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DOES THE ADOPTION PROCESS OF FINANCIAL TECHNOLOGY IN AFRICA FOLLOW AN INVERTED U-SHAPED HYPOTHESIS? AN EVALUATION OF ROGERS DIFFUSION OF INNOVATION THEORY

Tochukwu Timothy Okoli[1,2]* and Devi Datt. Tewari[3]

[1]Department of Economics, University of Zululand,
Private Bag X1001, KwaDlangezwa, 3886 South Africa,
[2] Economic Department, Federal University Oye-Ekiti (Fuoye),
Oye-Are Road, Oye-Ekiti, Ekiti State, Nigeria
[3] Faculty of Commerce, Administration and Law,
University of Zululand, Private Bag X1001, KwaDlangezwa, 3886 South Africa

*Corresponding author: tochukwu.okoli@fuoye.edu.ng

ABSTRACT

As the global financial system evolves towards a technology-enabled financial solution-Fintech, its implication to the future of the financial system becomes a policy concern. This study investigates non-linear/inverted U-shaped Fintech adoption process among a panel of 32 African countries spanning from 2002–2018. The study argues that Fintech adoption in Africa will continue to rise and not follow the inverted U-shaped process if sustained through greater trade openness. The dynamic system GMM techniques found a strong evidence for an inverted U- shaped adoption process for the 32 African markets and 24 frontier African markets but violated among the emerging (N = 3) and fragile (N = 5) groups. The first lag of Fintech compatibility and the contemporaneous levels of relative-advantage, complexity, trial-ability and observe-ability were its main determinants. The study concludes that Fintech will be replaced with new innovations in future irrespective of possible sustainability strategy. The need to strengthen African financial markets' innovativeness to have a competitive edge on Fintech's replacement is stressed.

Keywords: Fintech, nonlinear relationship, compatibility, complexity, Africa

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INTRODUCTION

The global growth of financial technology from 16% in 2015 to 33% in 2017 (Ernest & Young, 2017) is an indication that the adoption of financial technology has reached its critical mass[1]. According to Rogers (1995), this process will continue until the growth rate reaches its inflection point (maximum level) and afterwards begins to decline. This growth process of new innovation is described by Rogers (1995) to take an inverted U-shape; a process characterised with low levels of adoption at the early stages of adoption but grows exponentially as more people becomes aware of the innovation. However, as the technology evolves and new products with some levels of relative advantage over the existing ones are invented, the adoption of the old innovation begins to decline. This study therefore seeks to investigate this hypothesis within the context of African's financial technology (Fintech hereafter) adoption process.

Although this hypothesis may be theoretically plausible, its empirical justification could be subjected to some peculiar characteristics and conditions, particularly among African economies. In Africa for instance, approximately 80% of its population lack access to formal banking services (World Bank, 2017) and bank penetration rate is low (Demirguc-Kunt et al., 2015). In other words, less than 25% of the Sub-Saharan Africa adults have an account with a formal financial institution (Demirguc-Kunt et al., 2015). Therefore, this widespread financial exclusion in the continent makes the continual adoption of Fintech inevitable. Again, Fintech's development in the continent hinges on the ability of the industry to successfully reach customers at grass-root levels and adequately meeting their needs (Alexander et al., 2017). The ability of Fintech companies to effectively understand the distinctiveness and/or the peculiarities between the different users' groups can also help to improve its continuous use (Ryu, 2018). This means that Fintech in Africa is needs-driven unlike other regions of the world where it might be tailored towards meeting consumers' desires in terms of convenience.

A needs-driven Fintech adoption process in Africa is anchored on the industry's proper understanding of consumers' needs such as huge financial exclusion, inefficiencies and lags in financial service delivery, and the general poor financial development in the continent and effectively meeting them (Alexander et al., 2017). This is unlike other regions of the world such as the UK, Canada, China, etc. that have highly developed financial system, competent financial management with zero or minimum risk of financial loss when compared with Africa[2]. Therefore, the adoption of Fintech in these developed regions is basically a matter of the comfort it provides rather than on the needs it aims to solve.

Hence, the need Fintech is designed to solve drives its adoption process more than the comfort it provides.

Based on the foregoing, it is pertinent to note here that as good as Fintech adoption is, it still has some weaknesses which is capable of introducing structural transformations that can create lots of macroeconomic instabilities. Take for instance, the adoption of Fintech comes with technological unemployment especially within the financial institutions. It is on this background that Double and Bradley (2018) asserts that the adoption of Fintech has a double-edged nature of having both risks and benefits which hinders its adoption. Jugurnath et al. (2018) added that its disruptive impact on the conventional manners in which businesses and in particular banking is carried out limits the extent of its adoption. These, therefore, suggest that the adoption of financial technology comes with both problems and prospects. This makes some African economies uncertain about its future prospect and reliability (Ernest & Young, 2017). The uncertainties surrounding Fintech is capable of making it difficult to assign probabilities to the fundamental values of financial assets, thereby increasing the volatilities of financial assets (Hakkio & Keeton, 2009).

Given the huge Fintech prospects and potential problems, the question is therefore whether the adoption of Fintech particularly among Africa markets will follow the inverted U-shaped process in the long-run and if it does, what kind of innovation is likely to replace it? Though this can be subjected to empirical proofs, this study argues that Fintech's high adoption rate in Africa can be sustained into the long-run with greater globalisation/trade openness and as long as financial exclusion remains high in the continent. Therefore, this study aims to find its adoption determinants, investigate an inverted U-shaped adoption process and/or a threshold point with special reference to emerging, frontier and fragile African markets in what is referred to as modern diffusion of innovation theory.

THEORETICAL AND EMPIRICAL LITERATURE

Various theoretical and empirical pieces of literature have attempted to give an empirical justification on the factors that drives the adoption process of new innovations. Notable among these theories are the Diffusion of innovation (DOI) theory by Rogers (1995), the Technology Acceptance Model (TAM) by Davis et al. (1989), TAM2 by Venkatesh and Davis (2000), and the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al., (2003). This study critically assessed these theoretical models and integrated them to model an equation used to assess the objective of this study, with emphasis on the diffusion of innovation theory.

