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Article

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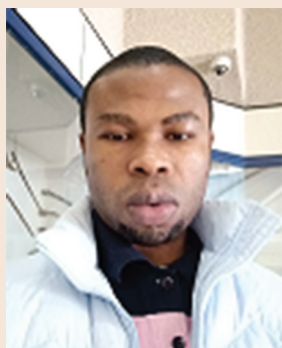
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FINANCIAL ECONOMICS | RESEARCH ARTICLE

Investigating the determinants and growth of financial technology depth of penetration among the heterogeneous Africa economies

Tochukwu Timothy Okoli^{1*} and Devi Datt. Tewari²

Abstract: The widespread financial exclusion in Africa despite the continent's high adoption of financial technology (Fintech) suggests that there is a gap between Fintech's adoption and its actual usefulness. This study seeks to measure Fintech's usefulness, its growth and identify its determinants in a panel of three emerging, twenty-four frontiers and five fragile African markets for the period 2004–2018.



Tochukwu Timothy Okoli

ABOUT THE AUTHORS

Tochukwu Timothy Okoli My name is Tochukwu Timothy Okoli, a postgraduate (PhD) student at the University of Zululand, South Africa. As the principal researcher in collaboration with my supervisor Professor Devi Datt Tewari, the ideas and findings in this study are entirely ours being one of the drafts from my PhD thesis which I have successfully completed. Some have been published while others are still under review. My areas of research interest are financial-technology, financial stability, and risk management, its dynamic short and long-run macroeconomic impact. I also excel in financial econometrics, quantitative economics, systemic risk analysis and econometric modeling with a number of publications in these areas. I have cognitive experience in research and teaching both locally and internationally and have had the privilege of working with renowned Professors and intellectuals round the globe. Presently, I am working on financial-technology and monetary policy effectiveness in Africa, triple-deficit hypotheses, and financial stability.

Professor Devi Datt Tewari On the other hand, Devi Datt Tewari is a Professor of financial economics and the principal supervisor of Tochukwu Timothy Okoli at the department of Economics, University of Zululand, South Africa. He has cognitive experience of more than thirty years in teaching and research. He joined university of Zululand in 2013 from the University of KwaZulunatal, Westville Campus, South Africa and served as the Dean of the faculty of Commerce, Administration and Law for a period of five year (2014–2018). He has produced over twenty-five PhD students with lots of publications during the course of his career. Moreover, he reviews articles for many journals. His supervisory role and mentoring has helped to fine-tune this work to this standard.

PUBLIC INTEREST STATEMENT

The adoption of financial-technology (Fintech) has not adequately permeated the financial system in Africa. This is evident from the large financial exclusion and poor financial service delivery in the continent, thereby suggesting that there is a gap between mere adoption of Fintech and its actual usefulness. This concept is referred to as Fintech depth penetration/usefulness. Therefore, the study aimed to measure it and identify its determinants and growth process among 32 heterogeneous African markets for the period 2004–2018. Fintech usefulness was measured with its ratio to gross domestic product. The adapted form of E. Rogers (2003) diffusion of innovation theory was used to build the model. Results from the generalised method of moments technique reveal that Fintechs' usefulness is driven by socio-economic, financial and psychological factors. Moreover, Fintech usefulness grew after 2009 financial crisis, which suggests that it can mitigate financial-risk. Institutional and human capital developments were recommended to promote Fintech usefulness.

A dummy variable interactive equation was modelled based on theory to account for heterogeneity between groups. Results from the system Generalised Method of Moments (GMM) estimation technique reveal that on average, Fintech usefulness in Africa is a dynamic heterogeneous process. Income per person, level of financial development, Fintechs' compatibility with users' experiences, users' risk perception, inflation rate and financial-openness were the main determinants of its usefulness. Its rapid growth after the 2009 financial crisis suggests that greater Fintech usefulness can mitigate financial crisis among Africa markets. In particular, the growth of Mobile-banking, ATM and Internet-banking as at 2018 are on average 41.8%, 0.4%, and 20.8% respectively greater than its average in the base year 2004. The study concludes that Fintech's usefulness is driven by economic, financial and psychological factors; therefore, structural transformation, financial development and improved literacy were recommended.

Subjects: Technology; Economics; Finance; Business, Management and Accounting

Keywords: financial technology; mobile banking; internet banking; ATM; African economies

Subjects: G00; G21; G24; O55

1. Introduction

As the global financial community moves towards a technology-enabled financial solution often referred to as financial technology, its relevance to Africa has become a policy issue, given the continent's widespread financial exclusion and poor financial development. Primary among this issue is the uncertainties that surrounds its adoption especially as some authors (Double and Bradley, 2018) affirmed that it comes with both prospects and problems. This asymmetric impact is juxtaposed with the gap between its high adoption rates and its inability to develop finance among the emerging markets like China and India (Ernest and Young, 2017). This indicates that there is a gap between financial technology adoption and its actual benefits. High financial technology adoption rate does not guarantee or transmit to greater diversification of its usefulness except its users deepen its usefulness.¹ Therefore, a better appreciation of this issue requires deeper understanding of these concepts, its measurements, justification and its determinants with special reference to African economies. In this study, we focus on both economic, financial and psychological factors as plausible determinants with emphasise on human capital development, and then investigate whether there is significant difference in the average growth of financial technology usefulness among the heterogeneous Africa.

The extent to which these factors will impact on financial technology's usefulness in Africa also depends on some peculiar factors inherent in that country. This suggests that the growth path of financial technology usefulness/depth among African economies is likely to differ between one economic group and another because they are at different stages of development as emerging, frontiers, and fragile markets. As a result, their financial technology deepening process will likely be defined differently. This necessitates the need to carefully assess these heterogeneities in Africa within the context of financial technology usefulness. Previous studies (Ernest and Young, 2017; F. J. Rogers, 1995; Wijayanti & Pradipta, 2017) placed more emphasis on the adoption rate and determinants of financial technology with no attention to the extent of its usefulness and the heterogeneous effects. This explains why financial needs and exclusion still widen in Africa despite huge financial technology adoption rate.

