromise operational efficiency. Consequently, the study supports the broader inference that banks operating in selected African markets should actively pursue technological advancements by partnering with Fintech companies.

The FFSI indicator utilized in this study is comprehensive, capturing bank-specific, social, economic, financial, and global dimensions pertinent to the African context. The evidence also underscores the importance of financial innovation for fostering competition, enabling market expansion, and contributing to financial stability. These results align with the study's H4 regarding Fintech's positive role in enhancing bank performance and resilience through competition, despite the negative Fintech externalities.

In light of these findings, it is recommended that banks adopt a proactive stance toward Fintech adoption, capitalizing on the benefits such technologies offer. At the same time, to ensure regulatory compliance and mitigate potential risks, banks should implement robust oversight mechanisms for their Fintech partnerships. This includes establishing dedicated teams of process engineers tasked with ensuring adherence to regulatory frameworks, both within the banks themselves and among their Fintech collaborators. Government and legal institutions should also come on board to ensure that Fintech developments do not outpace the regulatory framework.

Furthermore, the study's findings hold practical relevance for investors, policymakers, and broader society. For the investment community, it is established that investments in technological advancements may enhance financial performance and market position. For policymakers, it is suggested that governments, legal and financial institutions, and Fintech companies join hands to formulate a robust regulatory framework that balances innovation with consumer protection and institutional integrity. From a societal perspective, the results also imply that Fintech stimulates competition within the banking sector, thereby contributing to improved financial inclusion. Future research could focus on alternative methodologies and financial innovation policy formulation. A key limitation of the present study lies in the constrained sample size, which may affect the generalizability of the findings.

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Appendix A

Table A1. Dynamic panel VAR results of joint FFSI shock.

	Bank Performance Metrics			
	GMM Estimates			
	ROA	**ROE**	**CTI**	**Z-Score**
ROA (t − 1)	−0.0601			
	(0.106)			
Fintech (t − 1)	−0.00000784	−0.000709 *	−0.446	−0.00715
	(0.0000346)	(0.000377)	(0.306)	(0.00544)
BI (t − 1)	0.000510	−0.0150	−2.803 *	0.0799
	(0.00188)	(0.0117)	(1.527)	(0.146)
ROE (t − 1)		0.125		
		(0.106)		
CTI (t − 1)			−0.365 **	
			(0.183)	
Z-Score (t − 1)				0.473 ***
				(0.0425)
	GMM Estimates			
	Competition			
ROA (t − 1)	−0.0388			
	(0.0601)			
Fintech (t − 1)	0.00111 *	0.00110 *	0.00111 *	0.00113 *
	(0.000599)	(0.000598)	(0.000599)	(0.000609)
BI (t − 1)	0.809 ***	0.809 ***	0.809 ***	0.809 ***
	(0.124)	(0.124)	(0.124)	(0.123)
ROE (t − 1)		−0.0147		
		(0.0172)		
CTI (t − 1)			−0.00000172	
			(0.00000921)	
Z-Score (t − 1)				0.00242
				(0.00664)
N	1312	1312	1312	1312

Notes: The panel VAR is estimated by GMM. The robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2. Dynamic panel VAR results of a positive FFSI shock.

	Bank Performance Metrics			
	GMM Estimates			
	ROA	**ROE**	**CTI**	**Z-Score**
ROA (t − 1)	−0.0755			
	(0.0826)			
FintechP (t − 1)	0.0000515 *	0.000657 **	−0.00104	0.00520
	(0.0000204)	(0.000213)	(0.0135)	(0.00464)
BI (t − 1)	0.000161	−0.0202	−2.826	−0.00145
	(0.00171)	(0.0128)	(2.031)	(0.122)
ROE (t − 1)		0.0899		
		(0.0551)		
CTI (t − 1)			−0.359 *	
			(0.179)	
Z-score (t − 1)				0.443 ***
				(0.0404)
	Competition			
	GMM Estimates			
ROA (t − 1)	−0.00698			
	(0.0268)			
FintechP (t − 1)	−0.000373	−0.000367	−0.000373	−0.000447
	(0.000360)	(0.000360)	(0.000360)	(0.000362)
BI (t − 1)	0.802 ***	0.802 ***	0.802 ***	0.801 ***
	(0.103)	(0.103)	(0.103)	(0.103)
ROE (t − 1)		−0.00898		
		(0.00877)		
CTI (t − 1)			0.00000735	
			(0.0000126)	
Z-score (t − 1)				0.00921
				(0.00748)
N	1312	1312	1310	1312

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3. Dynamic panel VAR results of a negative FFSI shock.