The diffusion of innovation theory asserts that technology diffusion spreads across five distinct groups within a population and follows an inverted U-shaped process from its invention to its death. It's a five-stage process beginning with 2.5% inventors and grows to about 13.5% early adopters, a total of 16% adopters. The next stage is the 34% early majority adopters; hence adoption process becomes self-sustained at this point. Global adoption of Fintech has grown to this point with 33% regular users of Fintech in 2017 (Ernest & Young, 2017). The next stage is another 34% late majority adopters. At this stage, the adoption process gets to its peak with a total of about 84% adopters and therefore begins to decline[3]. The last stage is the declining stage of 16% adopters, which Rogers called the laggards. At this stage, new innovations with greater relative advantage have taken over the market. This process explains the inverted U-shaped hypothesis as shown in Figure 1.

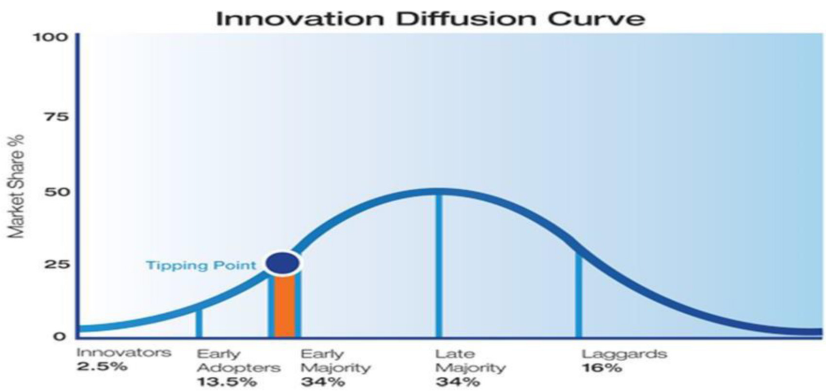

Figure 1. Innovation adoption rate [Source: Rogers' Diffusion of Innovation Theory (1995)]

This adoption decision depends on five basic determinants. They are relative advantage, compatibility, complexity, trial-ability and observe-ability. Relative advantage is the edge new innovation has over the already existing devices. For new innovation to be adopted, it must be perceived to outperform existing ones. Compatibility on the other hand, entails that new technologies must be consistent with existing norms and previous experiences of potential users, while complexity explains the extent to which users perceived a device as being simple to use so that their risk perception in accessing it is minimised. In assessing the factors that influence the adoption of a range of innovations, Tornatzky and Klein (1982) found that compatibility, relative advantage and complexity were the major determinants. A consistent finding was also made by Al-Jabri and Sohail (2012) in assessing the factors that drives the use of mobile phones to access financial services in Saudi Arabia. In addition to the above, they added that observability which explains how the outcome of the invention can be easily communicated to the public also drives the adoption of new innovations. Moreover, trial-ability is the ability to test-drive the innovation before using it. Dearing (2009) applied the diffusion of innovation theory to intervention development. He believes that trialiability is a major driver of technology diffusion.

Later theories such as the Technology Acceptance Model (TAM) by Davis et al. (1989) also emphasised on the importance of complexity and compatibility in technology diffusion process. They referred to these as “perceived ease-of-use”, and perceived usefulness respectively. These forms people’s belief system about an innovation overtime and determine the extent of its adoption. Therefore, actual use of an innovation may not be a direct or immediate consequence of present period’s attitudes and intentions (Davis et al., 1992). This assertion justifies the fact that technology diffusion process is a dynamic rather than a static stochastic process. This is because present decision is not sole dependent on the immediate conditions but on both past, contemporaneous and stochastic disturbances. However, the TAM theoretical model has been widely criticised on the ground that it has limited explanatory and predictive power, poor for experimental and empirical testing and lacks practicability (Chuttur, 2009).

More recent theories such as the Technology Acceptance Model 2 (TAM2) by Venkatesh and Davis (2000) and the UTAUT by Venkatesh et al., (2003) models tried to circumvent these weaknesses by introducing risk and benefits/trust as an adoption determinant. In exploring the factors that can spur or inhibit the use of Bitcoin, Abramova and Böhme (2016) found that different kinds of risks and fear of financial loss were its major deterrent. The implication of this is that customers’ perception of the potential risks and/or benefits about an innovation will determine the extent of its adoption (Ryu, 2018). Therefore, the speed of Fintech diffusion is gauged not only on its characteristics, need identification, and awareness creation, but also on the attitudinal differences of its users (Escobar-Rodríguez & Romero-Alonso, 2014); hence, Fintech adoption decision is an issue of reaching a balance or a trade-off between its perceived risks and benefits among potential users.

Just like the theoretical models, empirical findings also found that psychological, demographical and social factors drive the adoption of Fintech more than economic and financial variables. In assessing the factors that drive the adoption of financial technology Ryu (2018) further added that legal risks are its major deterrent whereas convenience is the main perceived benefit that promotes it. Moreover, Haddad and Hornuf (2019) also added that countries witness more Fintech adoption when the economy is growing and well-developed. However, Hu et al. (2019) asserts that perceived risk and perceived ease of use are not as strong as the users' trust in Fintech services in influencing the adoption decision. Invariably, these different views on what determines the adoption of Fintech is suggesting that these factors could be subjective and intuitive based on users' present and anticipated/future financial needs. This suggests the use of a dynamic model in assessing the determinants of Fintech. This study therefore adapted a scientific approach to these models with special emphasis on an augmented Roger's diffusion of innovation model. By contextualising these models, we argue that the adoption of Fintech will not decline in the long-run as was suggested in the diffusion theory if there is substantial sustainability of the state of art into the long-run.

