Determinants of Penetration of Financial Technology Among the Heterogeneous African Economies

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Abstract

Wide-spread financial exclusion and the inability of banks to meet the customers' expectations in service delivery in Africa have made most central banks seek technology-enabled solutions, especially as the global trend moves towards diversifying the range of financial service provider types. Some authors attributed these problems to the significant financial infrastructural gap in Africa. This study, therefore, investigated the determinants of fintech spreads in a panel of five emerging, 24 frontier, and three fragile African economies from 2002 – 2018. The dynamic panel system GMM estimation technique based on the epidemic and rank theories revealed heterogeneity and significant difference in internet and mobile banking penetration rate among economy types in Africa, with emerging markets reporting higher intercept and lower slope than frontiers and fragile markets. Also, information spread promoted penetration across units; whereas, population growth and literacy only increased it among frontiers and fragile economies but dampened it in emerging economies. This means that users of fintech among emerging markets began to diversify to new innovations aside from those used in this study, hence the decline. Moreover, Africa's average fintech adoption rate stood at 24%; in South Africa and Morocco, it stood at 43% and 40%, respectively, compared to the global benchmark of 33%. We, therefore, recommend that banks should collaborate with fintech companies to enhance their benefits in Africa.

Keywords : financial technology, spread of penetration, GMM

JEL Classification Codes : C82, G00, G40

Paper Submission Date : February 5, 2020 ; Paper sent back for Revision : December 10, 2020 ; Paper Acceptance Date : June 28, 2021 ; Paper Published Online : November 15, 2021

Financial technology, which is the innovative use of modern technology in the design and delivery of financial services, is fast growing at an alarming rate, especially among financially excluded regions like Africa. The reason behind this rapid growth could be traced to the way it extends financial services to the previously financially excluded, faster than conventional banking. Speaking on its growth process, an American Bank observed that about 73% of bank clients now preferred to do their banking via the internet and mobile phone (Bowmans, 2017). While this does not comprise a larger percentage of African society, Ernst & Young (2017) observed that the growth rate of financial technology in Africa was about 35%. This means that the growth of financial technology has reached the point where further adoption becomes self-sustaining. Therefore, to access its growth rate and peculiar determinants in Africa is the focus of this study.

This study is motivated by the significant financial exclusion in Africa in order to proffer ways to ameliorate it.

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DOI : https://doi.org/10.17010/ijf/2021/v15i11/166830

Although Legland and Schneider (2016) observed that in recent times, financial technology (fintech, hereafter) investment in Africa has increased significantly, however, this growth rate has not been able to transmit to a higher financial inclusion in Africa as still about 60 – 70% were unbanked among the adult African population, and about 80% of Africa's 1 billion population lacked access to formal banking services (The World Bank, 2017). Moreover, this problem could be attributed to the low literacy rate among this adult population in Africa. As a result of these problems and the sluggish development and poorly developed financial system, the rate of financial exclusion is very high. Moreover, part of the problems that could lead to this is the high level of bank distress in Africa, poor energy generation, and invariably high poverty level among the people.

Moreover, the level of development and efficiency of the financial system in Africa can be said to be one of the major hindrances of technology adoption within the industry and the reason for substantial financial exclusion in Africa. According to IMF (2018), such problems in financial systems interrupt financial intermediation and undermine the monetary policy's effectiveness. It can also exacerbate economic downturns, trigger capital flight and exchange rate pressures, and create enormous fiscal costs related to rescuing troubled financial institutions.

According to Ernst and Young (2017), with respect to the adoption rate of fintech across 20 economies, China had the highest adoption rate at 69%, and Belgium was at the lowest point, with a 13% adoption rate. South Africa is the only African country that made it to the list at an average rate of 35%, which is slightly above the global benchmark of 33%. Although this might not be a sufficient condition to say that Africa's fintech adoption rate is above the global average, it implies that Africa could have a higher propensity for fintech adoption in the future.

Moreover, Ernst and Young (2017) observed that where 33% of the respondents used fintech consistently globally, 46% used it consistently among emerging markets. This implies two things. One, the spread of fintech can be measured as the ratio of users to the total population in a region or country, and two, it grows more among the emerging group compared to others.

Empirical Literature Review

As a new area of research, much has not been done. Few studies tried to quantify the rate of fintech adoption without assessing the factors that drive it, and only a few studies concentrated on Africa. For instance, Ernst and Young (2017) asserted that the global growth rate of fintech was 33%, and about 79% of the South African respondents declared their interest in using fintech in the future, however, these results are both incomplete and contradictory. It is incomplete because the authors could not explain the factors that drive this high adoption rate. It is contradictory because some fintech firms, such as M-Pesa, failed to launch in South Africa (Alexander et al., 2017). The situation was different in Kenya and Tanzania, where M-Pesa recorded about 19 million and 6 million mobile phone subscribers, respectively (Vodafone, 2016). It failed to thrive in South Africa due to excessive regulation within its financial market, which was not the case in other regions (Bowmans, 2017). Therefore, this underscores the fact that fintech solutions are often country-specific. This is one of the gaps this study wants to fill by grouping the African countries according to their emerging, frontier, and fragile components.

Fintech in Africa is needs-driven, unlike other regions of the world, where it is designed to meet consumers' needs in terms of convenience. This could be attributed to the continent's large financial exclusion and poor financial development, as observed earlier. The bank penetration rate is low; hence, less than 25% of sub-Saharan African adults had an account with banks (Demirguc-Kunt et al., 2015). Due to the widespread financial exclusion in Africa, the continual adoption of fintech has become inevitable. Fintech innovation and revolution is the main instrument to achieve financial inclusion since it includes the financially excluded populace (Siddiqui & Siddiqui, 2020).

