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AN EMPIRICAL ASSESSMENT OF PROBABILITY RATES FOR FINANCIAL TECHNOLOGY ADOPTION AMONG AFRICAN ECONOMIES: A MULTIPLE LOGISTIC REGRESSION APPROACH

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ABSTRACT

The extent of financial exclusion in Africa drives the adoption of fintech across the continent, but the disruption it can cause hinders progress. This study therefore assesses both the probability and actual rates of fintech adoption in 32 African economies between 2002 and 2018. Based on the information spill-over and rank theories, multiple logistic regression analysis revealed that the average probability of fintech adoption for all, emerging and frontier African economies to be 50.9%, 83.1%, and 23.1%, respectively, whereas the actual rates are 27%, 40%, and 29%, respectively. The fragile economies, however, had no reasonable probability or actual rates of fintech adoption. Further, odds ratios of 1 or more- suggest a one-unit change in the predicators will exert no impact on these rates. Thus, it is concluded that emerging economies and mobile phone banking drive fintech adoption in Africa, and is largely dependent mainly on structural changes rather than economic and financial factors. The current study consequently recommends improved literacy, ICT training, and structural changes to promote fintech across the continent.

Contribution/ Originality: This study is one of very few studies that empirically investigate the probability and actual rate of fintech adoption in African economies. The findings reveal that the quality of human capital and the dissemination of information, particularly in emerging economies are the major driving force behind the adoption of fintech in Africa.

1. INTRODUCTION

Financial technology (fintech hereafter) is an emerging field in the world of finance, combining both financial models and information technology to extend financial services to the general public faster and at a lower cost (Arner, Barberis, & Buckley, 2015). Due to this unique quality, its adoption is inevitable especially in regions with high rates of financial exclusion such as Africa; however, its disruptive impact on conventional business etiquette, especially in the banking sector, raises both prospects and problems in Africa, hindering progress (Jugurnath, Bissessur, Ramtohul, & Mootooganagen, 2018). As a result, some African economies doubt its future potential and reliability (Ernest & Young, 2017)- and prefer to pursue raditional means of delivering and accessing financial services. Nevertheless, increasing global commercialization alongside customers' ever-growing demands on banks to meet their needs means the adoption of fintech is inevitable. This is evident in the rate of fintech adoption in the recent years globally from 16% in 2015 to 33% in 2017 (Ernest & Young, 2017) with a predicted rise to over 70% in the near future. In fact, of particular relevance to Africa, South Africa's adoption beyond the 33% global average at 35% was probably due to the extensive financial exclusion across the continent (Mihasonirina & Kpodar, 2012). It is essential to examine the rate and determining factors of fintech adoption in Africa which has previously been neglected by researchers.

Moreover, the variation in adoption among different economies suggests that the process could be country's or region's specific, implying that fintech will thrive in some areas but fail in others. The success of the mobile phone money transfer service, M-Pesa, in Kenya and Tanzania but not South Africa is an example (Alexander, Shi, & Solomon, 2017). Therefore, this study aims to identify not only the aforementioned rates and factors in Africa, but also the various economic groups across the continent to be able to predict future fintech adoption rates according to the unique attributes of different areas.

2. LITERATURE REVIEW

As a recent innovation in finance, there are few empirical studies of fintech. Most of those are limited in terms of scope and/or measurement tools. This section presents recent studies in this area such as Khatimah and Halim (2016). They adopted the theory of planned behavior, assessed the factors influencing the adoption of e-money in Indonesia, and found social influences could positively impact users' intentions. Their findings corroborated those of Abdulkadir, Galoji, and Razak (2013), who reported that not only social influences such as peer group pressures, but also perceived usefulness can greatly affect the adoption of mobile banking. Meanwhile, Oliveira and Martins (2011) employed the diffusion of innovation theory when assessing an organization's adoption of information and communication (ICT). They demonstrated individual external and internal characteristics of organizational structure were important factors influencing innovativeness. This suggests that a firm's or country's unique attributes are major determinants in the decision on adoption.

