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## Article

# Gauging the Impact of Digital Finance on Financial Stability in the Presence of Multiple Unknown Structural Breaks: Evidence from Developing Economies

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## Abstract

The implications of digital finance for financial stability has come under serious scrutiny since the aftermath of the 2008 global financial crisis (GFC). Empirical evidence on this nexus are somewhat inconsistent and ambiguous. This study therefore attributes this puzzle to multiple structural breaks (MSBs) which were long neglected by previous studies. Consequently, this study aims to identify possible MSBs in the digital finance–stability nexus and examine if its impact is consistent/weakened in the presence of MSBs in a sample of 41 developing African economies for the 2004–2023 periods. Results from the PCA index generation report that instability is more susceptible to bank crisis/Z-score. Again, the panel extension of BP98 MSBs detection identified three breaks with their confidence intervals overlapping the periods of the 2006–2011 GFC/subprime mortgage crises, the 2012–2016 Br-exit referendum and the 2017–2021 COVID 19 pandemic/Ukraine war. The quantile regression methodology also shows that these breaks weaken the impact of digital finance (i.e., mobile banking and internet banking) on financial stability, particularly for economies at lower quantiles of financial stability but with marginal effects for economies at higher quantiles. The study concludes that digital finance can stabilize the financial system of developing economies when shocks from structural breaks are controlled. Therefore, the study contributes to knowledge by developing a new econometric model for BP98 panel extension of MSBs detection, calibrating an index for financial stability and detecting valid break dates for three major breaks. Structural and financial development through policy coordination to forestall the effects of structural breaks were recommended.

**Keywords:** digital finance; structural break; financial stability; mobile banking; internet banking; quantile regression

**JEL Classification:** O33; C23; G18; G20; G21; C31



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## 1. Introduction

The role of digital finance in stabilizing the financial system has come under serious scrutiny since the 2008 global financial crisis. Researchers and policymakers have continued to examine this nexus with limited focus on financial and economic indicators only. A vast number of researchers believe that digital finance which is the use of modern technology in the design and delivery of financial services can mitigate financial crisis through wider and more efficient access to financial services (Yang et al., 2024; Risman et al., 2021; Ozili, 2018). This means that digital finance, which describes how new technologies could impact

the financial services industry through its various products, applications, processes and business models, has the capacity to transform the traditional way of providing banking and financial services. On the other hand, these studies also argued that it can worsen the financial crisis under volatile economic conditions. This asymmetric effect suggests that the impacts of digital finance on financial stability are contingent on different factors beyond financial and economic indicators. Therefore, a stable financial system is characterized by a stable financial environment, an effective financial intermediation that manages financial risks and that minimizes negative price fluctuations of financial or real assets that could endanger monetary resilience ([Ahmad, 2018](#)).

Although the need to consider both financial and real sector variables in the financial stability construct is stressed in this definition, the impact of structural breaks is also implied given recent global upheavals. Major breaks in the system with notable distortions are the 2007–2008 global financial crisis (GFC), the 2007–2010 subprime mortgage crisis, the 2016 Br-exit referendum, the 2020 COVID 19 pandemic and the recent war in Ukraine. These crises have caused high inflationary pressure, rising interest rate with high debt burdens among many African countries in recent times. Speaking on the impacts of these breaks, [Wullweber \(2020\)](#) hinted that most financial systems have been bedeviled with high insecure credit and debt structures have been building up. Apart from its structural effects, their economic implications especially among developing African economies could be enormous. These include tremendous increase in import over export, job loss, deindustrialization, capital flight, dependence on single commodity for export, poor growth and sluggish agricultural growth ([Lundvall, 2016](#)). Again, financial institutions in Africa experienced serious credit crunches, depleting profit margins and falling bank reserves with their attendant liquidity problems ([Akinsola, 2016](#)); these weaken the capital base of banks ([Olaosebikan et al., 2022](#)) and ultimately their stability level. This can affect the ability to extend loans/credit and financial instability in the region becomes inevitable.

Consequent upon these is the low financial inclusion with poor financial literacy that weakens policy thrust in stabilizing the financial system in the regions of Africa ([Kebede, 2022](#)). The large out of bank funds weakens the effectiveness of monetary policy instruments, especially in an open economy case. This lends credence to the Mundell–Fleming irreconcilable trilemma that an economy cannot simultaneously operate an independent monetary policy with fixed exchange rate and perfect capital mobility. Therefore, as the economy tries to adjust by (say) migrating to a flexible exchange rate system and/or restricting capital mobility, the supply shocks from abroad following the floating exchange rate could further weaken the stabilizing effect of monetary policy on the financial system. Consequently, the role of digital finance for inclusive finance which can ultimately lead to financial stability can be limited by financial illiteracy/level of financial development, the extent of digital regulation by the monetary authorities and pro-poor growth in the region. These dynamics are essential in financial stability assessment.

This study therefore argues that since the crisis first hit advanced economies through the systemic banking crisis in the United States and Europe ([IMF, 2009](#)) despite their strong digital resilience to crises, the impact of digital finance on financial stability can be weakened in the presence of structural breaks. This could be worse in regions with low compliance to digital finance like the regions of Africa ([Ramli, 2020](#)). In other words, low technology compliance among developing economies could be a deterrent to the impact of digital finance on financial stability. Despite the continent's poor adaptation to digital finance, financial systems in most African economies are undeveloped with poor resilience to external shocks ([Joseph et al., 2024](#); [Xia et al., 2022](#)). This among others can further limit the extent to which digital finance can restore stability in the system when

contemporaneous shocks hit the economies. Hence, varying or distorted impact on financial stability becomes inevitable.

Given this background, this study therefore employed the [Bai and Perron \(1998\)](#) (BP98) panel extension of multiple structural breaks detection to identify possible structural breaks in the system with reference to digital finance variables (internet banking and mobile banking). Furthermore, the quantile regression analysis was also adopted to examine whether the impact of digital finance on financial stability is consistent in the presence of multiple structural breaks. This gap is yet to be filled in the literature. The study focused on African region due to the continent's vulnerability to supply shocks coming from the west; hence, forty-one developing African economies were sampled for a period of twenty (20) years spanning from 2004 to 2023. These techniques have both scientific and practical significances because they do not only provide some novelty to the work but also gauge the extent to which digital finance drives financial stability at different quantiles.

This presents an obvious gap to be filled in the literature, especially as the views of previous studies were ambiguous and often inconsistent on the nexus between digital finance and financial stability. Besides the studies ability to bridge the empirical and conceptual gaps in the literature, the study is also very significant in presenting new scientific and practical approach to the detection of multiple structural breaks using panel data.

The remainder of the study is grouped into four unique sections. The second section explored different empirical literature on the subject, thereby pointing out the gaps in the literature. The next section presented the study's methodology, estimation techniques, data description, sources, and measurements. The model setting began with the principal component analytical test used in generating an index of financial stability. It is followed with data description, sources and scope; cross-sectional dependency test; slope homogeneity and panel unit root tests and finally, the quantile regression and structural break model specification. The last two sections discussed the results and draw conclusions based on findings with policy recommendations, respectively.

## 2. Literature Review

The extent and direction of the impact of digital finance on financial stability is contingent on both internal and external factors which could be peculiar to the given economy. Recent studies ([Lumingkewas, 2024](#); [Antwi & Kong, 2023](#); [Risman et al., 2021](#); [Pazarbasioglu et al., 2020](#)) on the subject have been inconclusive given their inconsistent empirical evidence. The common finding across these studies is that digital finance can improve financial stability. However, the recent surge of falling equity markets, the negative price fluctuations of financial or real assets, exchange rate upheaval and its attendant instabilities ([Kaya, 2017](#); [Osborne & Van Rijckeghem, 2000](#)) are indications that there could be some structural imbalances in the system, hence unknown distortions and asymmetric effects becomes inevitable.