Variable Measurements and Description

The variables used in this study were based mainly on the Diffusion of Innovation theory, with little improvements based on other theories that were reviewed and empirical literatures. The following variables were identified, measured and used to specify the model.

FINANCIAL TECHNOLOGY: Financial technology as a recent innovation in the field of finance is yet to be pinned down to a common measure with a wide range of data series. As a result, previous studies in this area made use of primary data analysis. However, given that this analysis is a panel analysis, primary data will not only be difficult but can as well be misleading. This is because different measures that constitute Fintech for a particular country might differ for another. Therefore, since Fintech outlets include mobile cellular subscription (MCS), internet services (ITS) and even the automated teller machines (ATM), this study follows the works of Samargandi et al. (2015) to construct a Fintech index using the principal component analysis (PCA). PCA is widely used to generate a small number of artificially uncorrelated variables accounting for most of the variance of the initial multidimensional dataset, thereby arriving at condensed data representation with minimal loss of information (Sinenko et al., 2013). Moreover, the PCA also adjusts for co-movement/multi-collinearity problem between indicators capturing possible structural characteristics among financial indicators (Sinenko et al., 2013); hence the need for its adoption in generating the index for financial technology.

The result as presented in Table 1 shows that three components were used to generate the Fintech indicator. Majority of the variability in the index was attributed to the first component to the tune of 63.6%, 27.99% to the second component and 8.39% to the last component. To be more specific, the generated index of Fintech among African economies were more susceptible to changes in the use of internet to access financial services in the first component, mobile transfers and payments (MCS) in the second component and Internet banking (ITS) again in the third component. Therefore, African Fintech is being driven more by mobile transfers and payments. This is consistent with the findings of Ernest and Young (2017).

Table 1
A principal component analysis for Fintech Index

Principal components/correlation (Number of Obs = 544)					Principal components (eigenvectors)				
Component	E. value	Diff.	Proportion	Cumulative	Variable	Comp1	Comp2	Comp3	Unexp
Comp1	1.9084	1.0686	0.6361	0.6361	ATM	0.609	–0.478	0.633	0
Comp2	0.8398	0.5880	0.2799	0.9161	ITS	0.668	–0.121	0.734	0
Comp3	0.2518	.	0.0839	1.000	MCS	0.428	0.870	0.246	0

Source: Estimation

The justification for this index is based on two basic yardsticks. One, there is a very high correlation between the three proxies used to generate the Fintech indicator, therefore, the inclusion of the three in a model can lead to multi-collinearity problem. Two, there is yet to be a comprehensive measure or indicator to measure Fintech. Bitcoins, eWallets and Blockchain technology are without a long data series to accommodate a certain degree of freedom. Although, Ernest and Young (2017) employed the use of primary data analysis for developed and emerging markets, however, no such study has been done among African economies.

RELATIVE ADVANTAGE: This is also referred to as relative efficiency in this study. It is the advantage new innovations have over existing ones. This is measured using Fintech's ratio to real gross domestic product (GDP). This is sourced from Okoli (2020).

COMPATIBILITY: This refers to Fintech's consistency with previous experiences of potential users. In other words, users' past experiences with similar devices determines his/her adoption decision. Davis et al., (1989) called it "perception of usefulness". Therefore, since the past experiences of potential users drive adoption in this sense, it will be measured with the first lag of the dependent variable (Fintech). This is sourced from Okoli (2020).

COMPLEXITY: In diffusion of innovation theory, this is the extent a person perceives Fintech as ease to use which depends on their literacy level. Davis et al. (1989) referred to this as "perceived ease-of-use" in the technology acceptance model (TAM). The higher the literacy level, the more Fintech will be perceived as easy to use. Therefore, complexity is measured with literacy rate/tertiary school enrolment (TSE). This is sourced from Okoli and Tewari (2020).

TRIALABILITY: Ability to use an innovation as explained above is a direct function of the individual's financial strength or income level. This will be measured with the growth rate of Gross Domestic Product (GDPR). This data is sourced from Haddad and Hornuf (2019).

OBSERVEABILITY: Rogers refers to this as the extent to which the outcome of an innovation is communicated to the public, which is a function of how many people that both adopts and spreads the information. The higher their number, the more likely such information spread and hence more adopters. This variable is measured with population growth rate (POPG) and sourced from Okoli and Tewari (2020).

PERCEIVED RISK: Perceived risk of an innovation is inversely related to its adoption level. Since risk is often measured using the standard deviation. This study used Fintech's standard deviation to measure its riskiness as sourced from Ryu (2018).

SUSTAINABILITY: The above models explain what could spur or inhibit the adoption of an innovation without a clue to its sustainability. This study aims to fill this gap by arguing that Fintech adoption can be sustained through some levels of trade openness/globalisation which will guarantee its continuous adoption. This is the point of departure from previous theoretical models. In other words, as an economy becomes more global and open to new innovations, the more likely and easier an innovation will be sustained overtime, thereby negating the inverted U-shaped hypothesis. Therefore, instead of an inverted U-shaped, the adoption curve will slope upwards and converge to steady-state equilibrium. This term will be measured with foreign direct investment (FDI) and/or trade openness (TOP).