Financial technology (Fintech afterwards) has lots of unique opportunities for African's financial system. It makes transactions more convenient and comfortable, ensures easy access to funds, and gives more efficient services faster and better than the conventional banks (Wijayanti & Pradipta, 2017); hence, it can close the wide financial exclusion gap in Africa. Despite these benefits, Fintech's adopters have not maximized its usefulness. Other services of Fintech such as

assets management, insurance, Robo-Advice, Crypto-currency have been neglected especially in Africa. Therefore, whilst Fintech's adoption rate is the number of its users to the total population of that region, its actual usefulness/depth of penetration as used in this study connotes the frequency and extent of usage for various purposes.² Ernest and Young (2017) observed that its adoption rate doubled between 2015 and 2017 to 33% without any remarkable increase in its usefulness. Based on this, this study argues that Fintech's ability to fix the problems of financial exclusion and poor financial development in Africa depends on the extent to which its users diversify its usefulness more frequently through improved human capital development.

2. Empirical and theoretical determinants of financial technology penetration

Fintech is an emerging idea in the field of finance, more so is the concept of depth of Fintech penetration or usefulness. Over the years, empirical studies (Ernest and Young, 2017; Haddad & Hornuf, 2019; Ozili, 2018; Schindler, 2017) and theoretical models³ have concentrated on the adoption of Fintech, its determinants and its nexus with financial inclusion. The general conclusion across these studies is that increased Fintech adoption is capable of fixing the problems of financial exclusion, payment lags and poor credit extension, especially among African markets. However, financial inclusion, access to credit and other financial services have not adequately permeated vast segments of the population despite huge Fintech adoption in Africa (G20 Summit, 2013). This suggests that there is a gap between the availability of Fintech, its accessibility and its usefulness (Ozili, 2018), and this has not been adequately captured and examined in the literature. Therefore, this study contributes to the existing literature and argues that the ability of Fintech to develop finance and permeate the economy depends on the extent and frequency of its usefulness rather than just mere adoption; hence, the measurement and determinants of Fintech usefulness are the main focus of this study.

The concept of Fintech depth/usefulness was first used by Schindler (2017). He explained it in terms of three different stages of development as surface, genuine, and foundational depths of an innovation. A proper understanding of these concepts will give a clear picture of how likely Fintech can develop financial markets' performance. According to him, surface depth does not change the fundamental nature of the financial service or product; however, their adoption can improve market flexibility if not subjected to excessive regulations. The implication of this is that the extent to which the depth of surface innovation can impact financial performance depends on the level of regulations by the financial authorities.

The genuine and foundational depths of innovation are the deepest form of Fintech usefulness and can change the operation of the financial market, unlike the surface depth of innovation. They have an underpinning structural transformation on the overall financial system and can be applied to even non-financial regulations. Therefore, these kinds of technologies occur very rarely because of their disruptive and high-risk effects on the operation of the financial system (Schindler, 2017). Whereas the surface depth does not require special expertise knowledge/skills to be used, the genuine and foundational depths of innovation/Fintech do; hence, the literacy level of potential users of Fintech and their risk perception are assumed to drive its usefulness. Abramova and Böhme (2016) found that different kinds of risks and fear of financial losses were the major deterrent of Bitcoin usefulness. Ryu (2018) also made a consistent conclusion that users' of Fintech perception of its potential risks⁴ and/or the profits drives its usefulness.

In their unified theory of acceptance and use of technology (UTAUT) theoretical model Venkatesh et al. (2003) also supports this view that perceived risk and perceived ease of use are strong factors that determines innovations usefulness. E. Rogers (2003) referred to the latter as innovations complexities. Jarvenpaa et al. (2003) and Teo and Pok (2003) found that complexity was a major determinant of mobile technologies usefulness. An innovation must be simple to use so that the consumers' perceived risk in processing information and requisite skills is minimized. The extent to which a consumer perceives an innovation to be simple depends on his skills, knowledge/literacy levels. This is consistent with Schindler (2017) affirmation that users' skills and literacy are necessary to deepen the usefulness of innovation. This suggests that human

capital development is necessary to promote Fintech usefulness. The compatibility of an innovation with users' needs, beliefs, values and previous experiences also determines the extent of its usefulness (E. Rogers, 2003). Teo and Pok (2003) and Wu and Wang (2005) found that compatibility significantly determines the use of mobile technology and service. Therefore, the more compatible and the less complex a given Fintech is perceived, the higher will be the extent of its usefulness. Haddad and Hornuf (2019) added that economic growth and the inability of banks to extend loans were the major drivers of Fintech.

Moreover, E. Rogers (2003) included the relative advantage, observe-ability and trial-ability in the determinants of innovation's usefulness construct. The ability of Fintech to outperform existing innovations (relative advantage), the extent to which the outcome of such innovation is communicated to the general public (Observe-ability) and the ability of individuals to try or test drive it (trial-ability) determines its usefulness. The relative advantage of Fintech ranges from its service delivery efficiency to its cost in comparison to previous ones. From the foregoing discussions, we have identified socio-economic, financial, and psychological factors such as literacy rate, income, the level of financial market development, perceived risk, that determines Fintech's usefulness. Therefore, this study assesses their relative impact on Fintech's usefulness among African markets with special attention to the heterogeneities between groups.

3. Data

Fintech was measured with three proxies which are automated teller machine (ATM), Mobile banking and Internet banking. Mobile and internet banking were proxy with mobile phone subscription and the percentage of the population using internet respectively. Previous studies used similar measures such as mobile phone by Mihasonirina and Kangni (2012), ATM by Eric (2017), mobile banking by Klein and Mayer (2011). Their depths of usefulness are the ratios of these proxies to Gross Domestic Product (GDP). See Table 1. The data were sourced from the World Bank (2019) and the International Monetary Fund databases (2019). The scope is a panel of 32 African economies disaggregated into 3 emerging, 24 frontiers and 5 fragile African economies⁵ using dummies to account for heterogeneity.⁶ The rationale behind the selection of these countries is that most of them are fast embracing Fintech as a new trend in their financial system (Ernest and Young, 2017; Johan Meyer, 2015). The data span is fifteen years from 2004 to 2018.

The endogenous regressors are Fintech's compatibility, its perceived risk, complexity, trial-ability and observe-ability as are presented under Table 1. The rationale for this is that they were determined within the theoretical model and as such is highly correlated with the present and past values of the error term. The strictly exogenous variables include inflation rate, financial openness and financial development indicators. This is because they were determined outside the model; hence, there variance-covariance matrix with the error term in the model is assumed to be zero.