Prominent among the literature on the asymmetric relationship between digital finance and financial stability are the works of [Anton and Afloarei Nucu \(2024\)](#) and [Okoli \(2024\)](#). According to them, digital finance will first improve financial stability when adopted within a certain threshold; however, it will begin to worsen it when adoption goes beyond that threshold. [Anton and Afloarei Nucu \(2024\)](#) added that this asymmetric relationship applies for both developed and developing economies. This finding accentuates that of [Okoli \(2024\)](#) who employed the generalized method of moment (GMM) estimation technique to examine an asymmetric relationship between financial technology adoption and bank stability among developing African economies. He found a U-shaped and an inverted U-shaped relationship between fintech and stability during the short run and long run, respectively. Similar conclusions were drawn among other studies ([Liang et al.,](#)

2025; Hordofa, 2024; Oanh & Dinh, 2024; Risman et al., 2021), that the relationship between digital finance and financial stability is asymmetric overtime. Studies with a positive nexus include but are not limited to Antwi and Kong (2023), Banna and Alam (2021), Risman et al. (2021) and Ozili (2018), while those with a negative relationship include Hordofa (2024), Lumingkewas (2024), Oanh and Dinh (2024) and Syed et al. (2022).

Furthermore, the asymmetric relationship between digital finance and financial stability twists between the short run and long run periods and widens overtime (Okoli, 2024; Syed et al., 2022). That is, the effect of digital finance on financial stability changes and deteriorates intermittently from one period to another, thereby suggesting possible structural breaks in the system. These ambiguous asymmetric evidences in the literature can make the policy response to shocks arising from the adoption of digital finance very uncertain given its varying effects. Moreover, the policy uncertainties of these varying effects are more pronounced among developing economies given their high financial volatilities and inconsistent policy measures (Mpofu, 2024; Syed et al., 2022). It can, as well, spread shocks among economies with low technology adoption thereby creating more breaks in the system. Previous studies (Anton & Afloarei Nucu, 2024; Hordofa, 2024; Risman et al., 2021; Arner et al., 2020) identified the COVID 19 pandemic and the 2008 GFC as potential structural breaks that can weaken the role of digital finance on financial stability. These, among other structural effects, motivates this study to see how different breaks can transmit shocks to the impact of digital finance on financial stability.

The 2007/2008 financial crisis is a major structural break among others that can weaken the impact of digital finance on financial stability. This is owing to the extent it affected the ability of banks in giving out loans, weakened their profitability, and made them more prone to risk (Caballero & Simsek, 2013; Gai & Kapadia, 2010), thereby worsening financial stability. Although the period of this crisis is known global to have commenced from February 2007 (Ditzen et al., 2025), its spillover effects across different economies vary over time. This makes it more difficult to access and quantify its effect on financial stability of these heterogeneous economies. Previous empirical studies have either examined such breaks in a time series analyses, using methods that are constrained to just one break (See: Karavias et al., 2023; Zhu et al., 2020). However, techniques that examined for multiple unknown number of breaks particularly within the contest of panel data relation among African developing economies have not been sufficiently explores in the literature.

In addition, the methodological gaps for panel analysis in detecting such breaks and the financial contagion of shocks from structural breaks can worsen stability, thereby creating some ripple effects in the system. Risman et al. (2021) observed that the systemic risk of such instability can increase the negative impact of digital finance on financial stability due to financial contagion. They added that the complexities of the financial system due to its interaction to size, business complexity, inter-institutional linkages and behavioral tendencies excessive from financial actors can further weaken policy response. This implies that shocks from one system can easily transmit to other system. Therefore, a highly complex networks can increase the likelihood of transmission risk (Gai & Kapadia, 2010; Caballero & Simsek, 2013; Reyes & Minoiu, 2011). This explains why most African economies were hit the worst by the recent COVID 19 pandemic, the Ukraine war, the GFC and the subprime mortgage crises (Lone & Ahmad, 2020).

The main weakness among studies that looked at the effect of multiple breaks (Ditzen et al., 2025; Kaddoura & Westerlund, 2023; Boldea et al., 2020) is their inability to account for the unobserved heterogeneity and individual fixed effects that are peculiar to a particular system. They further assume that the magnitude of the impacts of the breaks are uniform across the entire quantiles. Hence, unattended breaks can be mistaken for heterogeneity and vice versa (Ditzen et al., 2025), thereby worsening the systemic risk of



such breaks. Although Kaddoura and Westerlund (2023) and Boldea et al. (2020) hinted that unobserved heterogeneity can be augmented by using models that allows for special type of interactive random effects, this can worsen if the interaction is a source of shocks to the system. Since the interaction of the breaks with digital finance in this study are sources of shocks/crises, the ripple effects/contagion of such shocks cannot be augmented with such interaction. Li et al. (2016) tried to circumvent these weaknesses by employing techniques that allow for more general interactive effects and multiple breaks using a version of the (group fused) least absolute shrinkage and selection operator (LASSO) method. Although this approach is the most general approach available at the moment, it is rather complicated in that it assumes a nonlinear relationship with a number of tuning parameters (Ditzen et al., 2025). Consequently, it does not fit for the objective being investigated in this study since it is not designed to deal with models in which only a part of the coefficients is breaking<sup>1</sup>, and cannot allow for the construction of breakpoint confidence intervals.

In the present study, we followed an augmented approach to the multiple unknown break estimation by Ditzen et al. (2025) as a panel extension of the Bai and Perron (1998) (BP98)'s time series methodology in the Stata 14.2 software environment. The model to be estimated in Section 3, model 12 is a stepwise quantile regression with interactive fixed effects that allows for not only multiple structural breaks but also accounts for its impact at different quantiles. Unlike the LASSO approach and other break estimating models, the quantile regression does not estimate the impacts of the break at the mean value of the dependent variable but at various degrees. This allows both the readers and policymakers to gauge the extent of the impact of these breaks at various levels of the economies' financial stability. Moreover, the extent to which economies are hit by these breaks varies from one economy to another. According to the Sustainable Development Goals Report for 2022, economies with a high technology adoption rate and financial development are more likely to recover faster from shocks/breaks compared to lower-tech economies (United Nations). Consequently, empirical evidence assert that economies with low levels of financial development are more likely to experience poor digital effect on financial stability compared to those with high financial development (Hashemizadeh et al., 2023; Ozili, 2018). This suggests the need to include financial development in the financial stability constructs and employ models that gauges their impacts at different quantiles.

In addition to the financial contagion of shocks from structural breaks and the methodological gaps in the literature, most of the recent studies that examined this nexus (Meniago, 2025; Anton & Afloarei Nucu, 2024; Hordofa, 2024; Lumingkewas, 2024; Okoli, 2024, etc.) employed the short run GMM estimation technique with no long run policy implications. Consequently, the present study argues that besides using models that can examine the long run implications of digital finance on financial stability, it becomes imperative to also gauge this impacts at different quantiles. Hence, this study uses the quantile regression with fixed effect method to investigate the main objective of this study. Therefore, three main hypotheses were examined to answer the research questions.

First,

**H<sub>1</sub>** : *structural breaks have a negative impact on financial stability.*

Second,

**H<sub>2</sub>** : *the effect of structural breaks on the impact of digital finance on stability is weakened at higher levels of financial stability.*

And third,

**H<sub>3</sub>** : *control variables (financial development and real sector growth) moderate the impact of digital finance on financial stability.*

### 3. Methodology

The study's estimation techniques, both preliminary and major, are discussed in this section. The model specification, data measurements, sources and scope are among the various subsection to be in this section.