Table 2
Description of variable measurement and expected signs based on Equation (1)

Variables	Description/Measurement	Variable source	Expected signs
Fintech	Index of Fintech (Ft_{it}) generated with three components of ATM, Internet use and mobile cellular subscription using the PCA technique to avoid multi-collinearity problem	PCA Tech. & Samargandi et al. (2015)	Positive
Compatibility/ previous period Experience	First lag of Fintech Index ($Ft_{it\text{-}1}$)	Okoli (2020)	Positive
Relative efficiency	Ratio of Fintech index to gross domestic product (GDP) (Ft/gdp_{it})	Okoli (2020)	Positive
Complexity or literacy rate	Tertiary school enrolment (Lr_{it})	Okoli and Tewari (2020)	Positive
Trial-ability	GDP growth rate (GDPR) (ΔGDP/Current GDP *100)	Haddad and Hornuf (2019)	Positive
Observe-ability or information spread	Population growth rate (Popg)	Okoli and Tewari (2020)	Positive
Fintech risk	Fintech's standard deviation (SDf_t)	Ryu (2018)	Negative
Sustainability or globalisation	Trade openness (Top_{it}) and Foreign Direct Investment (FDI_{it})		Positive

Source: Author's compilation based on theory and empirical literature. Data source: World Bank Data (2017)

MODEL SPECIFICATIONS

The general form of the model as suggested from the theoretical and empirical reviews is specified, thus:

$$ft_{it} = f\left(ft_{it-1}, ft/gdp_{it}, lr_{it}, gdpr_{it}, popg_{it}, sdft_{it}, top_{it}\right) \quad (1)$$

Where

ft_{it} = The index of Fintech;
$fti_{t\text{-}1}$ = First lag of Fintech, a measure of compatibility/experience;
ft/gdp_{it} = Ratio of Fintech to gdp, a measure of relative efficiency;
lr_{it} = Literacy rate proxy with tertiary school enrolment, a measure of complexity;
$gdpr_{it}$ = Growth rate of GDP, a measure of trial-ability;

$popg_{it}$ = Population growth rate, a measure of observe-ability/information spread;
$sdft_{it}$ = Fintech's standard deviation, a measure of risk;
top_{it} = Trade openness, a measure of sustainability/globalisation.

The econometric dynamic form of Equation (1) is presented in its level reduced form, thus:

$$ft_{it} = \beta_0 + \beta_1 ft_{it-1} + BX'_{it} + \lambda Z'_{it} + d_t + (v_i + \varepsilon_{it}) \quad (2)$$

The variables remain as defined above except that ft_{it} and $\mathcal{E}_{it}$ are $N \times 1$ vectors of the dependent variable which is the generated Fintech index and the unexplained factors of ft_{it} respectively for country i in period t such that $\mathcal{E}_{it} \sim IID\ (0, \sigma_\varepsilon^2)$. β's and λ are $K \times 1$ vectors of unknown parameters, while ft_{it-1} and X_{it} are also $N \times K$ matrix of explanatory variables. We assume another matrix Z of $N \times M$ order for the strict exogenous instrumental variables so that, $E(Z`\ \mathcal{E}_{it}) = 0$; where, $M > K$. If this condition is fulfilled, it will help to fix the problem of endogeneity. Therefore, the Z matrix is a set of valid instrumental variables assumed to be highly correlated with the explanatory variables but orthogonal to the error term. Orthogonality in this sense means that the Z matrix comprises of variables that are not correlated with the error term. Moreover, we also assume that the instrumental variable Z must be less than or equal to the number of groups (N). Moreover, ft_{it-1} is the vector of first lag of the dependent variable, Z' is vector of the control variables, X' vector of the determinants of Fintech, d_t is the year dummies, β and λ are the vectors of the parameters to be estimated on the constant, explanatory and control variables respectively, and v_i *and* $\mathcal{E}_{it}$ are the country's specific effect and the unexplained portion of the dependent variable.

The system GMM technique uses the first difference of the equation, therefore by taking the first difference of Equation (2), the country's specific fixed effect such as policies and state of financial development in the country which might be correlated with the regressors disappears because it does not vary with time.

$$\mu_{it} - \mu_{it-1} = (v_i - v_i) + (\varepsilon_{it} - \varepsilon_{it-1}) \rightarrow \Delta\mu_{it} = \Delta\varepsilon_{it} \quad (3)$$

Therefore, the transformed form model of Equation (2) then becomes:

$$\Delta ft_{it} = \beta_0 + \beta_1 \Delta ft_{i,t-j} + \beta_n \Delta X'_{i,t-j} + \lambda_n \Delta Z'_{i,t-j} + d_t + \Delta\mu_{it} \quad (4)$$

Note that by taking the first difference, the fixed country-specific effect (v_i) is removed because it is a constant and does not change with time. Likewise, the correlation of the lagged dependent variable with the error term will diminish

(Roodman, 2006). It is pertinent to note here that the exogenous instrumental variables used to estimate Equation (4) are first lag of an index of financial development, gross capital formation ratio to GDP, interest rate, financial inclusion measured with commercial bank branches, and level of the endogenous regressor of population growth. This makes the endogenous variables predetermined; therefore, they are no longer correlated with the error term in Equation (4).

METHODOLOGY AND DATA

The inclusion of the lagged dependent variable ft_{it-1} and the short time dimension of the panel dataset (T = 17) with large cross-sectional identity/countries (N = 32) suggests the use of a dynamic system Generalised Method of Moments (GMM) techniques to investigate the determinants and the presence of an inverted U-shape in Fintech adoption among the 32 African markets. This is because it is more efficient when the cross-sectional observation of the panel is greater than or equal to its time observation (Caselli et al., 1996). A dynamic model was informed by theory and not necessarily because it is required by regression. Moreover, a system GMM eliminates the problems heteroscedasticity, serial correlation, unobserved country heterogeneity, omitted variable bias, measurement error and endogeneity problems that frequently arise in panel analyses (Caselli et al., 1996). It is considered more superior than the differenced GMM because it reduces potential bias and imprecisions associated with a simple difference GMM estimator (Arellano & Bover, 1995; Blundell & Bond, 1998).

Two specification tests were proposed by Arellano and Bond (1991) to fix the exogeneity and serial correlation problems that often characterise the GMM model. They are the Sargan test of over-identification restrictions for the overall validity of the instruments and the serial correlation test [AR(1) and AR(2)]. The null hypotheses are that all instruments as a group are exogenous and that the error term (μ_{it}) of the differenced equations are not serially correlated particularly at the second-order (AR2). Therefore, a higher *p*-value is desirable for both tests. One should not reject the null hypothesis of both tests; otherwise, the model is not good.