3.1. Econometric model specification

We first specify the model in its level general dynamic AR(1) form thus:

$$Dft_{it} = \delta Dft_{it-1} + \beta X'_{it} + \lambda Z'_{it} + d_t(v_i + \varepsilon_{it}) \quad (1)$$

Where Dft_{it} and ε_{it} are random variables of $N \times 1$ vectors of the dependent variables and the unexplained factors of Dft_{it} ⁷ respectively. Dft_{it-1} and $X'_{it} = (x_1 \dots x_k)$ are $N \times K$ matrixes of first lag of the dependent variables and the explanatory variables, respectively. θ 's are vector $K \times 1$ of unknown parameters. We assume another matrix $Z'_{it} = (z_1 \dots z_m)$, the instrumental variables that is $N \times M$ because of the presence of an endogenous term; where $M \geq K$. The Z matrix must be exogenous (i.e. $E(Z' \varepsilon_{it}) = 0$). The instrumental variables in matrix Z are 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.

Table 1. Fintech depth of penetration determining variables

Variable names	Variable description and measurements	Variable type	Variable source	Data source
Depth of ATM (DATM)	Proportion of income devoted to ATM usefulness (ATM/Real GDP).	Dependent Variable (Model 1)	Mike (2010)	WBD (2019)
Depth of Internet Banking (DINTB)	Proportion of income devoted to Internet Banking usefulness (Internet banking/Real GDP).	Dependent Variable (Model 2)	Haddad and Hornuf (2019)	WBD (2019)
Depth of Mobile Banking (DMB)	Proportion of income devoted to Mobile Banking usefulness (Mobile phone subscription/Real GDP).	Dependent Variable (Model 3)	Luarn and Lin (2005); Wu and Wang (2005)	WBD (2019)
Compatibility	A measure of users' past experiences and benefits derived from the use of Fintech. This is measured using the first lag of dependent variables	Endogenously Predetermined Variable	Teo and Pok (2003)	WBD (2019)
Fintech Risk (FR)	This measure the degree users' of Fintech perceive that it has no conflict with their needs and financial state. This is measured using the standard deviation of an index for Fintech	Endogenously Predetermined Variable	Ryu (2018); Abramova and Böhme (2016)	WBD (2019)
Complexity (COM)	A measure of the quality of human capital or Literacy rate. This is measured using the tertiary school enrolment.	Endogenous Explanatory Variable	Jarvenpaa et al. (2003) and Teo and Pok (2003)	WBD (2019)
Trail-ability and Observe-ability (TOB)	A measure of Fintech users' financial strength which defines their ability and extent of use. It is measured with Real GDP per capita	Endogenous Explanatory Variable	E. Rogers (2003)	WBD (2019)
Relative Efficiency	The advantage current innovations have over previous ones. Rogers believes it can be measured with cost. Therefore, this study measured it with inflation rate.	Strictly exogenous control variable	Kleijnen et al. (2004); Teo and Pok (2003)	WBD (2019)
Financial Openness (FO)	This measure the degree to which financial operators adapt to changes. Measured with financial mkt access index.	Strictly exogenous control variable		IFS (2019)
Financial Development (FD)	This is the level of financial market resilience and fragility. It is measured with financial development index	Strictly exogenous control variable		IFS (2019)

Source: Based on theoretical and Empirical Literature.

Moreover, we also assume that the instrumental variable Z must be less than or equal to the number of groups (N). d_t is the year dummies, while δ and λ are also $K \times 1$ vectors of the parameters to be estimated on lagged dependent variables and instrumental 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.

$$\mu_{it} - \mu_{it-1} = (v_i - v_i) + (\varepsilon_{it} - \varepsilon_{it-1}) \longrightarrow \Delta\mu_{it} = \Delta\varepsilon_{it} \quad (2)$$

The challenge in estimating this model is that while all the instruments are not correlated with the error term, therefore trying to force the corresponding vector of empirical moments, $E_N(Z' \varepsilon_{it}) \equiv (1/N)Z' \varepsilon'_{it}$, to zero leads to a system of equations that are more than the variables if $M > K$. hence, the specification is then over-identified. The solution then is to minimize the magnitude of the vector $E_N(Z' \varepsilon_{it})$. Again, since one of the objectives of this study is to investigate heterogeneity in average (intercept) of Fintech's depth of penetration among the emerging, frontier and fragile economic groups. We therefore incorporate this, using dummies. The transformed form model of equation (1) becomes:

$$\Delta Df_{it} = \delta_{i0} \Delta f_{it-1} + \rho_{i0} + \rho_{i1} D_{it}^1 + \delta_{i1} \Delta X_{it} + \delta_{i2} \Delta Z_{it} + \Delta\mu_{it} \quad (3)$$

Note that i_0, i_1 and $i_2 \in \{e, f, g\}$, $i_0 \neq i_1 \neq i_2$, D_{it}^j 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 $\delta_{i0} - \delta_{i3}$ are all the slope coefficients to be estimated. i_0 is the reference category (the emerging markets) and i_1 and i_2 represents frontier and fragile markets, respectively. The rationale for this is that emerging markets are assumed to have a stable financial system for Fintech deepening, therefore, it is expected that the rate of Fintech penetration among them will on average be greater than other economic groups. The study then uses two dummies for frontier and fragile markets to avoid a dummy variable trap. As the reference category, its average depth of Fintech penetration 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. The assumption of heterogeneity was not tested on the slope coefficient for the sake of simplicity. Moreover, most of the regressors, especially the control variables are exogenously determined; hence, they were not strictly endogenous, as a result, common slope assumption better fits the model. This assertion was strengthened in the theoretical model.

3.2. Methodology

The inclusion of the first lag of the dependent variable (see data description below) suggests the use of a dynamic estimation technique to analyse the data. Therefore, a dynamic panel System Generalized Method of Moments (GMM) will be employed to analyse the data because of its numerous advantages over an ordinary static model. It has the advantage of efficiency when the individual observation of the panel is more than or equal to its time observation. The individual units in this study are 32 countries ($N = 32$) whereas the time observation is 15 ($T = 15$), hence, a GMM technique is most suitable. Moreover, it eliminates the problems of serial correlation, endogeneity and heteroscedasticity (Caselli et al., 2004) and it is capable of correcting for unobserved panel heterogeneity, omitted variable bias, measurement error and endogeneity problems of the lagged dependent variable (Bond et al., 2001). A system GMM reduces potential bias and imprecision associated with a simple difference GMM estimator and is more superior to the difference GMM (Arellano and Bover (1995); Blundell and Bond (1998)).