#### 3.1. The Principal Component Analysis (PCA)

This technique is used to generate an index for financial stability among the African economies used in this study. As a multidimensional indicator, the use of a proxy will understate its true value. [Sarma \(2008, 2016\)](#) proposed that composite construct/index best defines indicators that are multidimensional in nature. Consequently, this study follows existing studies ([Anton & Afloarei Nucu, 2024](#); [Antwi & Kong, 2023](#); [Yen Hai Dang & Dao Thieu Thi, 2022](#); [Karanovic & Karanovic, 2015](#)) to operationalize an index for financial stability using four stability variables (See Table 1). The index is then normalized between zero mean and one standard deviation (0, 1) for all countries in the sample using the [Sere-Ejembi et al. \(2014\)](#) index normalization formula. This circumvents any aggregation distortion that is common with indexes with different means and standard deviations. The formula is thus:

$$FSI_{it} = \frac{x_{it} - \min x_{it}}{\text{Max}(x_{it}) - \text{Min}(x_{it})} \quad (1)$$

where  $FSI_{it}$  is the normalized index for country  $i$  in period  $t$ .  $x_{it}$  is the observations generated using PCA technique.  $\min(x)_{it}$  and  $\max(x)_{it}$  is the minimum and maximum observations in the series, respectively. The final normalized index is the ratio of the difference between each observation and the minimum value to the range of the series. This gives values ranging from 0 to 1. Hence, the closer the index is to one, the more stable the financial system and vice versa.

**Table 1.** Variables, measurements and sources.

Variables	Measurements	Sources	Expected Sign
Financial Stability Index (FS)	A bank Z-score, bank liquid reserve to assets ratio, bank non-performing loan to total loan ratio and bank capital to assets ratio	World Bank development Indicator and international Monetary fund Websites	Dependent Variable
Internet banking Digital finance (INTB)	Individuals using internet % of population	World Bank development Indicator Websites	Positive
Mobile banking Digital finance (MB)	Mobile Cellular Subscription	World Bank development Indicator Websites	Positive
Economic growth/Real Sector Variable (G)	GDP growth rate	World Bank development Indicator Websites	Positive
Financial Development (FD)	Credit to Private Sector % of GDP	World Bank development Indicator Websites	Positive
Dummy Variable for Structural Break (D)	Taking 1 for periods of break and 0 otherwise		Negative

Source: Compilation.

#### 3.2. Data Measurement, Sources and Scope

Overall, five unique variables were sampled across forty-one African economies for the period 2004–2023. The sample period was limited to these periods because of the non-availability of data beyond these points. They are the financial stability (FS) index, mobile banking (MB), internet banking (INTB), financial development (FD) and economic

growth rate (GDPG). The use of the growth rate of output rather than its real value is preferred because the study is looking at a process of advancement in financial stability and not current status. This captures the variability in the real sector better than its nominal value. The dependent variable, FS, was generated using four stability variables. They include the bank Z-score<sup>2</sup>, bank liquid reserve to assets ratio, bank non-performing loan to total loan ratio and bank capital to assets ratio. MB and INTB were the two measures of digital finance proxy with mobile phone subscription and individuals using the internet, respectively. Previous studies (Antwi & Kong, 2023; Bayar et al., 2021; Ismael & Ali, 2021) used similar indicators. In addition, they are sources of financial access, penetration and behavior. The FD and GDPG were the control/moderating variables. Three major structural breaks were considered, which are the 2007–2010 GFC/the subprime mortgage crisis, the 2016 Br-exit referendum and the 2020 COVID 19 breaks. These breaks were considered because they cut across the various economies under investigation and their spillover impacts on the nexus between digital finance and financial stability among developing economies cannot be overemphasized. The study therefore uses dummy variables which takes 0 for periods before the break(s), and 1 otherwise. The data are sourced from the world bank development indicators and the international monetary fund (IMF) websites. The multiple sources were because all the data were not available in only one source.

### 3.3. Cross-Sectional Dependency Test

This preliminary test offers useful insights into the presence of cross-sectional dependency (CD) among the countries that made up the panel. A cross-sectional independency is expected, otherwise there is a possibility that shocks from one of those countries could easily spread to others thereby weakening the validity of the coefficient estimate. This study follows the Pesaran (2004) CD test which is based on the residual cross-sectional augmented (CSDA) test regression expressed as follows:

$$\Delta \tilde{y}_{it} = \sigma \tilde{y}_{it-1} + \sum_{j=1}^N \Delta \tilde{y}_{jt-1} + \sum_{j=1}^N \gamma_j \tilde{x}_{ijt} - 1 + e_{it} \quad (2)$$

where  $\tilde{y}_{it}$  and  $\tilde{x}_{it}$  represents the transformed dependent and independent variables, respectively,  $\Delta$  and  $\sigma$  are the first difference operator and the parameter of the first lag of the dependent variable, respectively, while  $\gamma_j$  and  $N$  are the coefficients for the independent variables and the number of cross-sectional unit, respectively and  $e_{it}$  is the error term. Hence, the CD test statistics is based on the residual sum of square from Equation (2). The decision rule is to reject to null hypothesis of no cross-sectional dependency if the probability value of the Pesaran CD test is less than 5 per cent.

### 3.4. Slope Homogeneity and Panel Unit Root Tests

The test for slope homogeneity (SH) is also necessary to ascertain whether the factors that drives financial stability varies across the various countries that made up the panel or whether they are homogeneous across units. This test will determine the type of model to adopt in estimating the data. A one-way/two-way fixed effect quantile regression will be necessary if there is evidence of slope heterogeneity to control for unobserved time-invariant heterogeneity and country's fixed effects. Hence, the factors that drive financial stability varies across countries/units and time.

Moreover, the panel unit root tests were conducted using the cross-sectional Im Pesaran and Shin (CIPS) and the cross-sectional augmented Dickey–Fuller (CADF) panel unit root tests. The choice of these tests is influenced by the presence of CD and SH; hence, they are robust in the presence of cross-sectional dependency and slope heterogeneity (Pesaran, 2007), particularly at the second-generation testing. Therefore, by taking into account the common factors influencing each of the individual time series in the panel,



second-generation tests overcome the cross-sectional and slope homogeneity issues. The test second generation is expressed, thus:

$$x_{it} = \alpha_0 + \alpha_1 \pi_{it} + \varphi_i x_{i,t-1} + \mu_{it} \quad (3)$$

where  $x_{it}$  is the particular variable of interest for country  $i$  at time  $t$ ,  $\alpha_0$  and  $\alpha_1$  are the intercept and coefficient of the common factor  $\pi_{it}$ , respectively, while  $\varphi_i$  and  $\mu_{it}$  are the autoregressive coefficient (which is assumed to be less than 1, implying no unit root is found) and the error term, respectively. In order to account for cross-sectional dependency, the test is based on demeaned and detrended series.

### 3.5. Quantile Regression Model Specification

Recall that the traditional panel data models examine the relationship between the independent variables  $x$  and the conditional mean of the dependent variable  $y$ . However, taking this position on the dependent variable (financial stability) in this study will be erroneous since various economies are at various stages of financial stability, some are even completely unstable.