The study centred on a panel of 32 African economies disaggregated into three emerging, 24 frontiers and five fragile markets according to Financial Times Stock Exchange (FTSE) countries classification to account for possible heterogeneity among groups. The data span is 17 years (2002–2018) and they were sourced from the World Bank development indicators (2017) and the International Financial Statistics (2018).

RESULTS AND DISCUSSION

As a starting point, we follow the theoretical assumption to model a dynamic equation with the first lag of the dependent variable (Fintech) as a measure of previous periods/users' experiences (compatibility) so as to capture the degree of persistence. The rationale behind this is that, Fintech as a recent innovation in the field of finance is surrounded with lots of information; therefore, early users' experiences will determine the extent of its adopted. This factor and more suggests the use of a dynamic GMM estimation technique. Before incorporating an inverted U-shaped/nonlinear relationship, we consider the baseline results of Equation (4) which is presented in Table 3 for the entire 32 African economies, emerging, frontiers and fragile African markets as reported under Columns (1)–(4) or Models (1)–(4), respectively.

From Table 3, compatibility/users' experiences show a high degree of persistence as indicated by its positive statistical significance in the four models. Again, the contemporaneous impact of other determinants of Fintech adoption such as complexity/literacy rate (TSE), relative efficiency (REFF), and trial-ability/income growth (GDPR) under Model 1 reveal that they promote the rate of Fintech adoption among African markets at varying degrees of significances at 1%, 5% and 10%. This means that if compatibility (L.FNTH), complexity (TSE), relatively efficiency (REFF), and income (GDPR) increase by one unit, the adoption of Fintech will increase by 1.023%, 0.002%, 63.98% and 0.004%, respectively all things being equal. On the other hand, the significant dampening effect of observe-ability/population growth in Models 1 and 3 imply that a one unit increase in population growth will reduce the adoption rate of Fintech by 0.036% (Model 1) and 0.035% (Model 3). Perceived risk of Fintech raises its adoption rate at 0.027%, 10% significance level under Model 3. Whereas this does not follow theoretical prior expectation, it is an indication that population growth and perceived risk can have an asymmetric impact on Fintech adoption in Africa.

In other words, the negative significant contemporaneous effect of observe-ability/information-spread and perceived risk under Models 1 and 3 suggest that their effect could be nonlinear. Therefore, the need to investigate their nonlinear relationship on Fintech adoption is buttressed here. Recall that the main objective of this study is to investigate possible nonlinear/inverted U-shape hypothesis of Rogers (1995) in the adoption of Fintech in Africa. This uniqueness is investigated and presented under Table 4. It assesses the combined magnitude of the linear and nonlinear impacts of population growth/information-spread coefficients on Fintech adoption to further justify or debunk this result.

Table 3
The GMM results of Fintech adoption determinants: baseline result

	All sample (N = 32)	Emerging Africa (N = 3)	Frontier Africa (N = 24)	Fragile Africa (N = 5)
	Model 1	Model 2	Model 3	Model 4
Dependent variable	FNTH	FNTH	FNTH	FNTH
Constant	0.171 (4.26)	0.330 (1.11)	0.191 (3.60)	0.289 (1.82)
Compatibility (L. FNTH)	1.023 (155.15)***	0.967 (23.50)***	1.035 (117.42)***	1.098 (32.26)***
Complexity/ literacy rate (TSE)	0.002 (2.20)**	–0.010 (1.24)	0.000 (0.09)	–0.003 (0.63)
Perceived risk (S.D. FINTECH)	0.019 (1.17)	–0.093 (0.68)	0.027 (1.77)*	0.063 (1.35)
Relative efficiency (REFF.)	63.981 (1.74)*	586.984 (0.58)	61.874 (1.57)	–35.468 (0.42)
Trial-ability/ income growth (GDPR)	0.004 (1.84)*	–0.012 (0.36)	0.003 (1.32)	0.002 (0.89)
Observe-ability (POPG)	–0.036 (2.96)***	0.160 (0.94)	–0.035 (2.22)**	–0.045 (1.08)
AR2	0.685	0.226	0.087	0.975
Sargan Test of exogeneity of instrument	0.000	0.135	0.000	1.000
Observations	362	31	249	65
Number of group (CtryN)	31	3	21	5

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

Table 3 further presents the factors that drive Fintech adoption among the emerging and the fragile markets under Models 2 and 4, respectively. The result found that only the first lag of the dependent variable/compatibility raises the adoption decision among these groups. The reason behind this could be specification error especially under a GMM technique. Take for instance; the GMM estimate produced weak and biased estimates when the cross-sectional identity (N) is less than the time identity (T). Therefore, using a GMM model in this case makes the iteration process of the instrumental variables to lose lots of degrees of freedom and as such could not converge as the number of group (N = 3 for the emerging group; and N = 5 for fragile group) is less than the time identity (T = 17). The GMM estimation technique becomes inefficient under this condition; hence the reason for the weak relationship. Further studies in this area can circumvent this problem by using a single dummy variable interactive model for the entire groups.

Following the above baseline results and its biased/limited information problem, an augmented version of the diffusion of innovation theory was modelled by incorporating a nonlinear effect of information spread/observe-ability and the sustainability indicators of FDI and TOP[4]. This is necessary to verify the inverted U-shaped hypothesis of the diffusion of innovation theory and to see whether the sustainability assumption holds. That is, if the adoption process will be sustained. The result as presented under Table 4 is not significantly different from those under Table 3. This is because the compatibility of Fintech term still shows considerable degree of persistence across the four groups (Models 5–8). Its significance at 1% level for all the economic groups is an indication that previous users' experience is the main determinant of present period's adoption level. On the other hand, complexity/literacy rate significantly promotes Fintech adoption among the 32 sampled African and the frontier economies at 5% (Model 1) and 10% significance (Model 5), respectively. These suggest that previous users' experiences and improvement in the quality of human capital/literacy rate among African markets positively drives Fintech adoption in the continent. This result is consistent with those of Teo and Pok (2003), Jarvenpaa et al. (2003), and Wu and Wang (2005) who reached similar conclusion that compatibility and complexity affect consumers' adoption of mobile technologies.