Again, since some of the independent variables are not strictly exogenous, the application of a system GMM model will be better because it circumvents this problem. Moreover, this study favours the system GMM over a differenced GMM model because of the use of an unbalanced panel. Blundell and Bond (1998) suggest that the first difference GMM transformation produces weak estimates when there are gaps in the panel. This is because it subtracts previous

observations from the contemporaneous one thereby magnifying gaps. A system GMM circumvents this challenge by using orthogonal deviations in transforming the model. That is, it subtracts the average of all future available observations to minimize data loss, hence the need for two equations (i.e. the original equation and the transformed one). Finally, two specification tests of Sargan/Hansen and AR2 tests as proposed by Arellano and Bond (1991) and Blundell and Bond (1998) will be used to test for the overall validity of the instruments and the presence of serial correlation in the models, respectively.

4. Results and discussion: background information

As a starting point, we followed Bond et al. (2001) decision rule to choose between the difference GMM or system GMM estimators. According to Bond et al. (2001), a system GMM will be preferred to a difference GMM estimator if the coefficient of the lagged dependent variable in difference GMM estimate is below its fixed effect model estimate equivalence and close to or above its pooled regression equivalent estimate. The results as presented under the appendix section suggest that we use the system GMM. This technique is also necessary because the constant term in the system model represents the average Fintech depth of penetration among the reference group. Moreover, a one-step and two-step system GMM outputs were estimated for the three dependent variables.⁸

As a reminder, this study follows a scientific approach to E. Rogers (2003) diffusion of innovation theory to investigate the determinants of Fintech usefulness in Africa measured with three indicators. The output was organized and presented in four Tables with six different models each. The first six models (Table 2) are the main results which is the main focus of this study. It presents 3 one-step system GMM results each for the three dependent variables and another 3 two-step system GMM results for the three dependent variables. The next six models (Table 3) examined their robustness check using the robust command to account for heteroskedasticity and autocorrelation variance-covariance matrix. The next six models (Table 4) assess their baseline result which examined the objective of this study with a homogenous assumption among the three economic groups and the last six models (Table 5) reports the long-run coefficients of the significant variables obtained from the main results.

The model specification is same for the one-step and the two-step System GMM outputs both under the robust and none robust results except that the instruments sets were slightly changed due to convergence problem. Under the one-step models, the year dummies include years one to 14 while under the two-step estimators it ended in year seven due to convergence issues. The reason for this is because instruments outnumber the regressors; hence, the model could not run under the two-step system GMM outputs. The instrumental variables under the one-step system GMM estimates are all the exogenous variables, year dummies and two extra instruments of trade openness (TOP) and commercial bank branches (CBB) while under the two-step system GMM estimator, the external instruments are the first lag of all the exogenous variables only.

The common commands that apply to all the models are the `xtabond2`, `collapse`, `orthogonal`, `nodiffsargan`, `small` and the one-step/two-step commands. The `xtabond2` command was used to simultaneously implement both the difference and the system GMM estimators and it makes the two-step robust more efficient than the one-step robust (Roodman, 2009). The `collapse` command was used to avoid instruments proliferation problem. The rule of thumb is to keep the instruments less than or equal to the number of groups. The `orthogonal` command was used to implement a forward orthogonal-deviations transformation instead of using the first differencing given that our data set is unbalanced. The `orthogonal` command is necessary to avoid the loss of observations where there are gaps in the series (Roodman, 2009). On the other hand, `nodiffsargan` command informs Stata not to report the difference in Hansen tests of exogeneity of instruments since it makes no difference, especially with the `collapse` command. Finally, the `small` command is used because we prefer the T and F-statistics over the Z-statistics and Wald result.

Table 2. Heterogeneous system GMM: the main result

	One-step system GMM results			Two-step system GMM results		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	DMPB	DATM	DINTB	DMPB	DATM	DINTB
DFintech _{it-1}	1.346*** (14.38)	0.712*** (29.49)	1.131*** (15.65)	0.481*** (10.82)	0.453*** (15.68)	1.078*** (21.15)
Constant	172.8* (0.79)	-0.034** (1.97)	0.320 (1.54)	987.7*** (11.48)	14.462*** (4.53)	-0.188 (0.96)
Dummy Fron	866* (1.78)	0.024** (2.04)	-0.041 (1.07)	-208.5 (0.40)	0.333 (0.52)	-0.013 (0.33)
Dummy Frag.	143.4* (1.67)	0.012 (0.57)	-0.050 (0.65)	122.49* (1.96)	0.303 (0.43)	-0.033 (0.56)
Fintech Risk	-951.7* (1.69)	-0.053 (1.53)	-0.083* (1.72)	154.604*** (4.41)	0.040 (4.80)	-0.051 (1.10)
Literacy Rate	-5.261 (0.79)	0.001*** (5.74)	0.0003 (0.51)	117.490*** (3.72)	0.0003 (0.22)	0.0002 (0.53)
GDPPC _{it-1}	0.001*** (3.57)	-0.000001*** (2.96)	1.28e-08 (0.84)	0.002** (2.17)	-5.78e-08 (1.30)	-6.16e-10 (0.05)
Fin Opennes	-245.8 (0.46)	-0.038*** (2.68)	-0.062 (1.20)	735.275 (0.14)	-0.115 (0.15)	-0.036 (0.66)
Fin Dev.	3164.9*** (3.19)	0.080*** (3.96)	0.036 (0.64)	605.92 (1.60)	0.511 (2.47)	0.032 (0.67)
Inflation	-26.302*** (3.28)	-0.0002 (1.21)	-0.001*** (2.92)	173.345*** (4.07)	-0.0002 (0.02)	-0.001 (1.38)
F-Stat.	36.11***	94.97***	63.38***	2352.83***	32,546.35***	2046.8***
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
No of Obs.	343	343	343	348	348	348
Groups/Instr.	30/26	30/26	30/26	30/21	30/21	30/26
AR(2)	0.652	0.251	0.972	0.151	0.088	0.658
Sargan Test	0.118	0.170	0.001	0.469	0.595	0.001
Hansen Test	0.169	0.545	0.099	0.186	0.685	0.099

Absolute value of t statistics in parentheses.

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

Source: Estimation.