Meanwhile, studies such as Patel and Patel (2021) found that women who joined some economic empowerment groups were empowered significantly from the economic perspective. This suggests that the membership of certain economic groups promotes financial inclusion as well. Therefore, since previous studies revealed that fintech adoption is not proportionately related to financial inclusion, this study aims to discover why this discrepancy exists.

Among the factors that drive its adoption rate, Alexander et al. (2017) emphasized awareness creation and the ability of fintech to meet consumers' needs at the grass-root as the main drivers; whereas, these factors may have varying degrees of impact from region to region. Escobar-Rodríguez and Romero-Alonso (2014) also believed that the speed of fintech's diffusion was gauged not only from its characteristics, need identification, and awareness creation, but also from the attitudinal differences of its users. Also, Kuri and Laha (2011) believed that a greater degree of awareness of basic banking services, diversification of rural non-farm sector, literacy drive to rural households, and an expansion of household-level assets were quite germane in driving financial inclusion. Bhatt et al. (2020) asserted that the adoption of fintech promoted the emergence of micro finance institutions (MFI). This implies that the extent to which users of fintech perceive it as simple to use drives its adoption level. It is pertinent to note here that the inability to empirically quantify these factors into a measurable yardstick is the major deterrent or drawback that previous studies suffered. These are some of the challenges this study aims to circumvent. Still, on the factors that drive its adoption, Poushter (2016) further emphasized the need for improved education/high literacy rate and economic condition among developing and emerging markets for an increased fintech adoption. This implies that internet usage increases the technology penetration rate in Africa and improves growth potential, especially when the population is primarily literate.

Theoretical Framework of Determinants of Penetration of Fintech

The empirical analyses on which this study is based are the information spillover and rank theoretical frameworks. These theories emphasized different socioeconomic and demographic factors that can influence the adoption behavior of new technologies.

(1) Epidemic Model (Information Spillover Effect) : According to this model, also known as the information spillover model, the extent of information dissemination about new innovations is the main factor that drives its spread. This theory is supported by empirical evidence such as the work of Patel and Patel (2021), which supported that financial awareness is a significant factor that plays a pivotal role in bringing financial inclusion among the members of self-help groups (SHGs). In other words, as more and more users of a new technology pass information about the technology to non-users through different means, the number of adopters will increase. Therefore, a country's propensity to adopt fintech is positively correlated with the present or lagged level of adopters in the country or continent in which the country is situated. This suggests that the diffusion exhibits an S-shape trend, with a low diffusion speed in early periods of invention, which increases as the information spreads further to the tipping point where further adoption becomes self-sustaining. After this, it projects asymptotically to the ceiling or saturation point where a further spread of information adds little or nothing to the new innovation or technology. However, this depends greatly on the level of literacy/exposure of prospective adopters and their number, which will elicit acceptance or rejection, given the technical nature of fintech. This suggests the inclusion of the rank theoretical model as one of the technology diffusion theories in this study.

(2) Rank Model (A Country's Heterogeneous Determinants of Penetration) : The rank model is based on the individual or country's heterogeneous determinants of technology adoption. This theory affirms that particular individual, country, or region-specific factors determine whether or not and to what extent a new invention will thrive in that region. Looking at fintech's adoption, such factors could include the size of the country's or region's population, the quality of the human capital (whether literate or not), the level of income, etc. According to empirical evidence, the adoption of new technology can be facilitated by specific skills rooted in the human capital of a closed economy or a country promoting the acceptance of new or external technologies (Keller, 2004). In other words, human capital facilitates technology transfer between and beyond national boundaries (Keller, 2004; Kneller et al., 2010). Firms/countries with employees having a higher level of education, training, and experience are more able to assimilate and exploit new knowledge (Khalifa, 2016). Therefore, countries that invest heavily in human capital and research & development are likely to adapt quickly to new technology adoption. This is imperative to this study as evidence reveals that a fintech solution may thrive in one country but without success in another.

Methodology

This section comprises of the data measurements and sources based on economic theory, the design of the models, model specification, and the estimation techniques for data analysis.

Data Measurement and Sources

Fintech, as used in this study, considers three basic aspects. They are mobile cellular/phone banking, internet banking, and automated teller machine, respectively. As explained above, their spread of penetration will be ascertained by dividing these proxies with the total population. Other research works in this aspect considered similar measures such as ICT (Khalifa, 2016), mobile phone (Andrianaivo & Kpodar, 2012), ATM (Gourlay & Pentecost, 2002), and mobile banking (Hall, 2011). By the spread of mobile phone banking, we mean the total percentage of the population using mobile phones to send and receive money via a network provider.

On the other hand, the theoretical and empirical literature has identified the explanatory variables to be used in this study. They comprise of three basic measures: first lag of the dependent variable as an information spillover/epidemic model proxy, the growth rate of the population, and the literacy level in the country, which represents the country's specific attributes/rank model. The variables and their definitions are presented in the appendix Table A3.

The data were sourced from The World Bank 2018 database and the International Monetary Fund 2018 database. This is to make for international comparison and reliability, reviewed and validated according to our study's standard business practices and auditing rules. The study used a panel of 32 African economies for the period from 2002 – 2018.