In addition to this, relative efficiency/advantage, income of potential users/trial-ability, information spread or observe-ability and sustainability (TOP) strategy significantly raise the adoption decision of Fintech in Africa at average rates of 96.8%, 0.007%, 0.04% and 0.001%, respectively, 5% significance level all things being equal. Fintech's relative advantage over other channels of creating and delivering financial services had the greatest magnitude of impact on its adoption at about 96.8%.

Similar conclusion that an innovations relative advantage emits a stronger impact on its adoption than its complexity and compatibility was also reached by Al-Jabri and Sohail (2012) and Tornatzky and Klein (1982), though the later was basically an explorative study on innovation characteristics and adoption using a meta analytical technique. This explains why Fintech drives financial inclusion more than the conventional banking styles have done in years. This could be due to the speed, efficiency, comfort with little or no risk in creating and extending financial service over the conventional banks' styles. This finding is further accentuated by the non-significant impact of its perceived risk. This means that users of Fintech in Africa are not discouraged by any possible risk involved; hence risk perception of Fintech does not limit its adoption in Africa. This conclusion is not consistent with previous which found that customers' perception of the potential risks and fear of financial loss will determine the extent to which a new innovation can be adoption (Ryu, 2018; Abramova & Böhme, 2016).

Similar conclusions also apply to the frontier group (Model 7) except that income growth rate (GDPR)/trial-ability could not significantly influence the adoption rate among the frontier group. The implication of this is that majority of potential Fintech users among the frontier and the fragile groups live below the poverty line, hence their income level does not support Fintech trial process before adopting it. Based on this, it is expected that income should greatly impact on Fintech's adoption among the emerging group as they are assumed to live above the poverty line. However, that this was not the case under Models 2 and 6 with only compatibility/users' experiences of Fintech explaining its adoption under the emerging group could be blamed on model specification error, omission of important variable and/or wrong estimation technique as was discussed above. Further studies in this aspect should assess these irregularities.

Moreover, under Models 5 and 6, the sustainability indicator of trade openness positively raise the adoption decision of Fintech at average rates of 0.001% and 0.002% at 5% and 1% significance level for the 32 African economies and frontier group, respectively. This means that Fintech adoption in Africa will continue to rise as long as the economies are open to trade to attract foreign technology/innovations. However, the nonlinear relationship of population growth/observe-ability shows that adoption will not be sustained in the long-run but will fall as new innovations are introduced. This is evident from the negative significant impact of the squared observe-ability/population growth rate at –0.017%. This result suggests an asymmetric relationship; hence, too much negative information is leveraged. Therefore, as information about Fintech spreads and many people adopts it; overtime, the adoption rate will peak and afterwards begins to fall. The implication of this is that Fintech adoption in Africa follows an inverted U-shaped process as hypothesised by Rogers (1995) in his diffusion of innovation theory, irrespective of any sustainability measure put in place to ensure its continuous adoption.

Whereas an inverted U-shape adoption process was suggested among the entire sample and the frontier groups, a U-shape process holds for the fragile group. In other words, Observe-ability detracts from the adoption rate at the early stages of adoption at –0.989% but its nonlinear relationship is positively significant at 0.150% (Model 8). This contradictory result could be attributed to the level of literacy among these economic groups. However, caution is also taken to either accept or reject this conclusion by conducting a second order U-test for the nonlinear relationship using Lind and Mehlum (2010) U-test. This finding of a U-shaped effect of population growth on Fintech adoption in fragile African markets is consistent with Okoli (2020) who found that the adoption of financial technology will significantly dampen credit risk up to a certain threshold but increases it afterwards. Furthermore, studies like those of Samargandi et al. (2015), Arcand et al. (2012), Easterly et al. (2000), Gavin and Hausman (1998), and Sundarajan and Balino (1991).

The estimated models' validity and efficiency tests were carried out using two main tests. They are the Arellano and Bond (1991) serial correlation test (AR(1) and AR(2)) and the Blundell and Bond (1998) Sargan test the exogenity/over-identification restrictions for the overall validity of the instruments. As stated earlier, the null hypotheses are that the error term (µit) of the differenced equations are not serially correlated particularly at the second-order (AR2) and that all instruments as a group are exogenous. Therefore, a p-value that is greater than 5 per cent suggests that the model is good. The null hypotheses for both tests are desirable; otherwise, the models are not good. From the results of the models (see Table 4), we see that the P-values of the AR2 tests for both the baseline and the main results are more than 5%. This means that the error terms are not serially correlated with its previous values at the second order (AR2). The implication of this is that the estimated parameters are free from bias and as such can be employed for policy recommendations. On the other hand, the Sargan test for the exogenity of the instrumental variables reveals that we cannot reject the null hypothesis that they are valid and strictly exogenous. This is because the Sargan tests for almost all the models are greater than 5% which is desirable. Hence, the instruments are good.