Therefore, this study employed the quantile regression technique to examine the impact of the independent variables on the conditional quantiles of financial stability. This is most suitable for the estimation of the model given the assumption of asymmetries, heavy tails and the absence of a normally distributed series in this study. Consequently, the quantile regression provides a better summary of centrality than the pooled mean (POLS) regression. It also accounts for heterogeneous effects of covariates at different quantiles of the outcome variable. The panel quantile regression is defined by the following equation:

$$y_{it} = x'_{it} \delta_q + e_{it} \quad (4)$$

where  $y_{it}$  is the dependent variable, financial stability index (FS) to be investigated,  $x'_{it}$  and  $\delta_q$  are the vectors of explanatory variables and unknown parameters associated with the  $q$ th quantile, respectively, while  $e_{it}$  is the model's prediction error. Recall that quantile regression minimizes the sum of the asymmetric penalties  $q |e_{it}|$  for under prediction and  $(1 - q) |e_{it}|$  for overprediction, thus:  $\sum_i q |e_{it}| + (1 - q) |e_{it}|$  as against the sum of squares of the predicted error  $\sum_i e_{it}^2$  in pooled OLS and  $\sum_i |e_{it}|$  in median regression.

The  $q$ th quantile regression estimator  $\hat{\delta}_q$  minimizes over  $\delta_q$  the objective function

$$Q(\delta_q) = \sum_{i: y_i \geq x'_{it} \delta_q} q |y_{it} - x'_{it} \delta_q| + \sum_{i: y_i < x'_{it} \delta_q} (1 - q) |y_{it} - x'_{it} \delta_q| \quad (5)$$

where  $0 < q < 1$ . Therefore, in contrast to OLS and the maximum likelihood, quantile regression computational implementation uses linear programming methods. In this study, five quantiles will be examined at 0.1, 0.25, 0.5, 0.75 and 0.9 per cents. The rationale behind these five quantiles is to capture the heavy tails (90th and 75th), medium tail (50th) and lower tails (25th and 10th) quantiles of financial stability very appropriately. This technique can be examined under three conditions. The first condition is a homogeneity model which assumes that there is homogeneity in both the intercept and slope, thus:

$$Q_{y_{i,t}|x_{i,t}}(\tau) = \beta_\tau + \delta_\tau x'_{it} + e_{it,\tau} \quad (6)$$

where  $y_{i,t}$  is the dependent variable (index of financial stability),  $\beta_\tau$  and  $\delta_\tau$  represents the quantile-specific constant term and coefficient parameters, respectively,  $\tau$  and  $x'_{it}$  are the specific quantile of interest and vector of the dependent variables while  $e_{it,\tau}$  is the error

term at the chosen quantile. The second condition accounts for heterogeneity across the countries that makes up the panel as follows:

$$Q_{yi,t|xi,t}(\tau) = \beta_\tau + \beta_i + \delta_\tau x'_{it} + e_{it,\tau} \quad (7)$$

The variables remain in Equation (7) as defined in Equation (6) except that  $\beta_i$  captures the time-invariant differences in intercepts among countries. In addition to Equation (7), the time fixed effect  $\delta_t$  is used to capture time invariant differences from one period to another.

$$Q_{yi,t|xi,t}(\tau) = \beta_i + \delta_t + \delta_\tau x'_{it} + e_{it,\tau} \quad (8)$$

However, for the sake of simplicity and the uniqueness of the objective being investigated, this study assumes homogeneity in intercept and slope as suggested by the slope heterogeneity test in Table 2. Consequently, the time invariant differences ( $\beta_i$ ) and the heterogeneities across the slope coefficients ( $\delta_i$ ) as presented in model (8) are subsumed into the quantile-specific constant term ( $\beta_\tau$ ) and slope coefficients ( $\delta_\tau$ ), respectively. Therefore, given the assumption of homogeneity, the models' structural full form is expressed in Equation (9), hence, the relationship between the dependent and independent variables are presented as follows:

$$Q_{yi,t|xi,t}(\tau) = \beta_\tau + \delta_\tau INTB_{it} + \delta_\tau MB_{it} + \delta_\tau G_{it} + \delta_\tau FD_{it} + e_{it} \quad (9)$$

**Table 2.** Descriptive statistics and cross-sectional dependency test.

Variables	Obs	Mean	Std. Dev.	Min	Max	Skew	Kurt.	JB Stat	CD
FS	820	0.372	0.191	0	1	1.067	3.74	174.4 ***	101.24 ***
INTB	820	20.476	21.396	0.155	89.9	1.196	3.522	205.0 ***	115.25 ***
MB	820	69.584	43.345	0.207	191.508	0.346	2.383	29.4 ***	110.28 ***
GDPG	820	4.317	4.622	−20.81	37.999	−0.063	12.296	2953.0 ***	29.04 ***
FD	820	37.077	26.632	0.015	159.949	1.455	4.845	405.6 ***	47.63 ***

\*\*\*  $p < 0.01$ ; CD is cross-sectional dependence, Source: Estimation.

Financial stability being the dependent variable, internet banking (INTB) and mobile banking (MB) represent digital finance variables while economic growth (G) and financial development (FD) are the control variables.

#### Structural Break in Quantile Regression Model Specification

This study also follows the empirical work of [Ditzen et al. \(2025\)](#) to examine how digital finance can impact financial stability under different structural breaks. Following the spiral effects of the 2007–2008 GFC, the 2007–2010 subprime mortgage crisis, the 2016 Br-exit referendum, the 2020 COVID-19 pandemic, the 2022 war in Ukraine and the recent 2023 Israeli-Hamas War, various economies have experienced shocks that threaten their financial system ([Ditzen et al., 2025](#)). Although the start dates of these breaks were known, the periods and magnitudes of their spillover effects are yet undetermined. Consequently, this study adopts the [Bai and Perron \(1998\)](#) “BP98” technique for the identification of unknown multiple structural breaks to empirically identify and test the impacts of these breaks on financial stability. The null and alternative hypotheses for the breaks when the break date(s) is unknown is expressed as follows:

$$H_0 : \bigcup_{Z=2}^{Z_{\max}+1} [\delta_1 = \delta_2 = \dots = \delta_Z] \quad (10)$$

The null hypothesis ( $H_0$ ) is that there are no breaks at any given time such that period  $\delta_1$  is the same as period  $\delta_2$  all through to period  $\delta_z$  while the alternative hypothesis ( $H_1$ )

states that there is an unknown number of breaks ( $\delta_n \neq \delta_j \neq \delta_z$ ) that are bounded from above by some prescribed value  $Z_{max}$ .

$$H_1 : \bigcup_{Z=1}^{Z_{max}} \left\{ \bigcup_{\pi_Z \in \pi_{Zc}} \delta_n \neq \delta_j \dots n \neq j \right\} \quad (11)$$

Consequently, model 9 is therefore re-specified to capture the unknown  $Z$  structural breaks:

$$\begin{aligned} Q_{y_{i,t}/x_{i,t}}(\tau) &= \beta_\tau + \alpha_1 v_{it} + \delta_1 x'_{it} + e_{it} \text{ for } t = 1, \dots, T_1 \\ Q_{y_{i,t}/x_{i,t}}(\tau) &= \beta_\tau + \alpha_1 v_{it} + \delta_2 x'_{it} + e_{it} \text{ for } t = T_1+1, \dots, T_2 \\ Q_{y_{i,t}/x_{i,t}}(\tau) &= \beta_\tau + \alpha_1 v_{it} + \delta_{z+1} x'_{it} + e_{it} \text{ for } t = T_{z+1}, \dots, T \end{aligned} \quad (12)$$

where the variables remain as defined above. However,  $T_1, \dots, T_z$  are periods of the structural breaks such that  $T_0$  is the base year and  $T_{z+1} = T$ . The dependent variable  $y_{i,t}$ , the intercept term  $\beta_\tau$  and the error term  $e_{it}$  are scalars,  $\alpha_1$  and  $\delta_1, \dots, \delta_{k+1}$  are coefficients unaffected and affected by breaks, respectively, and they are assumed to be homogeneous across units while  $x_{it}$  and  $v_{it}$  are regressors with breaks and without breaks, respectively. However, if all the variables are affected by the break, we define  $\alpha_1 v_{it} = 0$ ; and introduce subsets  $\delta_j$  into the dummies which remain constant across periods in cases where the coefficients breaks at different times. The parameters with unique subscripts suggest the different distributional points of the independent variables within various quantiles; hence,  $\tau$  represents the distributional points,  $\beta_i$  and  $\delta_i$  are the fixed effects coefficients.