Design of the Models, Testing, and Estimation Technique

This is a quantitative research based on secondary panel data analysis of 32 African economies. The instruments/estimation techniques used to analyze the data include descriptive data analysis, pairwise correlation analysis, and the dynamic system generalized method of moments (GMM) estimation technique. The preliminary analyses — descriptive analysis and pairwise correlation analysis were necessary to verify the behavior of the data and ascertain the rate of fintech spread among the various groups. On the other hand, the primary analysis adopted the use of random effect and the dynamic system GMM techniques to assess whether there existed any unique difference among the economic group in fintech spreads (restricted model) and its determinants (unrestricted model), respectively. The GMM estimation technique is necessary for the following reasons. It corrects for serial correlation and heteroscedasticity problems. It also covers the endogeneity problem, and it is more efficient when the individual observation of the panel is more than or equal to its time observation (Caselli et al., 1996). Bond et al. (2001) showed that the system generalized methods of moments (GMM) dynamic panel estimation is capable of correcting unobserved country heterogeneity, omitted variable bias, measurement error, and endogeneity problems. A system GMM reduces potential bias and imprecision associated with a simple difference GMM estimator and is more superior to the difference GMM (Arellano & Bover, 1995; Blundell & Bond, 1998). The estimation was carried out using Stata 14 software.

Again, our model reveals that some of the independent variables are not strictly exogenous. This means that they correlate with previous and possibly current error realizations with fixed individual effects. This further suggests the use of a GMM estimation technique. As suggested by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998), two specification tests are used to dictate the problem. They are the Sargan/Hansen test of over-identification restrictions for the overall validity of the instruments, where the null hypothesis is that all instruments as a group are exogenous; hence a higher *p*-value is desirable and secondly that of serial correlation test (AR(1) and AR(2)). The serial correlation test examines the null hypothesis that the error term μ_{it} of the differenced equation is not serially correlated, particularly at the second-order (AR2), therefore, a higher *p*-value is also desirable. One should not reject the null hypothesis of both tests.

However, a major weakness of the GMM estimation technique is that it does not capture possible heterogeneity that could exist among the individual units/countries. We will account for this with the use of dummy variables in the GMM model. The argument here is that the factors that could determine fintech spread vary across units/countries and at various degrees, therefore, grouping them as one could be biased. It is on the basis of this that we disaggregate the economies into five emerging, 24 frontiers, and three fragile groups using two dummy variables, with the emerging market being the reference category. Moreover, the main analysis begins with the estimation of its restricted form using the random effect model, which is followed by the unrestricted result using the dynamic system GMM technique. The general form of the theoretical model used is specified thus:

$$ft_{it} = \beta_{i0} + \beta_{ij}\, ft_{it-1} + \beta x_{it} + \mu_{it} \tag{1}$$

where, ft is a vector of fintech spread of penetration, β is the vector of parameters of the explanatory variables, ft_{it-1} is a vector of various lags of fintech components, and x_{it} is the vector of the different measures of the determinants of fintech based on theory; whereas, μ_{it} is the unexplained portion of the dependent variable, hence $\mu_{it} \sim IID\,(0, \sigma_\mu^2)$.

Econometric Model Specification

Based on the theoretical and empirical literature, we specify a dynamic AR(1) model in its general but level form as :

$$Sft_{it} = \delta Sft_{it-1} + BX'_{it} + \lambda Z'_{it} + d_t + (v_i + \varepsilon_{it}) \tag{2}$$

where, Sft_{it} and ε_{it} are $N \times 1$ vectors of the dependent variables and the unexplained factors of Sft_{it}. Note that Sft_{it} is a vector of three dependent variables; thus, $SINTB_{it}$, $SATM_{it}$, and $SMPB_{it}$ are measures of the spreads of internet banking, automated teller machines, and mobile banking, respectively, for country i in period t. β's are vector $K \times 1$ of unknown parameters, while Sft_{it-1} and X'_{it} are $N \times K$ matrices of the first lag of the dependent variables and explanatory variables, respectively. We assume another matrix Z' of strictly exogenous control variables, that is, $N \times M$ because of the presence of an endogenous term, where $M > K$. The Z' matrix must be exogenous {i.e., $E(Z`\varepsilon_{it}) = 0$}. 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)*.

Furthermore, d_t is the year dummies, β and λ are the vectors of the parameters to be estimated on the explanatory and control variables, respectively, and v_i and ε_{it} are the country's specific effect and the unexplained portion of the dependent variable, hence $\varepsilon_{it} \sim IID\,(0, \sigma_\varepsilon^2)$. The country's specific fixed effect disappears after the first differencing because it does not vary with time.

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

Since one of the objectives of this study is to investigate heterogeneity in average (intercept) and slope of fintech's spread and depth of penetration among the emerging, frontier, and fragile economic groups, we incorporate this using dummies. The transformed form model of equation (2) becomes :

$$\Delta Dft_{it} = \delta_{i0}\,\Delta ft_{it-1} + \rho_{i0} + \rho_{i1}\,D^{i1}_{it} + \rho_{i2}\,D^{i2}_{it} + \delta_{i1}\,\Delta X'_{it} + \delta_{i2}\,D^{i1}_{it}\,\Delta X_{it} + \delta_{i3}\,D^{i2}_{it}\,\Delta X_{it} + \delta_{i4}\,\Delta Z'_{it} + \Delta\mu_{it} \qquad (4)$$

Note that i_0, i_1, and i_2 $\in \{e, f, g\}$ where $i_0 \neq i_1 \neq i_2$; D^i_{it} is a dummy variable identity, taking 1 if country type belongs to i category and 0 if otherwise. $\rho_{i0} - \rho_{i2}$ are all the coefficients of the intercepts to be estimated, while $\delta_{i0} - \delta_{i4}$ are all the slope coefficients to be estimated. i_0 is the reference category (the emerging markets), and i_1 and i_2 represent frontier and fragile markets, respectively. The rationale for this is that emerging markets are assumed to have a stable financial system for fintech adoption, therefore, it is expected that their rate of fintech adoption will, on an average, be greater than that in other economic groups. This argument is supported by Ernst and Young (2017). Two dummies for frontier and fragile markets are used to avoid the dummy variable trap. As the reference category, its average spread of fintech adoption rate is measured by the term ρ_{i0}, while that of frontier and fragile markets are $(\rho_{i0} + \rho_{i1})$ and $(\rho_{i0} + \rho_{i2})$, respectively. Likewise, the slope coefficient among the emerging, frontier, and fragile groups are δ_{i1}, $(\delta_{i1} + \delta_{i2})$ and $(\delta_{i1} + \delta_{i3})$, respectively.