	Performance Metrics GMM Estimates			
	ROA	**ROE**	**CTI**	**Z-Score**
ROA (t − 1)	−0.0736			
	(0.0819)			
FintechN (t − 1)	−0.00187	−0.0432 **	−14.04	−0.445 ***
	(0.000994)	(0.0132)	(9.836)	(0.132)
BI (t − 1)	−0.000573	−0.0371	−8.443	−0.168
	(0.00200)	(0.0202)	(6.721)	(0.211)
ROE (t − 1)		0.105		
		(0.0661)		
CTI (t − 1)			−0.333	
			(0.178)	
Z-Score (t − 1)				0.372 ***
	Competition GMM Estimates			
ROA (t − 1)	−0.0504			
	(0.0820)			
FintechN (t − 1)	0.0478 *	0.0468 *	0.0469 *	0.0565 *
	(0.0191)	(0.0187)	(0.0187)	(0.0220)
BI (t − 1)	0.822 ***	0.821 ***	0.821 ***	0.822 ***
	(0.106)	(0.106)	(0.106)	(0.107)
ROE (t − 1)		−0.0247		
		(0.0226)		
CTI (t − 1)			−0.0000812	
			(0.0000689)	
Z-Score (t − 1)				0.0182
				(0.00991)
N	1312	1312	1310	1312

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Notes

1 Fintech Partnerships: Synergy in Finance: The Impact of Fintech Partnerships on Nigerian Banks-FasterCapital.

2 H1a–H4a indicate the alternative hypothesis.

3 https://www.worldbank.org/en/publication/gfdr/gfdr-2016/background/banking-competition. Accessed on 9 May 2025.

4 Banking Competition.

5 Not all indicators featured in Bu et al. (2023) are utilized in this study due to limitations in data availability. Additionally, in contrast to Bu et al. (2023), this research incorporates additional financial inclusion factors, including MoMo platforms and deposits/loans held with credit unions. It is important to note that in certain African regions, credit unions evolved from traditional savings clubs (Stokvel) before formally transitioning into credit unions or deposit taking institutions.

6 $\det(A - \lambda I) = 0$ is the characteristic polynomial, and its roots are the eigenvalues.

7 The eigen vectors are linearly dependent, as for every computed eigenvalue, λ, we need to solve for non-zero v such that $(A - \lambda I)v = 0$.

8 Where $\alpha_i = (1 - \theta_i)u_i$ and $\beta_i = -(1 - \theta_i)$. Hence the null hypothesis of unit root becomes $0 = -1 + \theta_i \implies \theta_i = 1$. Moreover, $\Delta y_{it} = y_{it} - y_{i,t-1}$, subsequently substituting back into Equation (17) one gets:$y_{it} - y_{i,t-1} = (1 - \theta_i)u_i - (1 - \theta_i)y_{i,t-1} + \varepsilon_{it} y_{it} = (1 - \theta_i)u_i + y_{i,t-1} - (1 - \theta_i)y_{i,t-1} + \varepsilon_{it} y_{it} = (1 - \theta_i)u_i + y_{i,t-1}(1 - 1 + \theta_i) + \varepsilon_{it}$ as in Equation (16).

9 The PVAR models are estimated with a single lag, dictated by the short length of our panel, which precluded the generation of valid statistics for optimal lag length selection. Employing one lag also mitigates the risk of overfitting associated with the inclusion of multiple lags. Furthermore, one lag of the endogenous variable is utilized as an instrumental variable in the GMM estimation to address concerns related to instrument proliferation.

10 The results can be made available upon request. The results of non-response should be taken with caution due to a small sample size.

11 The models are also stable for positive and negative FFSI shocks.

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