Khalifa (2016) supported this conclusion in their assertion that a firm's absorptive capacity, structural features, information spill-over characteristics and environmental factors were key to Tunisian firms adopting ICT. However, this comprehensive study suffers two major drawbacks; first, it is based on a single country's survey and ICT in general, meaning it cannot be used to generalize about the adoption of fintech among African economies; second, despite examining robust determinants, the rate of was not explored through a binary discrete choice. This current study attempts to address these problems by investigating the rates of both the probability of and actual adoption of fintech in a broad representative sample of 32 African economies. Furthermore, from an international perspective, Glass and Saggi (2002) believed that the transfer/adoption of technology can be diffused through various channels; meaning that more than the usual determinants of fintech acceptance exists.

In Africa, the rate at which the use of mobile phones has spread and been exchanged for smartphones capable of financial transactions is extraordinary, bridging the digital-divide and enhancing financial inclusion in developing countries. According to Gough and Grezo (2005), the average penetration rate for mobile phones in Africa was 6.2%, with more recent studies reporting a higher rate (Ernest & Young, 2017).

According to a study using binary logistic regression Jugurnath et al. (2018) found that marital status and occupational group played a major role in the use of mobile banking in Mauritius; those from higher socioeconomic classes, married, and with no children were more likely to use mobile banking than those lower down the socioeconomic ladder (Jugurnath et al., 2018). These findings confirmed those of Kweyu and Ngare (2014) in Kenya and Fall, Ky, and Birba (2015) in Senegal, where personal income was very highly significant in the use of mobile banking. Likewise, Bhatt and Bhatt (2016) asserted that high-income earners who were married were more likely to use mobile banking. As this further suggests that economic and social attributes determine the adoption of new innovations, this current study will test the hypothesis the adoption of fintech in Africa depends on psychological, demographic and socioeconomic factors more than financial indicator variables.

3. THEORETICAL MODELS

The theoretical model is based on two distinct theories: information spill over and rank. The former theory states that as information about an innovation or new technology spreads (spills over) from users to non-users, the rate of adoption increases (Mansfield, 1961). Hollenstein (2004) and Battisti, Canepa, and Stoneman (2009) assert that information spillover is currently the principal driver of adoption in both developed and developing countries; the more frequently new and existing users come into contact and find out about new technology, the greater the number who will adopt it. This assertion implies that the adoption of new technology is directly correlated with the previous (lagged) level of adoption within a given social group; hence adoption is a function of previous users' experience. In this study, information spill-over model can be presented as Equation 1, taking the lag of previous users (fintech)-the dependent variable-in a first order autoregressive (AR 1) model.

$$Fintech\ Adoption_t = f(Fintech\ Adoption_{t-1}) \quad (1)$$

Where: Fintech $Adoption_t$ represents a vector of fintech adoption in the current period.

Fintech $Adoption_{t-1}$ represents a vector of fintech adoption in the previous period.

Equation 1 reveals that the level of adoption of fintech in the current period depends on previous levels of adoption or information spillover.

The second, rank theory states that a firm's/country's specific attributes or heterogeneities determine its adoption levels of technology. These attributes include psychological, demographic, and socioeconomic factors: the quality of human capital/literacy rate, population growth rate, extent of its financial openness, among others. This suggests that factors other than macroeconomic ones could be important drivers of fintech in Africa. Thus, as the quality of a country's human capital improves through educational achievement, potential users will perceive the usefulness of modern devices more easily and be more likely to adopt them for accessing financial services. Likewise, a rapidly growing population in countries with a high level of financial openness is more likely to lead to adopting fintech than in those with a declining population and strict financial repression. This model is therefore, expressed as:

$$Fintech\ Adoption_t = f(TSE_t, POPG_t, FO_t) \quad (2)$$

Where: Fintech $Adoption_t$ represents a vector of fintech adoption in the current period.

TSE_t represents tertiary school enrolment in the current period (a measure for literacy rate).