The panel model is unique because it allows for heterogeneity both in the intercept and in the slope coefficients, enabling us to treat each economic group as unique. It allows us to analyze the different economic groups on what determines their adoption rate. It also affords us the advantage to directly test whether there is heterogeneity in the intercepts and slope coefficients among the economies. Note that this assumption of heterogeneity is not tested on the slope coefficient of the control variables for the sake of simplicity. Moreover, as a control variable, they are exogenously determined; hence, they are not strictly endogenous, and as a result, the common slope assumption better fits it. This assertion is strengthened in the theoretical model.

Empirical Analysis and Results

This section discusses the preliminary results and the main estimation techniques: the random effect and the dynamic system GMM techniques. The two preliminary analyses that were conducted are the descriptive statistics and the correlation analysis to ascertain the weighted average fintech rate of adoption and the behavior of data with their peculiar characteristics.

Descriptive Statistics

This is used to understand the unique properties as it relates to averages, deviations from mean, and the range of the data. This is important to enable us to do a comparative analysis with other empirical work and see how these variables change over time. The mean of spread of internet banking (SITU) is already expressed in percentage, which is approximately 10.9% of the entire population; whereas, the means of other variables are not due to the nature of data that are available on these variables. This implies that, on an average, about 10.9% of the total

Table 1. ***Rate of Fintech Spread in Africa and Among Emerging Markets***

	SATM	*SINT*	*SMPS*	*WAFTS*
All Africa Used in the Sample	9.61%	10.95%	50.17%	24%
Algeria	1.20%	15.42%	73.30%	30%
Egypt	0.72%	21.01%	61.97%	28%
Morocco	5.07%	35.32%	80.46%	40%
Nigeria	0.50%	11.13%	44.27%	19%
South Africa	8.16%	24.27%	97.77%	43%
Weights	0.3333	0.3333	0.3333	

population of African economies used the web. The spread of mobile phone banking (MPB) was the highest at 50.1%, and then the spread of automated teller machine (ATM) was 9.6% (please note that the spread of the use of internet banking and ATM are already in percentages). This means that we can also convert the spread of mobile phone banking (SMPB) to percentage by multiplying by hundred. The high rate of spread of MPB is consistent with prior expectations as mobile phone penetration in Africa is fast increasing.

Table 1 depicts the weighted average estimate of the adoption rate of fintech spread in Africa and some selected economies. The rate of adoption in South Africa, for example, stood at 43% (refer to Appendix Table A2). By this calculation, South Africa actually out-weighs its previous record at 35% (Ernst & Young, 2017). This implies that the average adoption rate of 24% for the entire African markets was damped by those of the frontier and fragile groups. This, therefore, further intensifies the need for disaggregation.

Results of Correlation Test

As presented in Table 2, the results show that there is a potential trade-off among the variables. This exists between the different measures of fintech spreads, population growth, and per capita income. Meanwhile, all the three proxies of fintech show positive and significant trends, implying that the use of one increases the use of the other. However, that fintech spread is negatively related to the growth rate of the population suggests that people's attitude towards the adoption of fintech is negative, possibly due to the potential risk inherent in it. This will be verified further in this study. Hence, it suggests the need to incorporate a social factor as one of the determinants of fintech adoption. Another main finding is the positive relationship between the literacy rate. This is consistent

Table 2. ***Results of the Correlation Test Among the Variables***

	SATM	*SINT*	*SMPS*	*GDPP*	*ROE*	*POPG*	*TSE*
SATM	1.0000						
SINT	0.4188*	1.0000					
SMPS	0.3420*	0.8283*	1.0000				
GDPP	–0.0614	–0.1469*	0.0347	1.0000			
ROE	0.1936*	–0.1011*	–0.1028*	–0.0868	1.0000		
POPG	–0.2696*	–0.5319*	–0.4238*	0.2953*	–0.3515*	1.0000	
TSE	0.4195*	0.4861*	0.4414*	–0.2874*	0.2265*	–0.4879*	1.0000

Note. * indicates significance level at 5%.

with prior expectations. Although this might be a necessary condition, however, it is not a sufficient one. The use of further tests will justify this assertion.

Empirical Analyses and Discussion of the System GMM Results

This subsection analyzes and discusses the different factors that determine the spread of fintech among the heterogeneous African economies. The model specifications being a forward looking-dynamic panel approach to a dummy variable regression analysis justify the theoretical basis that the information spillover and country's specific attributes of the level of literacy (TSE) and population growth rate (POPG) are the major determinants of fintech's spread of adoption among the various economic types in Africa.

The analysis starts by first investigating whether fintech spreads among the three economic groups are uniquely different or similar. This is done by testing whether the average spread of adoption (say internet banking, for instance) of the frontier (f) and fragile (g) economies (i.e. $SINT^i = \frac{1}{NT} \Sigma^T_{it=1} SINT_{it}$, where, $i = f, g$) is different from the emerging economies by estimating equation (4) using a random effect technique with the slope coefficients set to zero and test the significance of the intercept coefficients. For the sake of clarity, the study assumes that the intercept coefficients of ATM for the emerging, frontier, and fragile groups are λ_{i0}, $(\lambda_{i0} + \lambda_{i1})$, and $(\lambda_{i0} + \lambda_{i2})$, respectively; whereas that for internet banking are β_{i0}, $(\beta_{i0} + \beta_{i1})$, and $(\beta_{i0} + \beta_{i2})$, and the coefficients for mobile phone banking are π_{i0}, $(\pi_{i0} + \pi_{i1})$, and $(\pi_{i0} + \pi_{i2})$, respectively. After estimating the restricted form model, the unrestricted version of equation (4) is also estimated so that heterogeneity will also be tested in its slope coefficients. Given that the reference economy is the emerging markets, β_{i1} or β_{i2}, λ_{i1} or λ_{i2}, and π_{i1} or π_{i2}, set equal to zero would indicate homogeneity with the emerging markets. That will imply that on an average, fintech spreads are influenced by similar factors among African economies.