4.1. Results and discussions: the main/heterogeneous system GMM results

The main results are presented in Table 2 (Models 1 to 6). The estimates were based on Rogers' diffusion of innovation theory to identify the factors that promotes or dampens the usefulness of Mobile banking, ATM and Internet banking in African. As a way of general findings across the models, the results reveal that Fintechs' compatibility with users' previous experiences, trial-ability/observe-ability in the previous periods, the contemporaneous effects of relative advantage, complexities, financial development, and risk were its major determinants. With the exception of Fintechs' risk which had a negative effect in most of the models, other determinants revealed an increasing impact on Fintechs' usefulness in most of the models. This is consistent with theory and empirical findings that an innovation's compatibility with users' previous experiences, complexity, and relative advantage promotes its usefulness (Jarvenpaa et al., 2003; Klein & Mayer, 2011; Teo & Pok, 2003; Tornatzky & Klein, 1982; Wu & Wang, 2005). The extent of users' perceived risk also significantly dampens its usefulness. This is consistent

Table 3. Robust check for the heterogeneous system GMM: main result

	One-step system GMM result			Two step system GMM result		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
	DMPB	DATM	DINTB	DMPB	DATM	DINTB
DFintech _{it-1}	1.346*** (16.92)	0.712*** (33.34)	1.131*** (18.87)	0.481*** (2.92)	0.453*** (6.28)	1.078*** (9.68)
Constant	172.8 (0.84)	-0.034 (0.89)	0.320 (1.54)	987.7*** (3.07)	14.462 (2.74)	0.188 (0.50)
Dummy Fron	866 (1.34)	0.024 (0.87)	-0.041 (0.92)	-208.5 (0.20)	0.333 (0.46)	-0.013 (0.28)
Dummy Frag	143.4 (1.12)	0.012 (0.27)	-0.050 (0.79)	122.49 (0.50)	0.303 (0.38)	-0.033 (0.64)
Fintech Risk(FR)	-951.7* (1.77)	-0.053 (1.15)	-0.083 (1.69)	154.604 (0.91)	0.040 (0.56)	-0.051 (0.54)
Literacy Rate(TSR)	-5.261 (0.42)	0.001 (1.09)	0.0003 (0.65)	117.490* (1.72)	0.0000001 (0.06)	0.002 (0.46)
GDPPC _{it-1}	0.001** (2.15)	-0.0000001 (1.26)	1.28e-08 (0.94)	0.002 (0.83)	-5.78e-08 (1.05)	-6.16e-10 (0.05)
Fin Openness(FMA)	-245.8 (0.27)	-0.038 (0.79)	-0.062 (1.08)	735.275 (0.05)	-0.115 (0.15)	-0.036 (0.71)
Fin Dev. (FDvI)	3164.9** (2.22)	0.080** (2.13)	0.036 (0.72)	605.92 (0.35)	0.511 (0.87)	0.032 (0.58)
Inflation (INF)	-26.302** (2.44)	-0.0002 (0.62)	-0.001** (2.22)	173.345 (0.94)	-0.000 (0.00)	-0.001 (0.61)
F-Stat.	94.97***	4924.95***	1259.03***	691.97***	890.13***	118.5***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No of Obs.	343	343	343	348	348	343
Group/ Instrumt.	30/26	30/26	30/26	30/21	30/21	30/26
AR(2)	0.550	0.173	0.946	0.522	0.598	0.679
Sargan Test	0.118	0.170	0.001	0.469	0.595	0.001
Hansen Test	0.169	0.545	0.099	0.186	0.685	0.099

Absolute value of t statistics in parentheses.

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

Source: Estimation.

with the studies of Abramova and Böhme (2016) and Ryu (2018) which concludes that the risk associated with Bitcoin such as fear of making financial loss inhibit its usefulness.

Compatibility (first lag of the dependent variable) showed a high degree of persistence as indicated by the positive statistically significance of the AR(1) regressor at 1% across all the models. This indicates that Fintech usefulness is a dynamic process; hence, past experiences were its major determinants. To be more specific, in Models 1 and 4 for instance, a percentage change in compatibility with users' previous experiences and the first lag of income per capita is associated with a 1.35% and 0.001% (Model 1) and 0.48% and 0.002% (Model 4) increase, respectively, in mobile banking usefulness in the short-run, at 1% significance level, on average ceteris paribus. Therefore, these relationships are more of an inelastic relationship than elastic. This means that a change in

Table 4. Homogenous system GMM results (without Country's dummy): baseline result

	One-step system GMM result			Two-step system GMM result		
	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
	DMPB	DATM	DINTB	DMPB	DATM	DINTB
DFintech _{it-1}	1.252*** (16.17)	0.730*** (30.29)	1.130*** (23.21)	1.302*** (33.82)	0.724*** (38.80)	1.079*** (26.32)
Constant	3226.4 (1.62)	-0.014** (2.22)	0.174* (1.84)	2237.35 (1.55)	-0.007 (0.97)	0.096 (0.84)
Fintech Risk (FR)	-1,007.5* (1.80)	-0.068* (1.85)	-0.054* (1.93)	-600.6 (1.62)	-0.065 (1.43)	-0.032 (1.04)
Literacy Rate (TSR)	-1.615 (0.27)	0.001*** (6.46)	0.00002 (0.05)	-5.189 (0.73)	0.0003 (0.51)	0.0003 (0.76)
GDPPC _{it-1}	0.001*** (3.17)	-9.43e-09** (2.15)	1.23e-08 (1.38)	0.0004* (1.77)	-6.96e-09 (0.86)	3.55e-09 (0.47)
Fin Openness (FMA)	-897.3** (2.23)	-0.055*** (5.24)	-0.018 (0.95)	-471.360 (1.15)	-0.016 (0.65)	-0.027* (1.80)
Fin Dev. (FDvI)	1,758.1*** (2.92)	0.068*** (4.33)	0.057* (1.72)	919.4 (1.34)	0.059** (2.71)	0.043* (1.76)
Inflation (INF)	-24.695*** (3.25)	-0.0002 (1.37)	-0.001*** (3.65)	-21.86*** (3.24)	-0.0002 (0.92)	-0.0003 (0.79)
Years	1.599 (1.62)	-0.000** (2.21)	0.00009* (1.83)	1.109 (1.55)	-0.000 (0.87)	0.00002 (0.84)
F-Stat.	39.69***	136.5***	111.03***	1307.20***	10,661.56***	1664.62***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No of Obs.	343	343	343	343	343	343
Groups/Instr.	30/26	30/26	30/26	30/26	30/26	30/26
AR(2)	0.581	0.236	0.906	0.543	0.218	0.441
Sargan/Hansen Tests	0.098	0.076	0.000	0.098/0.143	0.076/0.630	0.000/0.230

Absolute value of t statistics in parentheses.