#### 4. Results and Discussion

The result discussion begins with the descriptive statistics of forty-one developing African countries for a sample period of twenty years, making a total of eight hundred and twenty observations as presented under Table 2. The variables include financial stability (FS) index, internet banking (INTB), mobile banking (MB), economic growth rate (GDPG) and financial development. The average FS for developing African economies is 37.2 per cent with an average economic growth rate of 4.32 per cent.

The average adoption of digital finance stood at 20.5 per cent and 69.6 per cent for internet banking and mobile banking, respectively, while that of financial development is at 37.1 per cent. These average scores reveal that an economy's financial system is as stable as its level of development and mobile banking is more likely to stability than internet banking and growth. Moreover, the strong significance of the probability of the Jarque–Bera statistics suggest that the series are not normally distributed, hence the need for a quantile regression. This is because it offers more robust estimates than the mean regression when the normality assumption is violated.

Table 2 also presents results of the cross-sectional dependency test for each of the variables. The strong significance of each of the variables at 1 per cent means that the null hypotheses of no cross-sectional dependence is rejected for all the variables in favor of the alternative that there is cross-sectional dependence. This implies that shocks from one country can easily spread to other countries.

Results of the correlation test for all variables are reported in Table 3. The result shows that all the explanatory variables were highly correlated with financial stability. The high association-ship indicates that the extent to which they can predict changes in the dependent variable (FS) is high. Particularly, the high positive correlation between FS and digital finance measures is an indication that digital finance affects financial stability. However, a significant negative correlation was reported between financial stability and economic growth indicator. Although this is not consistent with prior expectation, it does suggest that growth among African economies is not pro-poor and/or African economies

on average are under developing. Similarly, the correlation between growth and digital finance indicators (Internet and mobile banking) is also significantly negative. This result is consistent with that of [Antwi and Kong \(2023\)](#) who also reported a negative correlation between growth and digital finance.

**Table 3.** Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)
(1) FS	1.000				
(2) INTB	0.812 *	1.000			
	(0.000)				
(3) MB	0.764 *	0.757 *	1.000		
	(0.000)	(0.000)			
(4) GDPG	−0.325 *	−0.201 *	−0.169 *	1.000	
	(0.000)	(0.000)	(0.000)		
(5) FD	0.655 *	0.607 *	0.489 *	−0.132 *	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	

\*  $p < 0.1$ . Source: Estimation.

The [Pesaran \(2021\)](#) cross-sectional dependence test for the entire model presented in Table 4 also confirms the presence of cross-sectional dependence among the entire variables. Moreover, findings from the slope heterogeneity (SH) test reveal that we can reject the null hypothesis of homogeneous slope in favor of the alternative that the slopes are heterogeneous. Consequently, whereas the CD test suggest the tendency of shocks spreading from a particular sampled country, the SH test refutes any claim that the effects of these shocks could be similar among units/countries. Hence, the need for stationarity tests that control for CD problem.

**Table 4.** Panel unit root and slope heterogeneity tests.

Vari.	CIPS I(0)	CIPS I(1)	CADF I(0)	CADF I(1)	Test	Statistics
FS	−2.450	−4.485 ***	−1.714	−1.757 **	Pesaran CD	4.407 ***
INTB	−2.325	−3.705 ***	−2.170	−2.132 ***	Friedman	47.751
MB	−3.162 ***	−4.075 ***	−2.176 ***	−2.898 ***	Frees' Q distribution	5.543
GDPG	−3.423 ***	−5.273 ***	−1.990 *	−2.537 ***	Slope Heterogeneity Test	18.458 ***
FD	−2.458	−4.328 ***	−2.150 ***	−2.864 ***	Slope Heterog. Test (ADJ)	22.062 ***

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; CD is cross-sectional dependence. CIPS is Pesaran unit root test and CADF is Augmented Dickey–Fuller test in the presence of cross-sectional dependence. Source: Estimation.

The [Pesaran \(2007\)](#) and the augmented panel unit root tests were used due to their ability to address the problem of cross-sectional dependence. The results presented in Table 4 reveal that we cannot reject the null hypotheses of unit root during the first generation for both tests particularly for FS, INTB and FD variables. However, by taking into account the common factors influencing each time series in the panel, second generation tests overcome the cross-sectional dependence problem. Hence, all the series became stationary after the first difference for both tests. Hence, the panel long-run cointegration relationship among the variables were examined using [Pedroni \(2004\)](#) and [Kao \(1999\)](#) tests. The findings from the result as presented in Table 5 reveal that the variables have a long-run relationship. This conclusion is drawn based on the significant panel PP and ADF statistics, weighted statistics and the Kao t-statistics. Hence, the null hypothesis of no co-integration is rejected in favor of the alternative that co-integration exists.

**Table 5.** Panel co-integration tests.

	Pedroni Co-Integration Test				Kao Co-Integration Test		
	Statistic	Prob.	Weighted Statistic	Prob.		t-Statistic	Prob.
Panel v-Statistic	−1037.25	1.000	−2.98871	0.999	ADF	−6.476567	0.000
Panel rho-Statistic	0.70414	0.759	2.77917	0.997	Residual variance	0.000475	
Panel PP-Statistic	−10.5006	0.000	−6.67877	0.000	HAC variance	0.000338	
Panel ADF-Statistic	−4.23714	0.000	−8.14987	0.000			

Source: Estimation.

#### 4.1. Breakpoint Testing and Estimation

The focuses here are to ascertain if there are any breaks present at all, what are the number of breaks and at what points are the breaks. With focus on digital finance indicators as the only breaking variable(s) due to their structural transformation at intervals on the financial system, this study assumes that the number of breaks are unknown and could vary among the two indicators (INTB and MB). The  $WDmaxF(Z_{max})$  statistics with null hypothesis of no breaks tested against the alternative of up to  $Z_{max}$  breaks is employed. The results of the tests presented in Table 6 reveal that the  $WDmaxF(Z_{max})$  tests for both variables identified at least three breaks. Their t-statistics values 26.15 and 22.5 (at their highest break point), respectively, were all greater than the appropriate critical values 15.28 and 14.8, respectively, at the most conservative 1% significance levels.

**Table 6.** Test for multiple breaks at unknown break-dates (Ditzen et al., 2025)  $H_0$ : no break(s) vs.  $H_1$ :  $1 \leq Z_{max} \leq 5$  break(s).

Bai and Perron Critical Values for Breaks in INTB					Bai and Perron Critical Values for Breaks in MB				
	Test Statistics	1% Crit. Value	Break Date	[95% Conf. Interval]		Test Statistics	1% Crit. Value	Break Date	[95% Conf. Interval]
Zmax	18.47	12.37			Zmax	149.72	12.37		
F(1/0)	18.07	12.29	2007	2006–2008	F(1/0)	149.72	12.29	2008	2007–2009
F(2/1)	19.43	13.89	2010	2009–2011	F(2/1)	35.72	13.89	2014	2013–2015
F(3/2)	27.02	14.80	2014	2012–2016	F(3/2)	22.50	14.80	2019	2017–2021
F(4/3)	26.15	15.28	2019	2017–2021					
Detected No of Breaks				4					3

Source: Estimation.