Table 4
The GMM results of fintech adoption determinants: Main result

	Entire Africa (N = 32)	Emerging Africa (N = 3)	Frontier Africa (N = 24)	Fragile Africa (N = 5)
	Model 5	Model 6	Model 7	Model 8
Dependent variable	FINTECH	FINTECH	FINTECH	FINTECH
Constant	0.018 (0.32)	–6.703 (1.53)	–0.021 (0.36)	1.746 (2.37)**
Compatibility (Lag FINTECH)	1.004 (112.46)***	1.018 (15.55)***	0.985 (79.73)***	1.106 (28.61)***
Complexity (TSE)	0.003 (2.40)*	–0.009 (0.32)	0.003 (2.09)**	–0.007 (1.07)
Perceived risk (S.D. FINTECH)	–0.005 (0.29)	–0.038 (0.17)	–0.002 (0.15)	–0.036 (0.93)
Relative Efficiency (REFF.)	967.646 (3.46)**	883.762 (0.55)	1,184.3 (3.47)***	–67.299 (0.62)
Trial-ability (GDPR)	0.007 (2.62)**	0.020 (0.23)	0.004 (1.53)	0.004 (1.13)
Observe-ability (POPG)	0.040 (1.86)*	7.272 (1.65)	0.043 (2.06)**	–0.989 (2.04)**
Observe-ability ($POPG^2$)	–0.017 (3.38)**	–1.883 (1.63)	–0.017 (3.50)***	0.150 (1.90)*
Sustainability (FDI)	–0.001 (0.59)	–0.030 (0.75)	–0.002 (1.38)	–0.003 (0.93)
Sustainability (TOP)	0.001 (3.41)**	0.005 (0.50)	0.002 (4.85)***	0.0002 (0.24)
AR2 (*p*-value)	0.135	0.900	0.095	0.997
Sargan test of Exogeneity iv (*p*-value)	0.648	0.118	0.999	0.018
Observations	292	20	246	67
Number of group(ctryn)	24	2	20	5

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

The Long-Run Analysis

The long-run result is presented in Table 5. This is necessary because we want to find out how the determinants of Fintech diffusion behave during the long-run. As a short-run analytical technique, the GMM coefficients could not account for long-run impacts of these variables on the adoption decision because it uses first difference estimator as modelled in Equation 4. Therefore, the long-run coefficients could be estimated by applying Equation 5 and evaluating it using ONLY the significant short-run parameters. This makes it easier to have a forward-looking model for policy issues.

$$Long\text{-}run\ coefficient = \frac{\beta_i}{[1-\delta]} \tag{5}$$

Where β_i is the individual significant parameter estimates from the short-run GMM estimates under models 5–8[5], whereas δ is the coefficient of the lagged dependent variable for each model.

Table 5

Long-run coefficients of the significant short-run variables in Models 5 to 8

	Model 9	Model 10	Model 11	Model 12
DEPENDENT VARIABLE	FINTECH	FINTECH	FINTECH	FINTECH
Constant	NSLS	NSLS	NSLS	–16.472
Compatibility (Lag FINTECH)	–251.0***	–56.556***	65.667***	–10.434***
Complexity (TSE)	–0.750*	NSLS	0.200**	NSLS
Relative Efficiency (REFF.)	–241911.5**	NSLS	78,953.33***	NSLS
Trial-ability (GDPR)	–1.75**	NSLS	NSLS	NSLS
Observe-ability (POPG)	–10.0*	NSLS	2.867***	9.330**
Observe-ability ($POPG^2$)	4.25**	NSLS	–1.133**	–1.415*
Sustainability (TOP)	–0.25**	NSLS	0.133***	NSLS

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

The results reveal a reverse effect when compared to the short-run estimate thereby suggesting that there are significant changes within the time horizon in the factors that affects Fintech adoption decision. In Model 9 for instance, Fintech compatibility with users' previous experiences significantly raises the adoption rate by 1.004% ceteris paribus during the short-run but significantly reduces it in the long-run at the speed of 251%. This suggests that the adoption decision is a dynamic stochastic process; hence present decision is a function of various factors that are subject to change. On the other hand, the result also reveals that the adoption process follows a U-shape process in the long-run as against an inverted U shape in the short-run. This assertion further strengthens the dynamic hypothesis.

Sufficient Condition for a Nonlinear Relationship

Although the GMM result presented in Table 6 suggests that Fintech adoption for the entire sample, emerging and the frontier groups follow an inverted U-shaped process as hypothesised by Rogers (1995), a sufficient condition is necessary to confirm or debunk this assertion. This is because the conventional econometric model is not suitable for testing the composite null hypothesis that the relationship will be decreasing at the left side of the interval but increasing at the right side, or vice versa (Lind & Mehlum, 2010). Put differently, the assumption of an inverted U shape is that the slope of the curve is positive at the initial stage, reaches a threshold and then turns to negative. Therefore, to confirm this finding of an inverted U shaped relationship, this study employed the Lind and Mehlum (2010) U test by re-specifying and re-estimating equation (4) in its reduced form thus:

$$FNTH_{it} = \alpha + \beta_i POPG_{it} + \delta_i POPG_{it}^2 + \lambda_i x_{it} + e_{it} \tag{6}$$

Taking the first derivative of equation (6) with respect to POPG yields the null and alternative hypotheses for the U test:

$$H_0\!:(\beta_i + 2\delta_i POPG_{lower\ bound}) \leq 0 \ and/or \ (\beta_i + 2\delta_i POPG_{upper\ bound}) \geq 0 \tag{7}$$

This can be rejected in favour of the alternative hypothesis:

$$H_1\!:(\beta_i + 2\delta_i POPG_{lower\ bound}) > 0 \ and/or \ (\beta_i + 2\delta_i POPG_{upper\ bound}) < 0 \tag{8}$$

The variables in Equation (6) are still as defined above. Note that the function $(POPG_{it})^2$ is the turning point of population growth rate, while β_i and δ_i are the intercept and slope coefficients of the function. The first derivative of the function is $\beta_i + 2\delta_i(POPG_{it})$ which depends on its intercept and slope coefficients. Therefore, $POPG_{lower\ bound}$ and $POPG_{upper\ bound}$ are the minimum and maximum points of population growth, respectively. If either H_0 lower bound and/or H_0 upper bound is rejected at a given level of significance, it means that we are accepting the alternative hypothesis of an inverted U-shaped relationship. Hence, we conclude that Fintech adoption will follow an inverted U-shaped process from its invention to its death.