The results of the restricted version of equation (4) are reported in its three unique models under Table 3. The Wald-Chi-square statistics for models (2) and (3) are significant at the 5% level, therefore, the null hypotheses of $\beta_{i1} = \beta_{i2} = \pi_{i1} = \pi_{i2} = 0$ are rejected. This implies that there is a significant difference in the rate of internet banking and

Table 3. ***Average Fintech Spread Among Different Economy Types in Africa***

	Model (1)	Model (2)	Model (3)
Dependent Variables	*SATM*	*SINT*	*SMPS*
Constant	3.13	21.43	0.72
	(0.01)	(5.23)***	(6.48)***
Dummy frontier *(Df)*	226.85	–11.93	–0.23
	(0.53)	(2.65)***	(1.89)*
Dummy fragile *(Dg)*	–2.63	–16.33	–0.45
	(0.00)	(2.44)**	(2.47)**
Model Specification	$SATM_{it} = \lambda_{i0} + \lambda_{i1} D^{i1}_{it} + \lambda_{i2} D^{i2}_{it}$	$SITU_{it} = \beta_{i0} + \beta_{i1} D^{i1}_{it} + \beta_{i2} D^{i2}_{it}$	$SMPS_{it} = \pi_{i0} + \pi_{i1} D^{i1}_{it} + \pi_{i2} D^{i2}_{it}$
R-sq	0.0116	0.1187	0.0722
Wald chi^2(2)	0.41	8.37**	6.49**
Obs	480	480	480
No. of group (CtryN)	32	32	32

Absolute values of z-statistics are in parentheses.

*significant at 10%; ** significant at 5% ; and *** significant at 1%.

mobile banking among the various economy types in Africa. Moreover, since β_{i1}, β_{i2}, π_{i1}, and π_{i2} are all negative ; whereas β_{i0} and π_{i0} are positive, it means that the emerging African economies, on an average, are more likely to experience a wider spread of fintech adoption than the frontiers and fragile groups. The estimated average of internet banking spread (SINT) among emerging markets is 21.43% (β_{i0}) but 9.5 % ($\beta_{i0} + \beta_{i1}$) and 5.1% ($\beta_{i0} + \beta_{i2}$) for frontiers and fragile groups, respectively. On the other hand, the estimated average of the spread of mobile phone banking (SMPB) among emerging African markets stood at 72% (π_{i0}), but for frontiers and fragile markets, it stood at 49% ($\pi_{i0} + \pi_{i1}$) and 27% ($\pi_{i0} + \pi_{i2}$), respectively. However, for automated teller machine, the null hypothesis of homogeneity cannot be rejected because the chi-square statistics are not significant, therefore, in terms of ATM spread, the results reveal that African economies have not attained any significant impact. In addition, a test of $\beta_{i1} = \beta_{i2}$ and $\pi_{i1} = \pi_{i2}$ is also rejected because there is a significant difference between frontier markets' average spread of internet banking and mobile banking to that of the fragile ones. This means that while the adoption rate of emerging markets is greater than that of frontier and fragile markets, frontier markets have a higher level of adoption than that of fragile markets.

The unrestricted versions of the models are presented in Table 4 as a dynamic panel regression based on theoretical undertones. Having considered three main aspects of fintech, the results reveal that the fintech market in Africa is a dynamic heterogeneous process (first lag of the dependent variable) as suggested by the theory. This suggests that random factors such as financial, economic, social, and even demographic are capable of influencing the spread rate of fintech among African economies. The results show that the spread of information positively promotes the spread rate of automated teller machine, internet banking, and mobile banking at a rate of 0.463%, 1.11%, and 1.02%, respectively.

The findings further reveal a consistent result with that of the restricted version in Table 3. Hence, emerging markets report higher level of fintech spread (for the three models) than the frontier markets, while the frontier markets report a high value than the fragile markets. This is because the intercept coefficient of emerging markets for the three models (λ_{i0} = 11,256.35; β_{i0} = 10.98, and π_{i0} = 2.68) are all greater than that of those of frontier ($\lambda_{i0} + \lambda_{i1} = -824.18$; $\beta_{i0} + \beta_{i1} = 3.23$; and $\pi_{i0} + \pi_{i1} = 0.10$) and fragile economies ($\lambda_{i0} + \lambda_{i2} = -7642.24$; $\beta_{i0} + \beta_{i2} = -43.8$; and $\pi_{i0} + \pi_{i2} = 2.496$), respectively. This assertion is supported by both other empirical findings/tests in this study and prior expectations.

Moreover, the results further reveal that literacy rate and population growth rate significantly promote spread among the frontiers and fragile markets but dampens it among emerging markets. This can be justified on the grounds that fintech spread among emerging markets has crossed its tipping point where continuous adoption is self-sustaining and has entered the saturation point, hence the decline. Therefore, as the population and level of literacy in such economies grow, the majority of the populace will continue to invent new technologies and divert attention to such, thereby abandoning previous innovations. This is why the dynamic term in the model is highly significant at the 1% significance level. However, for the frontier and fragile markets, the growth rate of the population and literacy will still spur further adoption of fintech because these are still at their developmental stage or what Rogers calls the early majority.