$POPG_t$ represents population growth rate in the current period.

FO_t represents financial openness in the current period.

Equation 2 models the heterogeneities that affects the adoption of fintech in a particular country, which is expressed as a function of the quality of human capital/literacy rate, population growth and financial openness in the current year.

Although other theories such as the technology acceptance model (TAM: Davis, Bagozzi, and Warshaw (1989) and the unified theory of acceptance and use of technology (UTAUT: Venkatesh, Morris, Davis, and Davis (2003) are widely used, information spill over and rank models are the dominant theories for explaining the adoption of new technologies (Canepa & Stoneman, 2004). Moreover, these theories are consistent with the objective to investigate binary discrete choice based on socioeconomic drivers for adopting new innovations (Mercer, 2004). Consequently, both theories were combined to form a single unique model to investigate this relationship.

3.1. Model Specification

The two models expressed in Equations 1 and 2 were merged to re-express a final model on Equation 3; however, due to the data on financial openness not being available for all countries, as well as for simplicity, the FO predicator was removed. The final model is expressed as:

$$Fintech\ Adoption_t = f(Fintech_{t-1}, TSE_t, POPG_t) \quad (3)$$

This empirical logistic model estimated in its econometric form, expressed as:

$$y_{it}^{*} = \beta_0 + \beta \chi_{it} + \mu_{it} \qquad \text{.... (4)}$$

Where y_{it}^{*} is a latent dummy variable representing whether a country either adopts (y_{it}^{*} = 1) or does not adopt (y_{it}^{*} = 0) new Fintech.

β_0 is a constant.

β is the vector of coefficients associated with the vector of explanatory variables χ_{it}

μ_{it} is the error terms whose cumulative distribution is assumed to be logistic.

As the natural logarithm of the odds ratio is equivalent to a linear function of the independent variables, taking the antilog of the odds ratio enables the solving of the probability (*p*):

$$\log it(Y) = \ln\left(p/1-p\right) = \beta_0 + \beta_{it}\chi_{it} + ... + \beta_n x_n \qquad ...(5)$$

Transforming the binary model in Equation 5 means the probability of African economies adopting fintech can be calculated:

$$\frac{\hat{p}}{1-\hat{p}} = e^{\beta_0+\beta_{it}x_{it}+..+\beta_n x_n} = \hat{P}(y_{it} = 1/x_{ij},..,x_n) = \frac{e^{\beta_0+\beta_{it}x_{it}+..+\beta_n x_n}}{1+e^{\beta_0+\beta_{it}x_{it}+..+\beta_n x_n}} \qquad ... (6)$$

Where: $\hat{P}$ is the estimated probability of the logistic model;

β_0 is the Y intercept.

βij's are the regression coefficients.

Xs are a set of predictors.

Equation 6 is used to solve $\hat{P}$ for each of the fintech proxy measures- internet banking (INTB), mobile phone banking (MPB), and automated teller machines (ATM) - for all the economic groups - emerging, frontier and fragile African economies. Moreover, the odds ratios were reported to verify whether a one unit increase in the average value of the explanatory (independent) variables affected the level of fintech adoption. The assumption is that – if the confidence intervals of the odds ratio crosses 1, then the explanatory variables do not affect the level of adoption.

3.2. Methodology and Data

A multiple logistic regression (MLR) analysis was conducted to predict the logit of fintech adoption (the event outcome) from the set of predictors. The logit - the natural logarithm of the odds (probability/[1 - probability]) was then transformed into a measure of probability with which to validate that high probability is associated with a high level of adoption, and vice versa, using the actual outcome variables as specified in Equation 3. This model can be estimated as follows:

$$natural\log(odds) = \ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = \beta_{it0} + \beta_{it1} f\,\mathrm{int}\,ech_{it-1} + \beta_{it2} TSE_{it} + \beta_{it3} POPG_{it} \qquad (7)$$

Taking the anti-log of each side of Equation 7 and the model can be transformed to calculate the probability of African economies adopting fintech.

$$\hat{P}(y_{it} = 1 / x_{ij}, .., x_n) = \frac{e^{\beta_{it0} + \beta_{it1} fintech_{it-1} + \beta_{it2} TSE_{it} + \beta_{it3} POPG_{it}}}{1 + e^{\beta_{it0} + \beta_{it1} fintech_{it-1} + \beta_{it2} TSE_{it} + \beta_{it3} POPG_{it}}} \quad (8)$$

Equations (7) and (8) are the closed-form models of Equations 5 and 6, respectively, using the predictors selected for investigation.