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

Source: Estimation.

Table 5. Long-run coefficients of the significant short-run variables in models 1 to 6

	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
	DMPB	DATM	DINTB	DMPB	DATM	DINTB
DFtch _{it-1}	-3.889***	2.47***	-8.611**	0.926***	0.829***	-13.82
Constant	-4993	-0.116*	NSLS	1,902,639***	26.446***	NSLS
Fintech Risk	2749.5	NSLS	0.635	297.83***	NSLS	NSLS
Literacy Rate	NSLS	0.003***	NSLS	226.3***	NSLS	NSLS
GDPPC _{it-1}	-0.002***	0.00000002**	NSLS	0.005*	NSLS	NSLS
Fin Openness	NSLS	-0.130***	NSLS	NSLS	NSLS	NSLS
Fin Dev	-9143.1***	0.278***	NSLS	NSLS	NSLS	NSLS
Inflation	75.98***	NSLS	0.011*	333.9***	NSLS	NSLS

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

NSLS = No Short-run and Long-run Significance.

Source: Estimation.

compatibility and income will trigger a less than proportionate change in mobile banking usefulness. Moreover, the risk associated with mobile banking and the rate of inflation significantly dampens its usefulness at the 10% and 1% levels of significance during the short-run *ceteris paribus* under model 1, but significantly increase mobile banking usefulness under model 4 at 1% significance *ceteris paribus*. This difference could be attributed to the differences in simulation of the instrumental variables. Again, literacy rate—a measure of users' complexity significantly promotes the usefulness of mobile banking (Model 4) at 117.5% in the short-run, at 1% significance level, on average *ceteris paribus*; hence, literacy rate exhibits an elastic relationship with the depth of Mobile banking.

The usefulness of ATM under models 2 and 5 was also raised by its compatibility with users' previous experiences at 0.712% (Model 2) and 0.453% (Model 5) during the short-run at the 1% significance level, on average *ceteris paribus*. Financial development, literacy rate, income, financial openness and the risk associated with ATM use also raised the level of its usefulness as seen under models 2 and 5. Looking at the determinants of Internet banking usefulness as presented under models 3 and 6, the results reveal that a 1% increase in compatibility is associated with 1.131% (model 3) and 1.078% (model 6) increase in the depth of its usefulness in the short-run at the 1% significance level, on average *ceteris paribus* for the one-step and two-step results, respectively. Under model 3, internet banking usefulness was also damped by users' perceived risk at 10% and inflation rate at 1% significance levels. The high dampening impact of Internet banking riskiness is an indication that it is a vulnerable to high cybercrimes.

The results further show that there is a significant difference in the average depth of Fintech usefulness among the economic groups. In model 2 for instance, there is a significant difference in the average usefulness of ATM between the emerging and the frontier groups as indicated by the significance of intercept term (ρ_{i0}) and frontier markets dummy (D_{it}^1) at 5%. On average, emerging markets' depth of ATM usefulness is -0.034% (ρ_{i0}) while that of frontier markets' is -0.01% ($\rho_{i0} + \rho_{i1}$). This means that frontier markets reports a higher usefulness of ATM than the emerging markets. This condition also holds for the average use of mobile banking under models 1 and 4 at 10% significance level. In model 1, the average use of mobile banking for emerging group is 172.8% (ρ_{i0}), 1038.8% ($\rho_{i0} + \rho_{i1} = 172.8 + 866$) for the frontier group and 316.2% ($\rho_{i0} + \rho_{i2}$) for the fragile group. This higher average usefulness of Fintech in frontier and fragile groups suggests that Fintech has reached its saturation point among the emerging group and has begun to decline. Therefore, the null hypotheses that $\rho_{i0} = (\rho_{i0} + \rho_{i1}) = (\rho_{i0} + \rho_{i2})$ are rejected for models 1, 2 and 4 but accepted for models 3, 5 and 6; hence, on the average, there is heterogeneous usefulness of Mobile banking and ATM among African economies.

Two major diagnostic tests were used to assess the efficiency of the model estimates as were proposed by Arellano and Bover (1995) and Blundell and Bond (1998). They are the Sargan/Hansen tests of over-identifying restrictions for the overall validity of the instruments and the serial correlation test. The null hypothesis of the Sargan/Hansen tests for the overall validity of the instruments is that all the instruments as a group are strictly exogenous. On the other hand, 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, higher p-values are desirable for both tests. The results in Table 2 show that we cannot reject the null hypotheses of instruments' validity and no second-order serial correlation because their p-values are all greater than 5%. We conclude that the instruments are valid, strictly exogenous, less than the number of groups and the original error term is serially uncorrelated at the second order; hence, the moment conditions are correctly specified.

4.1.1. Results and discussions: robustness check based on the main result

On the other hand, we tested the robustness of the results to account for heteroscedasticity. The models are still the same except for the inclusion of the robust command which informs Stata to

provide a heteroscedastic and autocorrelation consistent (HAC) variance-covariance matrix. The robust command reduces the standard errors thereby inflating the t-statistics. However, same results hold for the coefficients and the Hansen tests. In addition, a robust one-step and two-step system GMM results were also estimated without the countries dummies to check if the results will significantly change under the assumption of homogeneity among the economic groups.

The results as are presented in [Table 3](#) revealed some consistent conclusions with those under [Table 2](#). This is because Fintechs' compatibility (first lag of the dependent variable), literacy rate (complexity), financial development, perceived riskiness, and inflation rate were found to be the main determinants of its usefulness (models 7–12). Whereas the first three factors promote its usefulness, the last two dampens it. To be more specific, the results reveal that Fintechs' compatibility positively drives its usefulness across models 7 to 12 at 1% significance. However, unlike models 1, 2 and 4, the assumptions of heterogeneity in the average Fintech usefulness were violated for models 7 to 12 since the intercept and groups' dummies were insignificant, thereby suggesting that there was no difference between groups in terms of the average usefulness of Fintech. These differences could be attributed to the rise in the t-statistics by the robust command; however, it suggests the need to test for a homogenous/baseline relationship of Fintech usefulness and its determinants among the economic groups as presented under [Table 4](#).