Table 6
The results of the Sasabuchi-Lind-Mehlum (2010) test for U-shaped relationship

	Entire sample (N = 32)	Emerging group (N = 3)	Frontier group (N = 24)	Fragile group (N = 5)
Slope at $POPG_{Min}$	0.128*** (2.84)	3.10* (1.64)	0.132*** (3.01)	–0.36** (–2.22)
Slope at $POPG_{Max}$	–0.09*** (–3.57)	–1.27 (–1.23)	–0.089*** (–3.61)	0.19 (1.26)
Extreme Point	1.20	1.93	1.27	3.29
SLM test for inverse U shape	2.84	1.23	3.01	1.26
p-value	0.002	0.123	0.001	0.107

Note: *t*-value in parenthesis. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$. Source: Author's estimation

The U-test result presented in Table 6 reveals that the lower bound slope of POPG is significantly positive for the entire sample at 0.128% while its upper bound slope is significantly negative at –0.09%. This means that at low levels of population growth, it will be promoting the adoption of Fintech at the speed of 0.128% per annum. However, as the adoption process reaches a certain threshold of 2.84%, continuous increases in population growth rate will significantly reduce the adoption of Fintech at an average speed of –0.09%. At this point, the quality of population growth has improved to make better use of new innovations with greater relative efficiency over the present day Fintech; consequently, the number of people that adopts or uses Fintech begins to fall even with a greater increase in population growth. Therefore, the null hypothesis of U-shaped relationship/ absence of a nonlinear relationship is rejected and we conclude that the adoption process of Fintech among African markets follows an inverted U-shaped adoption process for the 32 sampled African economies. In other words, the Rogers (1995) hypothesis that innovation rises gradually at its early stages of invention, peaks and afterwards begins to decline until it eventual dies holds in terms of Fintech adoption in Africa. The empirical finding is consistent with Okoli (2020), Abdul Bahri et al. (2019) and Loayza and Rancière (2006).

This test is also conducted for the sub samples. Similar conclusion of an inverted U-shaped hypothesis is reached among the frontier group with a threshold point of 3.01% but was rejected among the emerging and the fragile groups. This is because the emerging and fragile African markets' lower bound and upper bound limits were not both significant even at 10% significance level. This finding has a lot of policy implication for the fragile group.

CONCLUSIONS AND POLICY IMPLICATIONS

This study adopted a scientific approach to an augmented diffusion of innovation theory to empirically investigate the presence of an inverted U-shaped hypothesis in the adoption of Fintech among a sample of 32 African markets for a period of seventeen years. This study is motivated by the huge financial exclusion, poor financial infrastructure and innovations in Africa, despite the speed and prospects of Fintech adoption in continent. Based on this, this study argues that the adoption of Fintech in Africa may not follow the inverted U-shaped process if it is sustained through trade openness.

Generally, we found using the dynamic system GMM estimation technique a strong evidence for an inverted U-shaped Fintech adoption process in Africa and among the frontier group despite the sustainability strategy of trade openness. This conclusion was reached by both the first order and the second order Lind and Mehlum (2010) U-test sufficiency tests. The linear and the nonlinear impact of population growth/observe-ability were positively and negatively significant at 5%, respectively. This implies that the adoption of Fintech will first grow at the early stages of its invention, reach a threshold point and afterwards declines as new technology with greater relative efficiency than the presnt day Fintech are invented. Hence, the need for African's financial institutions to improve their innovativeness in order to have a competitive edge is amplified in this study.

Moreover, Fintech's relative advantage over previous technologies, compatibility with users' previous experiences and complexity significantly promotes its adoption at 5% significance level. These conclusions are consistent with those of Ryu (2018) and Hu et al. (2019). According to them, Fintech's perceived ease of use, trust, convenience, and risk were its major drivers. Therefore, it implies that the adoption of Fintech is capable of fixing the large financial exclusion problem in the continent of Africa. This is because aside from the advantage of ease accessibility, it is consistent with existing norms and previous experiences of potential users; hence, their risk perception in accessing it is highly minimised. Consequently, Fintech adoption in Africa is more likely to be in continuous adoption as long as potential users' perceived usefulness of it is high and/or perceived risk of using it is low. However, these conclusions vary between one economic group and the other. As a result, the policy measures needed to harness the benefits and arrest the risks inherent with Fintech adoption will also vary between one economic group and the other. Again, since African's financial system is highly underdeveloped with lots of financial infrastructural gaps and/or structural imperfections, the adoption process of Fintech is likely to be very slow and steady. Therefore, monetary authorities in Africa should promote financial sector development in the continent through greater trade and financial openness, ensure stronger and stable financial system, and knowledge transfer from the technologically advanced countries through financial integration in order to fortify the operational network of banks. This is an area of further research and this study recommends that future research in this area should investigate the role financial regulations, financial development and structural transformation can have on Fintech adoption in Africa.

Finally, the strong significance of the first lag of the dependent variable/a measure of compatibility suggests that African's Fintech adoption is a dynamic stochastic process. The implication of this is that various indicators such as economic, financial, demographic, and psychological factors could be responsible for Fintech adoption decision in Africa; therefore, Fintech adoption in Africa maybe more susceptible to structural changes than policy driven.

NOTES

1. This is a point in the adoption process of new innovations where continuous adoption of the new innovation is self-sustained. This is otherwise known as the tipping point.
2. Based on the findings made by Ernest and Young (2017).
3. This is the inflection point were further awareness or publicity about the innovation will have no impact on its adoption level; hence the product has reached its saturation point and therefore begins to decline.
4. Please refer to the meaning of FDI and TOP as well as what they represent under the variable measurements and definitions above.
5. Recall that Models 5–8 represents the main models of interest in this study because they tested the major objective of the study.

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APPENDIX

Classification of African Economies

Table A.1: Classification of African economies used in this study

Emerging economies	Frontier economies				Fragile economies
Egypt	Algeria	Ethiopia	Mali	Seychelles	Chad
Morocco	Angola	Ghana	Mozambique	Swaziland	Cote d'Ivoire
South Africa	Botswana	Kenya	Namibia	Tanzania	Niger
	Burkina Faso	Madagascar	Rwanda	Tunisia	Sudan