In the MLR analysis, the outcome variable, "(Y)", is a binary/dichotomous variable; taking value of 1 (if fintech is adopted and 0 (zero) otherwise. The probability of cases in which Y = 1 is defined as π = P(Y=1), with Y = 0 as 1 - π = P(Y = 0), hence, based on theory and empirical reviews, the set of predictors, relate to and determine Y. In addition, a comparative probability assessment was conducted for the three economic groups used in this study (see Appendix A, Table A.1). Furthermore, time periods selected for the study were consolidated by a principal component analytical (PCA), conducted to generate fintech indices for the three proxy measures that showed the negative values before 2008 became positive afterwards for most countries, especially those with emerging economies (see Appendix B. Tables B.1 and B.2).

The three proxy measures of fintech were the automated teller machines (ATM), also used by Nina (2007) the number of mobile phone subscriptions as a proxy for mobile phone banking (MPB), previously used by Gough and Grezo (2005) as a proxy for mobile banking (Jugurnath et al. (2018); and the number of individuals using internet banking (INTB). Therefore, the current study treats the concepts of fintech in a limited sense. This study is a panel analysis of 32 African economies over the period 2002 - 2018[1], disaggregated into 3 emerging, 24 frontier and 5 fragile economies based on the Financial Times Stock Exchange FTSE (2017) classification of countries, which takes into account the heterogeneity of these economic groups. Finally, the data were extracted from the online World Bank Data Base (2018) and the International Financial Statistics Database (2018).

4. RESULTS AND DISCUSSION

The results of the analyses are presented in two parts in the section. The first subsection discusses the descriptive analysis that ascertained the rate at which the economic groups adopted fintech, while the second subsection explores the empirical results from the MLR analysis.

4.1. Descriptive Statistics for Fintech Adoption Rate

The summary of the descriptive statistics are shown in Table 1. The overall weighted average rate for all African economies adopting fintech is approximately 27%, below the global average of 33% (Ernest & Young, 2017), but that for emerging African economies is above it at 40%; however, frontier and fragile African economies show averages only 29% and 12%, respectively. These results suggest that the rate of adopting fintech in Africa is undermined by fragile economies; thus, further analysis using advanced estimation methods are needed.

These results further reveal that, with an average of 57%, mobile phone banking is the most used fintech by all economic groups, which implies that about 71% of the total African population are using this fintech. Moreover, with a 40% rate of fintech adoption, emerging African economies constitute about 49% of total African population using mobile phone banking. This corroborates the findings of Ernest and Young (2017) that around 46% of fintech adoption occurs in emerging economies. Such success could be attributed to high income levels, greater financial

[1] See' classification in Aappendix A, Table A 1.

development and openness, high quality human capital, as well as significant funding in research and development compared with other African economies.

Table-1. Percentage adoption rate of fintech among African economies

Economies	ATM	Internet Banking	Mobile Phone Banking	Average	Percentage of Total
Emerging	23.85	25	70.7	40	49 units
Frontier	6.56	12.1	68.1	29	36 units
Fragile	1.33	2	32.22	12	15 units
All	10.58	13.03	57.01	27	
Percentage	13	16	71		100 units

The results shown in Table 1 are further represented on a bar chart in Figure 1, which provides more comprehensive view of the average rate of fintech adoption across the different economic groups. It is evident once more that mobile phone banking is the fastest growing therefore strongest driver for fintech in Africa. It can also be seen that emerging economies are experiencing the highest growth rate for all three proxy measures, although followed closely by frontier economies. On average, the rates of adoption in Africa measured by ATM, INTB and MPB are 10.58%, 13.03%, and 57.01%, respectively.