For instance, in the case of mobile banking, a 1% increase in the population level will raise the spread rate by 1.09 in frontier markets, 0.14 among fragile markets, but dampens it by 1.09 among emerging markets. On the other hand, a one-unit increase in literacy level among frontier and fragile economies will raise the spread of mobile banking by 0.02 units and 0.043 units, respectively, and reduce it by 0.02 units among emerging economies. The same assertions are true for automated teller machines and internet banking, though with different magnitudes except for the case of frontier markets where these two factors (population growth and literacy rate) could not explain the spread of internet banking.

Finally, on this part, the diagnostic check of the entire model considers the Arellano - Bond first order and second-order tests of autocorrelation, Sargan tests of over-identifying restrictions and exogeneity tests, and the

Table 4. *GMM Panel Estimates of the Determinants of Fintech Spread in Africa*

Dependent Variables	Model (1) *SATM*	Model (2) *SINT*	Model (3) *SMPS*
First Lag of Dependent Variable	0.463	1.11	1.02
	(8.05)***	(53.82)***	(33.64)***
Constant	11256.35	10.98	2.68
	(2.93)***	(2.14)**	(3.34)***
Dummy frontier *(Df)*	–12080.53	–7.75	–2.58
	(3.04)***	(1.42)	(3.15)***
Dummy fragile *(Dg)*	–18898.59	–54.78	–0.184
	(1.76)*	(3.29)***	(0.09)
First Lag of *POPG*	–5850.69	–2.88	–1.09
	(3.15)***	(1.17)	(2.55)**
First Lag of *TSE*	–64.70	–0.08	–0.02
	(3.61)***	(1.88)*	(4.22)***
First Lag of *(Df*TSE)*	118.56	0.03	0.02
	(5.38)***	(0.67)	(4.06)***
First Lag of *(Dg*TSE)*	148.88	0.77	0.043
	(1.75)*	(4.11)***	(2.24)**
First Lag of *(Df*POPG)*	5776.188	2.23	1.09
	(3.10)***	(1.02)	(2.56)**
First Lag of *(Dg*POPG)*	8988.85	12.98	0.14
	(2.41)**	(2.57)***	(0.18)
AR(2)	0.260	0.123	0.145
Year Dummy	Yes	Yes	Yes
Sargan Test of Overid. Restrictions	0.001	0.000	0.025
Sargan Test of Exogeniety of Instrumental Variables	0.109	0.217	0.118
F-Statistics (9, 438)	486.2***	1009.54***	1342.88***
Observation	448	448	448
No. of groups (CtryN)	32	32	32
Absolute values of *i*-statistics are in parentheses.			

Note. *significant at 10%; ** significant at 5%; and *** significant at 1%

overall validity of the instrumental variables. The null hypothesis for the Arellano and Bond serial correlation test at second-order states that the error term of the differenced equation is not serially correlated with past error terms, particularly at the second order (AR(2)). We cannot reject this hypothesis because all three models have higher p-value greater than 5%: 0.260, 0.123, and 0.145, respectively. This is desirable, therefore, the instrumental variables of the models represent the true instruments for the model.

On the order hand, the null hypotheses for the Sargan tests of the exogeneity of the instrumental variables state that all instruments as a group are exogenous. This condition is also met because their p-values are greater than 5%, therefore, the instrumental variables are strictly exogenous and suitable for the models; however, the over-identification restriction reveals that our instruments are weak. This implies that although they are strictly exogenous and suitable for the model, their explanatory power in predicting the values of the variables is not reliable. This is another major drawback of this study. Further studies in this area should identify and use instruments that will be both strictly exogenous and whose prediction power is also very strong. This problem is circumvented to a great extent by the significance of the *F*-statistics for the overall model at the 1% level of significance. Therefore the whole model is good, and all the variables jointly impact the dependent variables.

Conclusion

This study investigates the factors of the growth rate of fintech adoption and its determinants among the heterogeneous African economies. The study is motivated by the global diversification from fintech to create higher financial services and its inability to raise financial inclusion in Africa. This study argues that the adoption of fintech as a means of financial service delivery will improve financial development if the factors that influence its adoption are adequately identified and controlled. The term 'spread of fintech penetration' means the percentage of the total population that uses fintech. The study, therefore, examines these determinants over a cross-section of five emerging markets, 24 frontier markets, and three fragile markets (see countries' specification in the appendix) of African economies spanning the period from 2002 – 2018 to incorporate heterogeneity between groups using dummy variables. The reference group being the emerging markets, therefore, two dummies are used for frontiers and fragile markets to avoid a dummy variable trap.

The rank theoretical framework and the information spillover effect or the epidemic theories are the theoretical frameworks employed. Based on the dynamic system GMM model, which is suggested by theories, finds evidence to support other empirical findings that the fintech market is a dynamic stochastic process. This is due to the strong significance of the first lag of the dependent variable as one of the regressors. It also reveals that heterogeneity exists among the economies and that the information spillover and countries' peculiar attributes are the major determinants of its spread in Africa. The results show that while population growth and literacy level significantly promote the spread of fintech among frontiers and fragile markets, it dampens it in emerging African economies. This reveals that fintech adoption among emerging African markets might have been diversified to new devices/innovations rather than the ones used in the study. Ernst and Young (2017) supported this finding when they affirmed that emerging markets' adoption rate would reach its saturation point in the near future. Therefore, further studies should ascertain what constitutes fintech adoption among emerging markets and what determines its adoption rate.