The result further reveals that the variables break differently with internet banking reporting a maximum of four (4) breaks whereas mobile banking reports three (3). Bai and Perron (1998) observe that this will not pose much challenge if the break intervals coincide. Results of the 95% confidence intervals suggests that the first break, 2006–2008 and 2007–2009 for INTB and MB, respectively, coincides with the period of the GFC. The second and third breaks coincide with the 2009–2011 subprime mortgage crisis and the 2016 Br-exit referendum whereas the last break revolves around the spiral effects of the COVID 19 pandemic. These have strong implications for digital finance and financial stability in the regions of Africa. Therefore, for the sake of simplicity, models (12) will be estimated with three breaks, with the first break spanning from 2006 to 2011, the second break spanning from 2012 to 2016 and the third break from 2017 to 2021. This is sufficiently large enough to cover all relevant breaks. Consequently, the analyses aim to see if the coefficients in models (12) are sensitive to changes in  $z$  at different quantiles.



#### 4.2. Quantile Regression Analyses Under Detected Multiple Structural Breaks

Results of the quantile regression analyses are presented in Tables 7–9 to account for the three structural breaks of financial crisis/subprime mortgage crisis, the pre and post 2016 Br-exit referendum and the COVID 19 pandemic/Ukraine war, respectively. Results for the five quantiles (0.1, 0.25, 0.5, 0.75, 0.90) were reported in all the Tables. By incorporating the effects of financial crisis/ subprime mortgage crisis dummy which spans from 2006 to 2011, the result in Table 7 reveals that MB significantly and positively drives financial stability before the break across the five quantiles, with the highest impact at the 75th and 90th quantiles (0.3% \*\*\*). Similarly, FD positively and significantly drives financial stability with a marginally same magnitude across the entire quantiles. However, economic growth emits a relatively equal negative significant impact on financial stability across the five quantiles (0.6% \*\*\*). This is inconsistent with the works of Antwi and Kong (2023) who reported a positive nexus between growth and financial stability. The result further reveals that the coefficient of the financial crisis/subprime mortgage crisis dummy ( $\delta_1$ ) is significantly negative in the 25th, 75th and 90th quantiles with the highest magnitude reported under the 90th quantile. This implies that the GFC/subprime mortgage crisis has the greatest effect on economies with the highest level of financial stability. This could be attributed to high financial contagion among economies with high technology adoption (Bączyk, 2021).

**Table 7.** Quantile regression results for the first break/financial crisis ( $\delta_1$ ).

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	FS (0.10)	FS (0.25)	FS (0.5)	FS (0.75)	FS (0.90)
Constant ( $\beta_\tau$ )	0.148 *** (0.023)	0.154 *** (0.008)	0.161 *** (0.012)	0.181 *** (0.016)	0.229 *** (0.023)
Dummy 1 ( $\delta_1$ )	−0.012 (0.027)	−0.017 * (0.01)	−0.016 (0.014)	−0.048 *** (0.019)	−0.073 *** (0.027)
Int. Banking ( $\alpha_1$ )	0.004 (0.003)	0.002 ** (0.001)	0.001 (0.002)	−0.0003 (0.002)	−0.003 (0.003)
Mobile Banking ( $\alpha_2$ )	0.001 * (0.001)	0.001 *** (0.0002)	0.002 *** (0.0003)	0.003 *** (0.0004)	0.003 *** (0.001)
GDP Growth Rate ( $\alpha_3$ )	−0.006 *** (0.002)	−0.006 *** (0.001)	−0.006 *** (0.001)	−0.005 *** (0.001)	−0.006 *** (0.001)
Financial Dev. ( $\alpha_4$ )	0.001 (0.0003)	0.001 *** (0.0001)	0.002 *** (0.0002)	0.002 *** (0.0002)	0.003 *** (0.0003)
Int. Banking $\times$ Dum 1 ( $\alpha_1 \times \delta_1$ )	−0.001 (0.003)	0.001 (0.001)	0.003 * (0.002)	0.005 ** (0.002)	0.007 ** (0.003)
Mobile Banking $\times$ Dum 2 ( $\alpha_2 \times \delta_1$ )	0.001 (0.001)	0.0002 (0.0002)	−0.001 *** (0.0003)	−0.001 ** (−0.0004)	−0.001 (0.001)
Observations	820	820	820	820	820
Pseudo R <sup>2</sup>	0.4525	0.5409	0.5845	0.6219	0.6414

Standard errors are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Source: Estimation.

**Table 8.** Quantile regression results for the second break/subprime mortgage crisis ( $\delta_2$ ).

	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
	FS (0.10)	FS (0.25)	FS (0.5)	FS (0.75)	FS (0.90)
Constant ( $\beta_\tau$ )	0.1442 *** (0.0146)	0.1485 *** (0.0062)	0.1638 *** (0.0073)	0.1688 *** (0.0123)	0.1969 *** (0.0183)
Dummy 2 ( $\delta_2$ )	−0.0189 (0.0332)	−0.0133 (0.0142)	−0.0398 ** (0.0165)	−0.0573 ** (0.0281)	−0.0911 ** (0.0416)

Table 8. Cont.

	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
	FS (0.10)	FS (0.25)	FS (0.5)	FS (0.75)	FS (0.90)
Int. Banking ( $\alpha_1$ )	0.0032 *** (0.0005)	0.0036 *** (0.0002)	0.0042 *** (0.0002)	0.0041 *** (0.0004)	0.0033 *** (0.0006)
Mobile Banking ( $\alpha_2$ )	0.0011 *** (0.0002)	0.0011 *** (0.0001)	0.001 *** (0.0001)	0.002 *** (0.0002)	0.0019 *** (0.0003)
GDP Growth Rate ( $\alpha_3$ )	−0.0057 *** (0.0012)	−0.005 *** (0.0005)	−0.0059 *** (0.0006)	−0.0049 *** (0.001)	−0.0056 *** (0.0015)
Financial Dev. ( $\alpha_4$ )	0.0007 ** (0.0003)	0.0011 *** (0.0001)	0.0015 *** (0.0001)	0.0019 *** (0.0002)	0.0028 *** (0.0003)
Int. Banking $\times$ Dum 2 ( $\alpha_1 \times \delta_2$ )	−0.0011 (0.0012)	0.001 * (0.0005)	0.0004 (0.0006)	0.0007 (0.001)	−0.0911 (0.0015)
Mobile Banking $\times$ Dum 2 ( $\alpha_1 \times \delta_2$ )	0.0006 (0.0006)	0.0001 (0.0002)	0.0006 ** (0.0003)	0.0005 (0.0004)	0.0012 * (0.0007)
Observations	820	820	820	820	820
Pseudo R <sup>2</sup>	0.4527	0.5439	0.5871	0.6111	0.6345

Standard errors are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Source: Estimation.

Table 9. Quantile regression for the third break/COVID 19 pandemic and war structural breaks ( $\delta_3$ ).