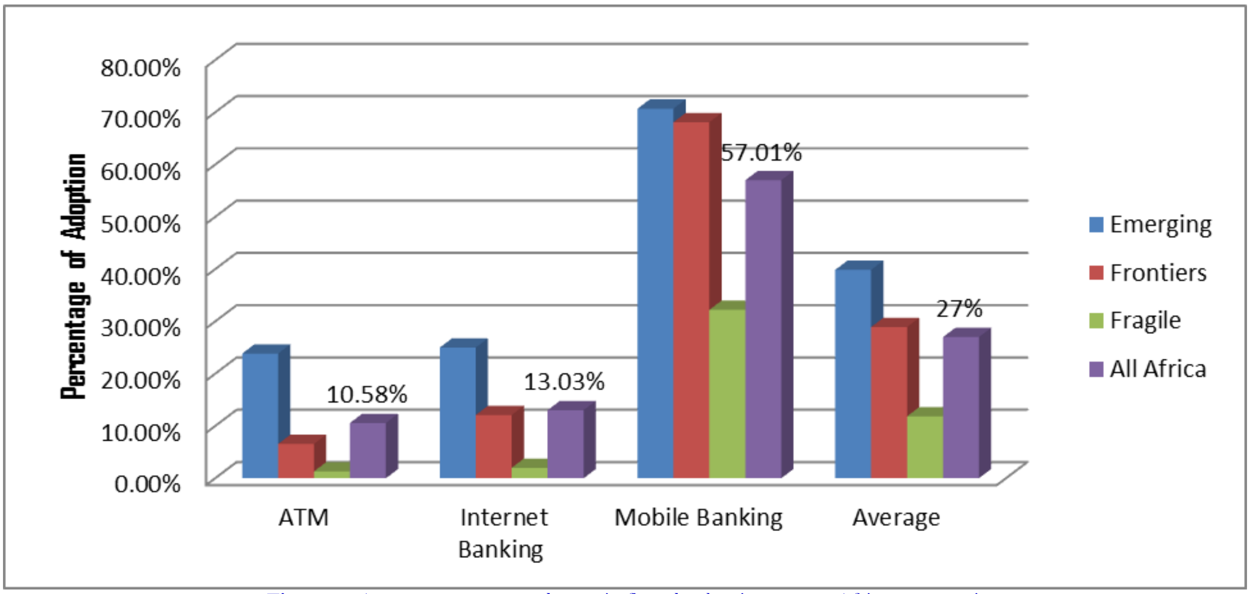

Figure-1. Average percentage change in fintech adoption among African economies.

4.2. Multiple Logistic Regression Results

It should be recalled that the dependent variable, - *Fintech, in Equation 3 is a* vector of three unknown proxies, ATM, INTB, and MPB, which the probability of adoption in all 32 African economies was calculated using Equation 8. This calculation involved inserting the coefficient estimates (β's) of the significant variables and evaluating the resultant probabilities against the average values shown in Table 1. The MLR results are presented in Tables 2, 3 and 4.

4.2.1. Multiple Logistic Regression Results for African Economies

The results for all 32 African economies shown in Table 2, reveal that the major drivers for adopting fintech were information spillover and the literacy rate of potential adopters. This implies that the more users interact and discuss their experiences with non-users, the higher the rate of adoption, while the quality of human capital also positively drives fintech; this is called it perception of ease-of-use in the TAM (Davis et al. (1989). This finding explains why the population growth exerts no significant impact, although there is a simultaneous increase in the quality of human capital. Thus, despite Africa's large population, the adoption rate is still very low (Muzari, Gatsi, & Muvhunzi, 2012).