There were no significant differences between the conclusions reached under the main result of model 1 and its robust heteroskedasticity and autocorrelation consistent variance-covariance option in model 7. Both results reveal that risk perception and inflation rate significantly decrease the usefulness of mobile banking while previous income per person and financial development significantly increases its usefulness. These are consistent with prior expectations. Similarly, the two-step robust system GMM result for the determinants of mobile banking reveals a consistent conclusion with that under the main result of model 4. A percentage increase in compatibility and complexity is associated with 0.481% and 117.5% increase in mobile banking during the short-run at 1% and 10% levels of significance, respectively, *ceteris-paribus*.

On the other hand, while financial development and inflation rate had asymmetric impacts on the usefulness of ATM and Internet banking at 5% significance levels in the robust one-step system GMM estimator, it could not explain variations under its two-step robust result. This was also consistent with what was obtained under the main result as presented in [Table 2](#). This suggests that financial development and inflation were very central in determining the extent to which users of Fintech can deepen the usefulness of ATM and Internet banking.

4.1.2. Results and discussions: the baseline-homogenous system GMM results

The fact that the heterogeneity assumption among the different economic groups could not hold under the robust system GMM output results suggests that African economies could possibly define the average Fintech depth in the same way. Hence, the need to further re-estimate a baseline form of models 1–6 for robustness check arises. Under here, we assume a homogenous relationship among the cross-sectional units/economic groups and conclude that on the average, emerging, frontier and fragile African markets reports the same level of Fintech usefulness.

The results as presented in (Models 13–18) show a negative average of ATM depth (Model 14) and a positive average depth of Internet banking (Models 15) at the 5% and 10% significance levels, respectively. This is consistent with models 1, 2 and 4 under the main result. Therefore, while we could conclude on heterogeneous average mobile banking, we cannot conclude same for ATM and Internet banking. Again, Fintechs' compatibility (lagged dependent variable) raises Fintech usefulness across all the models as were the case in the main result. It had a high degree of persistence as indicated by its positive significance at 1%. The magnitude of its association-ship with respect to the usefulness of mobile banking and Internet banking penetration reveals an elastic relationship (Models 13, 15, 16 and 18), whereas it had an inelastic relationship with the usefulness of ATM (Models 14 and 17). The one-step system GMM results further reveal that the lag of income per person and financial

development significantly raise the usefulness of mobile banking and ATM at 1%, 5% and 10% levels of significance. Literacy rate which measures Fintech simplicity/complexity only raises the depth of ATM usefulness significantly during the short-run at 1% significance level *ceteris paribus*. Whereas the risk associated with Fintech usefulness, financial openness and inflation rate was its major deterrent across most of the models at 10% and 1% level of significance.

Results from the baseline two-step system GMM further reveal that apart from Fintech compatibility (lag of the dependent variable) which is a measure of users' previous experiences, lag of income per person, financial openness, financial development and inflation rate were other major determinants of Fintech depth of penetration. In a more specific sense, lag of income per person and financial development significantly raises the depth of Mobile banking, ATM and Internet banking at 10%, 5% and 10%, respectively. Similar dampening effect of inflation rate on Mobile banking was also found in the two-step result (model 16) as was the case in its one-step estimate. Hence, inflation which is a measure of Fintech relative efficiency, the risk associated with Fintech and financial openness generally dampens its usefulness whereas Fintechs' compatibility, complexity and financial development basically raise its usefulness.

The diagnostic tests of serial correlation and the Sargan/Hansen tests for the validity of the instruments conducted for all the models. Their results reveal that the null hypotheses of no serial correlation and the exogeneity of instruments cannot be rejected. This is because their p-values are more than 5%. This implies that there is absence of serial correlation in the initial model therefore the moments conditions were correctly specified. Likewise, the instruments are validity hence the model is robust and was not weakened by too many instruments. However, we found that the null hypothesis of the Sargan test of instrument validity is rejected for models 3, 9 and 15 because their p-values for the Sargan test is less than 5%. This means that the models are weakened by too many instruments and as such is not good for policy implication.

4.1.3. Results and discussions: the long-run analysis

Since a GMM output result is a short-run analysis, we also estimated the long-run coefficients for only the significant short-run coefficients of models 1–6. This is necessary to have a forward looking model. The long-run effects for the K_{th} parameter are estimated by using equation 4 and the coefficients are presented in Table 5:

$$\text{Long-run coefficients} = \beta_k / (1 - \delta) \quad (4)$$

where β = the individual parameters while δ is the coefficient of the lagged dependent variable for the corresponding equation. The results as presented Table 5 in reveal some inconsistent or reverse effects between the two periods, the short and the long-run coefficients. In model 19 for instance, mobile banking compatibility with users' experience significantly raises its usefulness during the short-run but significantly dampens it in the long-run. The same situation holds for lag of income per person, financial development and inflation. Moreover, the magnitude of the impact seems to be more in the long-run than they were in the short-run. This has lots of policy implications. The none significance of Mobile banking riskiness and Internet banking riskiness in the long-run (Models 19 and 21) is an indication that its users have become more conversant with it during the long-run; hence, it could no longer limit the extent of its use.

Finally, the coefficients of the year dummies were extracted and plotted to see how Fintech has grown over the years from the base year (2004). The result as presented under Table 6 shows both the coefficients and how the growth rate of the various measures of Fintech has grown in comparison to its base year average. Take for instance, in 2006; our result revealed that the depth of mobile banking is on average and *ceteris paribus* 0.025% (100–99.975) lower than its average rate in 2004 because of the negative coefficients between 2006 and 2009. On the other hand, in 2018, mobile banking is on average *ceteris paribus* 41.82% higher than its average value