The average fintech adoption rate for the entire African markets used in this study stood at 24%. However, most emerging African markets' adoption rate is well above this average, such as South Africa, Morocco, Egypt at 43%, 40%, and 28%, respectively. This finding is consistent with that of Ernst and Young (2017), who affirmed that the average fintech adoption among emerging markets oscillated around 35% and 46%. Furthermore, the correlation analysis reveals that a substantial level of trade-off exists between fintech and bank performance measured in terms of return to equity. This implies that the adoption of fintech in Africa emits some risk on the profitability of bank financial institutions. This assertion will be investigated in future studies. Therefore, given the above results and conclusions, this study recommends that African economies will benefit from fintech diffusion through improved financial service delivery and proper sensitization of the populace and financial institutions about the advantages and future prospects of fintech.

Implications

Based on the above conclusion, the following implications are drawn:

- Fintech spread of adoption in Africa is a heterogeneous stochastic dynamic process due to the strong significance of the first lag of the dependent variable. Moreover, it further suggests that the information spillover theoretical model is a strong model to describe the factors that drive fintech.
- The results further reveal that emerging markets report higher adoption rates than frontiers and fragile markets. This implies that the adoption process of fintech in Africa is country-specific, as suggested by the rank theoretical model.
- With a higher slope coefficient for the frontier economies than the emerging groups, the study suggests that although they (frontier) have a lower intercept, they will converge with emerging groups in higher fintech adoption and possibly overtake them.

Limitations of the Study and Scope for Further Research

As no study is exhaustive in itself, this study is not without some limitations that can stand as a guide for further studies. They are summarized thus:

- The study could not consider psychological factors that influence fintech adoption, such as perceived risk, perceived ease-of-use, and individuals' personal income. Further studies in this area should investigate the impact of these.
- The study concentrated only on fintech adoption behavior among African countries; further studies should try and make a comparative analysis between developed and developing economies to understand the path developed countries follow for higher adoption for African countries.
- The major weakness of this study could lie in the measures used to account for fintech. Though this was circumvented in the study as other studies used similar measures; however, future researchers should use more conventional terms such as cryptocurrencies, BitCoin, etc.

Authors' Contribution

Dr. Okoli Tochukwu Timothy conceived the idea and developed qualitative and quantitative design to undertake the empirical study. He also did an extensive and intensive literature review from reputable journals; filtered these based on their major contributions, weaknesses, and keywords ; and generated concepts and codes relevant to the study design. After that, Okoli Tochukwu Timothy did a test run on the data to verify the right analytical techniques to be adopted and, with the supervision of Prof. Davi Datt Tewari, estimated the data using Stata 14 and interpreted the outcomes. Prof. Davi Datt Tewari also appraised the outcome and drew conclusions and policy implications based on the findings from the analysis. Dr. Okoli Tochukwu Timothy wrote the manuscript in consultation with Prof. Davi Datt Tewari.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Acknowledgement

The authors acknowledge that a small stipend was given to the principal researcher (Dr. Okoli Tochukwu Timothy) at the beginning of this study in 2018 for this research.

References

Alexander, A. J., Shi, L., & Solomon, B. (2017). *How fintech is reaching the poor in Africa and Asia* : *A start - up perspective*. International Finance Corporation, World Bank Group. https://openknowledge.worldbank.org/handle/10986/30360

Andrianaivo, M., & Kpodar, K. (2012). Mobile phones, financial inclusion, and growth. *Review of Economics and Institutions, 3*(2), Article 4. http://www.rei.unipg.it/rei/article/view/75

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data : Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies, 58*(2), 277–297. https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*(1), 29 – 51. https://doi.org/10.1016/0304-4076(94)01642-D

Bhatt, N., Patel, R., & Kaur, A. (2020). A study of ICT adoption and its impact on selected MFIs of Gujarat. *Indian Journal of Finance, 14*(2), 7 – 20. https://doi.org/10.17010/ijf/2020/v14i2/150553

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115 – 143. https://doi.org/10.1016/S0304-4076(98)00009-8

Bond, S.R., Hoeffler, A., & Temple, J.R. (2001). *GMM estimation of empirical growth models*. https://ssrn.com/abstract=290522

Bowmans. (2017). *Fintech in Africa: Unpacking risk and regulation*. https://www.bowmanslaw.com/wp-content/uploads/2017/10/Fintech-In-Africa-Conference-Summary.pdf

Caselli, F., Esquivel, G., & Lefort, F. (1996). Reopening the convergence debate: A new look at cross-country growth empirics. *Journal of Economic Growth, 1*(3), 363 – 389. https://link.springer.com/article/10.1007/BF00141044

Demirguc-Kunt, A., Klapper, L., Singer, D., & Van Oudheusden, P. (2015). *The Global Findex Database 2014: Measuring financial inclusion around the world* (The World Bank Policy Research Working Paper No. 7255). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2594973

EFInA. (2010). *EFInA access to financial services in Nigeria 2010 survey.* https://efina.org.ng/wp-content/uploads/2018/12/EFInAAccess-to-Financial-Services-in-Nigeria-2010-surveyKey-Findings.pdf

Ernst & Young. (2017). *EY fintech adoption index 2017: The rapid emergence of fintech.* https://assets.ey.com/content/dam/ey-sites/ey-com/en_gl/topics/banking-and-capital-markets/ey-fintech-adoption-index-2017.pdf?download

Escobar-Rodríguez, T., & Romero-Alonso, M. (2014). The acceptance of information technology innovations in hospitals: Differences between early and late adopters. *Behaviour & Information Technology, 33*(11), 1231–1243. https://doi.org/10.1080/0144929X.2013.810779

Gourlay, A. R., & Pentecost, E. J. (2002). The impact of network effects on technology adoption: An empirical analysis. *The Journal of Manchester School, 70*(2), 185 – 203.