Table 2 also demonstrates that an odds ratio of 1 represents a one-unit increase in that particular predictor that will not significantly change the probability of fintech adoption if the confidence interval crosses 1 or the odds ratio includes a whole number, then a one-unit increase in the explanatory variable will exert no effect on the independent variable; however, an odds ratio of 0 or less than one means that a one-unit change in the predictor will change the probability of adoption. As can be seen, except for population growth rate, the odds ratios of the predictors were greater than one and thus cannot significantly change the probability of fintech adoption.

Table-2. Multiple logistic regression result and estimated probability of fintech adoption among African Economies (N=32).

Predictors	Adoption of ATM		Adoption of INTB		Adoption of MPB	
	Coefficient	Odds Ratio	Coefficient	Odds Ratio	Coefficient	Odds Ratio
Information Spillover	5.378	216.480	3.830	46.058	0.0000013	1.000
	(8.910)***	(8.910)***	(8.76)***	(8.760)***	(5.15)***	(5.15)***
Population Growth (POPG)	6.414	610.242	0.771	2.161	-0.397	0.672
	(1.81)	(1.810)	(0.300)	(0.300)	(0.200)	(0.200)
Literacy Rate (TSE)	1.999	7.379	0.554	1.741	0.973	2.646
	(4.820)***	(4.820)***	(1.61)	(1.610)	(3.90)***	(3.900)***
constant	-75.531	7.85e-35	-51.700	3.52e-23	-26.947	1.98e-12
	(5.930)***	(5.930)***	(6.69)***	(6.690)***	(6.69)***	(6.690)***
Observation	425		425		425	
No in Group	32		32		32	
LR (Chi Squared)	89.470***		87.170***		65.630***	
Eq. 3.7 (sig variables only)	0.576		-2.102		1.257	
Probability of Adoption (Eq 3.8)	0.6402 or 64.02%		0.1090 or 10.9%		0.779 or 77.9%	

Note: Absolute value of z-statistics in parentheses *** significant at 1%; ** significant at 5%; LR=Long-run.

Finally, the estimated probability of fintech adoption in Africa comprises 64.02%, 10.9%, and 77.85% for ATM, INTB and MPB, respectively; meaning that mobile phone banking and ATMs are more likely to be used than internet banking. Specifically, the current population of Africa totals about 1.3billion (United Nations Organisation, 2019) 832,260,000 (0.6402*1.3billion) people will use ATMs, 141,700,000 internet banking, and 1,012,050,000 mobile phone banking.

Furthermore, with reference to Table 1, since 49% of fintech users in Africa reside in emerging, 36% in frontier, and 15% in fragile economies, of those 1,012,050,000 mobile banking users, 495,904,500 come from emerging economies, 364,338,000 frontier and 151,807,500 from fragile economies. Therefore, it can be concluded that African economies will adopt ATM and MPB but probably not internet banking in the near future, which can now be compared with the rates of fintech adoption in emerging and frontier economies, identifying in which fintech adoption in more probable.

4.2.2. Multiple Logistic Regression Results for Emerging African Economies

The current study studied the hypothesis that emerging economies drive fintech adoption and promote financial integration in Africa by investigating the probability of adoption in Egypt, Morocco, and South Africa. Emerging economies are defined as having established financial system, a relatively knowledgeable population or work force, and a high inflow of foreign direct investment (Latif et al., 2018) which previous studies (Ernest & Young, 2017) have confirmed by demostrating a higher rate of adoption than the 33% global average.

The MLR results for the three emerging economies presented in Table 3 are consistent with those for all the African economies, except that the probability of fintech adoption is reasonably high for all proxy measures – 79.81%, 73.49%, and 95.89% for ATM, INTB and MPB, respectively; thus it appears that Egypt, Morocco, and South Africa are the major driving force behind fintech on the Africa economies. In particular, information spillover and the literacy level of potential adopters were once more the major drivers of fintech adoption, however, the odds ratios reveal that a one-unit increase in these predictors will again not significantly affect the probability of adoption decision. In contrast, while the population growth rate does not necessarily exert a positive impact on fintech adoption, an odds ratio less than 1 implies that a one-unit change in this predictor can improve the probability of adoption.