	Model (11)	Model (12)	Model (13)	Model (14)	Model (15)
	FS (0.1)	FS (0.25)	FS (0.5)	FS (0.75)	FS (0.9)
Constant ( $\beta_T$ )	0.1396 *** (0.0193)	0.1506 *** (0.0067)	0.157 *** (0.0083)	0.1718 *** (0.0106)	0.2025 *** (0.0221)
Dummy 3 ( $\delta_3$ )	0.0077 (0.044)	−0.024 (0.0152)	−0.0307 (0.0189)	−0.0563 ** (0.0242)	−0.1015 ** (0.0502)
Int. Banking ( $\alpha_1$ )	0.0026 *** (0.0007)	0.0035 *** (0.0002)	0.0041 *** (0.0003)	0.0042 *** (0.0004)	0.0033 *** (0.0007)
Mobile Banking ( $\alpha_2$ )	0.001 *** (0.0003)	0.0013 *** (0.0001)	0.0013 *** (0.0001)	0.0019 *** (0.0002)	0.002 *** (0.0003)
GDP Growth Rate ( $\alpha_3$ )	−0.0058 *** (0.0016)	−0.0059 *** (0.0006)	−0.0061 *** (0.0007)	−0.0057 *** (0.0009)	−0.0057 *** (0.0019)
Financial Dev. ( $\alpha_4$ )	0.0007 * (0.0004)	0.001 *** (0.0001)	0.0017 *** (0.0002)	0.0018 *** (0.0002)	0.0025 *** (0.0004)
Int. Banking $\times$ Dum 3 ( $\alpha_1 \times \delta_3$ )	0.0012 (0.0012)	0.0006 (0.0004)	0.0005 (0.0005)	0.0016 ** (0.0007)	0.003 ** (0.0014)
Mobile Banking $\times$ Dum3 ( $\alpha_2 \times \delta_3$ )	−0.0008 (0.0007)	−0.0001 (0.0002)	−0.0001 (0.0003)	−0.0004 (0.0004)	−0.0004 (0.0007)
Observations	820	820	820	820	820
Pseudo R <sup>2</sup>	0.4505	0.5421	0.5867	0.6196	0.6373

Standard errors are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Source: Estimation.

Results in Table 7 further show that the post GFC break impact of INTB on financial stability were positively significant though with no prior pre crisis impact. Its marginal increase of 0.3% to 0.5% and then to 0.7% from 50th, 75th and 90th quantiles, respectively, suggests that economies with higher financial stability are disposed to greater digital drive after the crisis. That MB reported a marginally reversed/negative significant impact after the break supports the asymmetric argument of digital finance on stability in the literature. This finding is supported by the inconsistent empirical evidence in the literature (Banna & Alam, 2021; Risman et al., 2021; Hordofa, 2024; Lumingkewas, 2024; Oanh & Dinh, 2024; Syed et al., 2022; Liang et al., 2025; Anton & Afloarei Nucu, 2024; Antwi & Kong, 2023). Therefore, the impact of financial crisis on the nexus between digital finance and financial stability is monotonic.

The second break which coincides with the 2012–2016 pre and aftermath of the 2016 Br-exit referendum was also used to examine this nexus. A dummy variable ( $\delta_2$ ) represents this break in the study. The results in Table 8 reveals that unlike models 1–5, the inclusion of the  $\delta_2$  structural dummy strengthened the impact of digital finance on financial stability across the entire quantiles. Consequently, INTB and MB emit positive significant impact on financial stability with the highest magnitude recorded under the 50th and 75th quantiles, respectively. However, the negative significant impact of  $\delta_2$  across the 50th, 75th and 90th quantiles, with the highest magnitude reported in the 90th quantile at  $-9.11\%$  per annum, could not spread to weaken the impact of digital finance on stability for the period under investigation. This suggests that  $\delta_2$  could be the real sector driven rather than the financial sector. This finding was consistent with that of [Morgan and Zhang \(2017\)](#) who examined the impact of mortgage crisis on financial stability and found that the former does not transmit negatively to the latter but beyond certain threshold. Therefore, the positive effect of digital finance on financial stability in the presence of the pre and aftermath effects of the 2016 Br-exit referendum structural crisis suggests that digital finance moderates the negative effect of this crisis on financial stability.

Moreover, the result further reveals that real sector performance (GDPG) significantly dampens the level of financial stability across the entire quantiles with the highest recorded in the 50th quantile. This strengthens the claim that the  $\delta_2$  crisis could have affected the real sector negatively than the financial sector. FD emitted consistent positive significant impact on financial stability across the entire quantile when the models were impacted by financial/subprime mortgage crisis. Hence, FD is crisis invariant. However, this result is inconsistent with that of [Batuo et al. \(2018\)](#) who examined the link between FD, financial instability and growth among 41 African economies and found evidence that while FD dampens financial stability, growth spurs it. This study therefore argues that these inconsistent conclusions could be attributed to the inability of previous studies to control for structural breaks that affects the entire system; hence, the major gaps that this study aims to fill.

Another kind of break spanning from 2017 to 2021, which corresponds to the pre and post effects of COVID 19/Ukraine war crisis, was identified and its impacts were examined. The result of the quantile regression presented in Table 9 reveals that this break is only negatively significant at higher quantiles (i.e., the 75th and 90th quantiles). This implies that economies with high financial stability are more likely to be susceptible to external shocks arising from the COVID 19 pandemic/Ukraine war. While this finding was supported by previous studies ([Shipalana & O’Riordan, 2022](#); [Jackson & Schwarcz, 2021](#); [Batuo et al., 2018](#)), they argued that the extent of financial development and policy intervention with high technology compliant financial system will dampen its effect. This explains why although with a relatively lower FD impact (when compared with models 1–10 and quantiles 75th and 90th), the impact of digital finance on stability is strengthened at higher quantiles despite the negative effects of the break.

Moreover, the negative impact of economic growth indicator (GDPG) on stability across the entire quantiles strengthens the previous claim that structural breaks transmits greater risk to the real sector than to the financial sector. This finding is consistent with that of [Shahbaz et al. \(2023\)](#) who found strong evidence to support this claim and concludes that the impact of growth on financial development is weakened in the presence of structural breaks.

Finally, the study synchronized all the breaks to examine their interplay on stability under three quantiles, the low, medium and highest (10th, 50th and 90th) quantiles (Table 10). The objective here is to ascertain their simultaneous impact on financial stability rather than treating them in isolation. The results reveal that the average levels of

financial stability among African economies are 14% ( $=\beta_{\tau}$ ), 3.4% ( $=\beta_{\tau} + \delta_1 + \delta_2 + \delta_3$ ), and  $-9.9\%$  ( $=\beta_{\tau} + \delta_1 + \delta_2 + \delta_3$ ) for the 10th, 50th and 90th quantiles, respectively<sup>3</sup>. That is,  $\delta_1 = \delta_2 = \delta_3 = 0$  in the 10th quantile. This means that economies with low prospects for financial stability are likely to report a higher take-off average of digital finance ceteris paribus. This could be attributed to the absence of financial contagion arising from shocks that affects large financial systems given their high openness to financial frictions. Consequently, financial integration and contagion are inversely proportional and they pose a systemic threat to the stability of the global financial system (Oprea, 2017).