Table 6. Fintech growth rate in relation to its base years average penetration

Years	Coeff. of DMPB	Coeff. of DATM	Coeff. of DINTB	Grth rate of MPB	Grth rate of ATM	Grth rate of INTB
<i>Formular</i>	<i>B</i>	<i>B</i>	<i>θ</i>	$[100-e^{\theta}]%$	$[e^{\theta}-1]*100$	$[e^{\theta}-1]*100$
2004	0	0	0	100	100	100
2005	0	0	0	100	100	100
2006	-3.67	0.008	-0.195	99.975	0.803	-17.717
2007	-3.83	-0.01	-0.192	99.978	-0.995	-17.469
2008	-3.77	0.002	-0.182	99.977	0.200	-16.640
2009	-3.63	-0.002	-0.18	99.973	-0.200	-16.473
2010	3.73	0.007	0.189	58.185	0.702	20.804
2011	3.86	0.003	0.191	52.318	0.300	21.046
2012	3.73	0.003	0.189	58.185	0.300	20.804
2013	3.86	0	0.191	52.318	0.000	21.046
2014	3.73	0.004	0.189	58.185	0.401	20.804
2015	3.86	0.003	0.191	52.318	0.300	21.046
2016	3.73	0.005	0.189	58.185	0.501	20.804
2017	3.86	0.003	0.191	52.318	0.300	21.046
2018	3.73	0.004	0.189	58.185	0.401	20.804

Source: Estimation.

in 2004 due to the positive sign of its coefficients between 2010 and 2018. Again, the usefulness of internet banking penetration in 2006 is on average 17.72% lower than its average depth in 2004 but about 20.8 higher in 2018. In a nutshell, the growth rates of the various proxies of financial technology reveal that there was a remarkable increase in the growth rate after 2009 with positive coefficients. This suggests that countries embraced a technology-enabled financial solution as a risk mitigating tool after the 2009 financial crisis (Alexander et al., 2017).

4.2. Conclusions and policy implications

This study investigates the determinants of financial technology’s depth of penetration or usefulness among the heterogeneous African markets. The study is motivated by the discrepancy between high rates of Fintech adoption and the persistent high level of financial service needs, high financial exclusion and poor financial development in Africa. This suggests that greater adoption does not guarantee greater financial inclusion and development, except the users of Fintech diversifies and deepens its usefulness. Therefore, we provide empirical evidence on the determinants of Fintechs’ usefulness/depth of penetration based on the diffusion of innovation theory in a heterogeneous panel of three emerging, 24 frontier and 5 fragile African markets over the period 2004–2018.

Generally, we found strong evidence of heterogeneity in the average depth/usefulness of mobile banking, weak evidence in the average depth/usefulness of ATM but a homogenous average depth/usefulness of Internet banking among the various economic groups. This implies that on average heterogeneous factors could be responsible for the way users of Mobile banking and ATM diversifies its usefulness among African economies while common factors might have defined Internet banking usefulness. Therefore, Fintech’s policy response in Africa should differ depending on the aspect of Fintech issue that is being considered.

Another major finding in the study is that the factors that raise the extent of Fintechs’ usefulness are basically users’ previous experiences/compatibility, income per person in the previous period and the contemporaneous levels of literacy rate and financial development. These are measures of Fintech’s compatibility, trail-ability, complexity and financial resilience/fragility, respectively. On the other hand, the factors that limit the extent of Fintechs’ usefulness include its perceived risk, financial openness

and the inflation rate.⁹ Our findings do not change significantly in the models' one-step and two-step system GMM results as well as under various robustness checks. The fact that institutional, psychological and economic factors of financial development, risk and inflation respectively significantly drives its usefulness is an indication that Fintechs' depth of penetration in Africa is a dynamic heterogeneous process and can be more susceptible to institutional, psychological and economic changes rather than financial upheavals. Moreover, literacy rate which is a measure of Fintech complexity could only significantly raise the depth of ATM both at the main result and at its robustness baseline result. This implies that since ATM is not always easily accessible and handy as Mobile banking and Internet banking,¹⁰ its users must be literate enough before they can diversify its usefulness.

The general findings across the growth process of Fintechs' depths of penetration among African markets are that it was mainly negative before 2009 and positive afterwards. Moreover, there is a sharp increase in this growth rates after the global financial crisis of 2009. This is consistent with Alexander et al. (2017) assertion that many central banks have sought for a technology-enabled financial solution after the global financial crisis of 2009. The implication of this is that financial technology is efficient in mitigating financial risk because it raises the level of financial intermediation and development thereby making economies less vulnerable to crises as they widen access to liquidity and allow assets to be traded more easily during periods of stress (Gai et al., 2008). Hence, the continuous increase in its depth rate of penetration since the inception of the global financial crisis. This study therefore recommends greater Fintech diversification through improved literacy, institutional development, financial liberalization and continuous innovation. This will help to remove the bias that Fintech is very risk to the continual existence of banks; hence, financial institutions should collaborate with Fintech companies to harness their full advantage.

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Notes

1. Financial technology usefulness, otherwise referred to as the depth of financial technology penetration as used in this study entails the frequency and extent of its usage for more than just its primary purpose of financial service delivery.
2. This various purposes include financing, payments, assets management, Robo-Advice, Insurance, Blockchain and Cryptocurrency, etc.
3. These includes Venkatesh et al. (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) and the E. Rogers (2003) diffusion of Innovation theoretical models
4. Fintech riskiness and disruptive impact can be seen in the way it performs the roles that were the exclusive preserve of banks such as credit transfers, fund raising, loan extension, etc.
5. This disaggregation is based on the Financial Times Stock Exchange (FTSE) and Standard and Poor's

Index Provider (SPIP) economy classifications (2018)

6. See the selected countries under the appendix section
7. Note that Dft_{it} is a vector of three variables of $DINTB_{it}$, $DATM_{it}$, and DMB_{it} which are measures of the usefulness/depths of internet banking, automated teller machine and mobile banking respectively for county i in period t .
8. Please refer to the various measures of the variables in Table 1
9. Please note that inflation in this sense was not only used in its common sense of an economic indicator but also is used to proxy for Fintechs' relative efficiency over previous innovations. The rationale behind this choice is discussed under the theoretical framework of Roger's diffusion of innovation model.
10. We can easily access these Fintechs within the comfort of our rooms.

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Appendix

Table 1A: Economic groups used in the study

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

Source: Author's Compilation Based on FTSE and SPIP (2017) World Economic Groupings.

Table 2A. Bond et al. (2001) rule of thumb between the difference or system GMM estimator

Estimators	Coefficients of the lagged dependent variable		
	DINTB	DATM	DMPB
Pooled OLS estimate	0.995	0.810	0.9898
FE estimate	0.776	0.786	0.865
Difference GMM (One-step)	0.714	0.728	1.283
Difference GMM (Two-step)	0.692	0.735	1.402

Decision Rule: If the estimate of δ in the difference GMM result is below or close to FE estimate, then it is downward biased, hence a System GMM is better, otherwise use the Difference GMM.

Source: Estimation.



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