Hall, C. M. (2011). Consumerism, tourism and voluntary simplicity: We all have to consume, but do we really have to travel so much to be happy? *Tourism Recreation Research, 36*(3), 298–303. https://doi.org/10.1080/02508281.2011.11081675

International Monetary Fund. (2018). *Financial system soundness.* http://www.imf.org/en/About/Factsheets/Financial-System-Soundness

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature, 42*(3), 752–782. http://dx.doi. org/10.1257/0022051042177685

Khalifa, A. B. (2016). Determinants of information and communication technologies adoption by Tunisian firms. *Journal of Innovation Economics & Management, 2,* 151 – 177. https://www.cairn.info/revue-journal-of-innovation-economics-2016-2-page-151.htm

Kneller, R., Pantea, S., & Upward, R. (2010, August). Does absorptive capacity affect who benefits from international technology transfer? In, *Twelfth Annual Conference.* https://www.knowledge4all.com/Temp/Files/683babf9-bffc-464d-bd74-22837481529e.pdf

Kuri,P. K.,& Laha, A.(2011). Determinants of financial inclusion : A study of some selected districts of West Bengal, India. *Indian Journal of Finance, 5*(8), 29 – 36. http://www.indianjournaloffinance.co.in/index.php/IJF/article/view/72491

Legland, P., & Schneider, D. T. (2016). *Can equity crowdfunding crowd-out other alternative sources of finance?* https://www.vernimmen.net/ftp/160912_Thesis_David_Schneider_vF.pdf

Patel, R., & Patel, N. (2021). Does microfinance empower women from economic, social, and political perspectives ? : Empirical evidence from rural Gujarat. *Prabandhan: Indian Journal of Management, 14*(3), 32 – 48. https://doi.org/10.17010/pijom/2021/v14i3/158154

Poushter, J. (2016). Smartphone ownership and internet usage continues to climb in emerging economies. *Pew Research Center, 22*(1), 1– 44. https://www.diapoimansi.gr/PDF/pew_research%201.pdf

Siddiqui, T. A., & Siddiqui, K. I. (2020). Telecommunication, socioeconomic, and financial inclusion: An empirical evidence from Bihar. *Prabandhan: Indian Journal of Management, 13*(10–11), 46–61. https://doi.org/10.17010/pijom/2020/v13i10-11/156008

The World Bank. (2018). *World development indicators (2018).* http://data.worldbank.org/region/sub-saharan-africa.

Vodafone. (2016, April 25). *Vodafone M-Pesa reaches 25 million customers milestone.* https://www.vodafone.com/news/press-release/mpesa-25million

Appendix

Table A1. ***Descriptive Statistics of Variables for Fintech***

	SATM	*SINT*	*SMPS*	*DATM*	*DINT*	*DMPS*	*FO*	*GDPP*	*POPG*	*TSE*
Mean	9.610191	10.95376	0.501672	0.000338	0.000562	626.3464	0.041019	231199.1	2.384294	23.27514
Median	3.666576	4.935000	0.411838	1.59E-05	4.17E-05	26.79746	0.000000	140823.6	2.656222	15.22490
Maximum	71.80106	58.27124	1.656498	0.004832	0.006524	9868.435	0.508587	1912360.	3.843262	103.1983
Minimum	0.000000	0.072402	0.000707	0.000000	7.19E-07	0.197368	0.000000	245.235	–2.628656	0.000000
Std. Dev.	14.71626	13.61115	0.414421	0.000693	0.001238	1522.901	0.110803	275807.0	0.870879	23.64873
Skewness	2.173938	1.678452	0.705098	3.258683	3.121938	3.575226	3.029149	2.119488	–1.147002	1.437561
Kurtosis	7.290685	5.079203	2.625222	14.81425	12.89554	16.79938	11.04782	9.711769	5.276447	4.485862
Jarque-Bera	746.2800	311.8379	42.58226	3641.049	2738.153	4831.037	2029.407	1260.335	208.8934	209.4823
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	4612.891	5257.807	240.8027	0.162459	0.269906	300646.3	19.68891	1.11E+08	1144.461	11172.07
Sum Sq. Dev.	103736.3	88741.12	82.26560	0.000230	0.000734	1.11E+09	5.880779	3.64E+13	363.2882	267886.6
Observations	480	480	480	480	480	480	480	480	480	480

Table A2. ***Economy Types***

Emerging			**Frontier**			**Fragile**
Algeria	Angola	Kenya	Cote d'Ivore	Rwanda	Tunisia	Chad
Egypt	Botswana	Madagascar	Ethiopia	Senegal	Zambia	Niger
Morocco	Burkina Faso	Mali	Ghana	Seychelles	Namibia	Sudan
Nigeria	Burundi	Malawi	Mauritius	Swaziland	Togo	
South Africa	Cameroon	Mauritania	Mozambique	Tanzania		

Table A3. ***Fintech Spread: Adoption of Determining Variables***

Theories and Measurements	**Characteristics**	**Variables**	**Variable Type**	**Expected Signs**
Spread of ATM	The percentage of the population that uses automated teller machines (ATM).	ATM/Total Population	Dependent	Model 1
Spread of Internet Use	The percentage of the population that uses the internet (INT).	INT/Total Population	Dependent	Model 2
Spread of Mobile-Phone Subscription	The percentage of the population that subscribes to mobile phone online services (MPS).	MPS/Total Population	Dependent	Model 3
Rank Theory	Country's heterogeneous attributes or structural characteristics.	Population Growth Rate and Tertiary school enrolment	Independent	Positive (+)
Epidemic Theory	Spread of information from previous users to non-users.	Lag of the dependent variable	Independent	Positive (+)

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