**Table 10.** Quantile regression under three different breaks.

	Model (16)	Model (17)	Model (18)
	FS (0.1)	FS (0.5)	FS (0.9)
<b>Constant (<math>\beta_{\tau}</math>)</b>	0.14 *** (0.026)	0.182 *** (0.01)	0.24 *** (0.026)
<b>Financial Crisis Dum 1 (<math>\delta_1</math>)</b>	−0.007 (0.031)	−0.037 *** (0.012)	−0.061 * (0.031)
<b>Subprime Mort. Crisis Dum 2 (<math>\delta_2</math>)</b>	−0.015 (0.044)	−0.053 *** (0.016)	−0.138 *** (0.044)
<b>Br-Exit and COVID 19 Dum 3 (<math>\delta_3</math>)</b>	0.007 (0.045)	−0.056 *** (0.017)	−0.139 *** (0.045)
<b>Int. Banking (<math>\alpha_1</math>)</b>	0.003 *** (0.001)	0.004 *** (0)	0.004 *** (0.001)
<b>Mobile Banking (<math>\alpha_2</math>)</b>	0.001 ** (0.001)	0.001 *** (0)	0.002 *** (0.001)
<b>GDP Growth Rate (<math>\alpha_3</math>)</b>	−0.006 *** (0.002)	−0.006 *** (0.001)	−0.006 *** (0.002)
<b>Financial Dev. (<math>\alpha_4</math>)</b>	0.001 * (0)	0.001 *** (0)	0.002 *** (0)
<b>Int. Banking <math>\times</math> Dum 1 (<math>\alpha_1 \times \delta_1</math>)</b>	−0.002 (0.002)	0 (0.001)	0.001 (0.002)
<b>Mobile Banking <math>\times</math> Dum 1 (<math>\alpha_2 \times \delta_1</math>)</b>	0.001 (0.001)	0.001 *** (0)	0.001 (0.001)
<b>Int. Banking <math>\times</math> Dum 2 (<math>\alpha_1 \times \delta_2</math>)</b>	−0.001 (0.002)	0.001 * (0.001)	0 (0.002)
<b>Mobile Banking <math>\times</math> Dum 2 (<math>\alpha_2 \times \delta_2</math>)</b>	0.001 (0.001)	0.001 *** (0)	0.002 ** (0.001)
<b>Int. Banking <math>\times</math> Dum 3 (<math>\alpha_1 \times \delta_3</math>)</b>	0.001 (0.001)	0.001 ** (0.001)	0.003 * (0.001)
<b>Mobile Banking <math>\times</math> Dum 3 (<math>\alpha_2 \times \delta_3</math>)</b>	0 (0.001)	0 (0)	0 (0.001)
<b>Observations</b>	820	820	820
<b>Pseudo R<sup>2</sup></b>	0.4598	0.6099	0.6512

Standard errors are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Source: Estimation.

Furthermore, the result further shows that there are significant differences in the impacts of the slope coefficients of digital finance on financial stability as you advance from lower to higher quantiles. For instance, a unit increase in internet banking and mobile banking under the 10th quantile is on average and ceteris paribus associated with 0.3% and 0.1% increases, respectively, in financial stability at 1% significance level<sup>4</sup>. At the 50th quantile, the impacts of their slope coefficients are 0.6% and 0.3% whereas they are 0.7% and 0.4%, respectively, at the 90th quantile. This implies that there are marginal changes/increases in the slope effects of digital finance on financial stability as economies advance higher in the financial stability spectrum. This conclusion is consistent with

the findings made by Ozili (2018) among developed economies with relatively advanced financial system.

Finally, the impact of GDP growth rate and financial development were relatively stable across the three (10th, 50th and 90th) quantiles. In other words, a unit increase in growth and financial development is on average and *ceteris paribus* associated with about 0.6% decrease and 0.1% increase, respectively, on financial stability at 1% significance level. Similar results were reported when the breaks were treated independently across the five unique quantiles. This implies that the role of growth and financial development on its stability is neither structurally driven nor conditioned on the extent of the economies' financial stability.

## 5. Conclusions and Policy Recommendation

This paper provides a new insight into the nexus between digital finance and financial stability in a panel of 41 African countries with interactive effects and multiple structural breaks. The study is motivated by the inconsistent and often contradictory findings on this nexus as well as the dearth of literature on the effect of structural breaks on this nexus. Therefore, the study aims to both identify possible multiple structural breaks with focus on the GFC, Br-exit referendum and the COVID 19/Ukraine war, examine their impacts on financial stability and to see if they weaken the impact of digital finance on financial stability for the period 2004–2023. Having measured digital finance with two indicators of internet banking and mobile banking, the principal component analysis was employed to generate an index for financial stability using four stability variables.

The panel extension of BP98 multiple structural breaks detection was used to ascertain the number of breaks particularly on the digital finance variables, whereas the quantile regression with fixed effects were employed as the estimation technique. Three breaks were found to be very significant. The first break spanning from 2006 to 2011 coincides with the period of the GFC and the subprime mortgage crisis, the second break spanning from 2012 to 2016 corresponds to the pre and post Br-exit referendum while the last break which spans from 2017 to 2021 overlaps with the pre and aftermath of the COVID 19 pandemic. Among these three breaks, the third break, which coincides with the pre and aftermath of the COVID 19 pandemic, had the greatest negative impact on financial stability especially at higher quantiles. This implies that the effects of the COVID 19 pandemic on financial stability is more pronounced than that of financial and Br-exit crises for economies at higher levels of financial stability than those at lower levels.

According to the empirical results from the quantile regression, internet and mobile banking as proxies for digital finance had positive impact on the stability of financial systems in Africa before the breaks with higher magnitude reported at higher quantiles. Their impacts twist after the breaks with no clear direction of impact particularly at lower quantiles. Overall, we conclude that digital finance can significantly promote financial stability among the selected economies when stability has reached higher thresholds and the structural effects of different breaks are controlled. Otherwise, the impact of digital finance on financial stability will be ambiguous and distorted. Moreover, the marginally increasing positive impacts of financial development on stability from low to higher quantile implies that both are positively related while the stable negative impact of growth across the entire quantiles and breaks implies that real sector performance might require a transmission channel to impact financial stability.

Finally, the policy recommendation based on the findings are enormous. First, the study recommends that government of developing African countries should adopt supply side policies such as technology skill acquisition, financial market reform and/or liberalization, legal institutional development and structural transformation in order to improve the



impact of digital finance on financial stability. This will, as well, weaken the distorting and ambiguous effect of structural breaks on the impact of digital finance on stability. Again, policymakers should promote real sector performance through labor efficiency, foreign direct investment and fiscal and monetary policy coordination to improve the impact of economic growth on financial stability

#### *Weakness/Limitation of the Study and Areas for Further Studies*

Since no study is exhaustive in itself, there still remain some areas of weaknesses in this study that were not thoroughly examined due to certain constraints. First, the study assumed that all the countries that made up the panel are at the same stage of development. This is a major weakness that should be investigated by classifying the economies into their emerging, frontier and fragile groups to capture their unique heterogeneity. Hence, the use of quantile regression to examine this nexus at different tails is a necessary but insufficient condition. Another area for further studies that would be a real contribution to the related literature is the assessment of the severity of financial contagion from one economic group to another. This would show the extent to which the 41 African economies have been affected by the international breaks.

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**Data Availability Statement:** The data used in this study are available in public domains of the World Bank development indicators viz: <https://databank.worldbank.org/source/world-development-indicators#> (accessed on 5 May 2025).

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## Notes

- <sup>1</sup> Note only the digital finance variables (INTB and MB) were allowed to be breaking in this study because they are specific to the banking sector and situational to the crises being investigated. On the other hand, GDPG and FD are more general to the economy.
- <sup>2</sup> Bank Z-score is a metric used to assess bank's financial stability in a given region. It measures the distance a bank capital is from bankruptcy.
- <sup>3</sup> Note that the three crises dummies were not significant under model 16 which is the 10th quantile, consequently the constant value only represents the average level of financial stability.
- <sup>4</sup> Note that the interactive effects of digital finance with the three dummies are not significant under the 10th quantile; hence,  $\alpha i \times \delta i = 0$ . In the 50th quantile, only  $\alpha 1 \times \delta 2 \neq \alpha 2 \times \delta 2 \neq \alpha 1 \times \delta 3 \neq 0$  whereas only  $\alpha 2 \times \delta 2 \neq \alpha 1 \times \delta 3 \neq 0$  in the 90th quantile.

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