Furthermore, the high probability rate among the emerging economies reveals that they have a very high propensity for adoption than the other economies under consideration. The analysis further strengthens the earlier assertion that the information spill over and quality of human capital had positive impact across the three models, whereas population growth rate does not.

Table-3. Multiple logistic regression result and estimated probability of fintech adoption among emerging African economies (N=3).

	Adoption of ATM		Adoption of INTB		Adoption of MPB	
Particulars	**Coefficient**	**Odds Ratio**	**Coefficient**	**Odds Ratio**	**Coefficient**	**Odds Ratio**
Information Spillover	0.1319***	1.2482**	0.087***	2.3428**	0.00000019***	1.000**
Population Growth (POPG)	-146.5	0**	-1.1989***	0**	0.601***	0**
Literacy Rate (TSE)	1.835***	2.0155***	0.011***	1.9310	1.023***	5.873**
Constant	-45.718***	0.1930**	2.042	3.4152**	-31.386***	0.121**
Observations	37		37		37	
No in Group	3		3		3	
LR (Chi Squared)	25.35**		25.35***		25.35**	
Eq. 3.7 (sig variables only)	1.375		1.020		3.149	
Probability of Adoption (Eq 3.8)	0.7981 or 79.81%		0.7349 or 73.49%		0.9589 or 95.89%	

Note: *** significant at 1%; ** significant at 5%; LR= Long-run.

4.2.3. Multiple Logistic Regression Results for Frontier African Economies

The 24 frontier African economies, with generally less liquidity than their emerging counterparts are those with an increasing lower middle-income class, rapid economic growth leading to rising living standards, low levels of internal and foreign debts, poorly developed stock markets, and a low level of urbanization, but implementing economic reforms to promote further economic growth (Broome & Seabrooke, 2007). Although, the population growth rate again exerted no significant impact on fintech adoption as can be seen from Table 4, neutral technical changes as a result of fintech can in theory, improve the quality of human capital, the workforce. This assertion was supported by Hicks (1932) when he theorized that a technical change that arises from innovations is capable of improving labour productivity and quality. It is possible to test this hypothesis empirically.

Once more, it is more likely that frontier economies will use mobile phone banking than internet banking or ATMs, although in this case, the ATMs are least to be adopted. This inconsistent result could be attributed to certain phenomena or specification errors; since certain factors fintech adoption differently in frontier and emerging economies, the same predicators cannot be assumed for both types of economy. This could explain the reason for MPESA, a mobile phone-based money transfer service, proving more popular in Kenya, Tanzania, and other frontier economies but failing to launch in the emerging economy of South Africa (Alexander et al., 2017). These heterogeneous factors that affect the adoption of fintech in emerging and frontier economies is therefore a unique area for further research.

Table-4. A Multiple logistic regression result and a probability table for fintech adoption among frontier African economies (n=24).

Predictors	Adoption of ATM		Adoption of INTB		Adoption of MPB	
	Coefficient	Odds Ratio	Coefficient	Odds Ratio	Coefficient	Odds Ratio
Information Spillover	3.319	27.642	2.887	17.942	0.000001	1
	(1.890)**	(1.890)**	(5.510)***	(5.510)***	(4.790)***	(4.790)***
Population Growth (POPG)	6.939	1031.300	3.895	49.159	-0.219	0.803
	(1.200)	(1.20)	(1.460)	(1.460)	(0.130)	(0.130)
Literacy Rate (TSE)	1.635	5.131	0.943	2.569	1.223	13.398
	(2.770)***	(2.77)***	(2.780)***	(2.780)***	(4.740)***	(4.740)***
Constant	-60.718	4.27e-27	-52.042	2.50e-23	-27.386	1.28e-12
	(4.270)***	(4.270)***	(4.380)***	(4.380)***	(7.040)***	(7.040)***
Observations	314		314		314	
No in Groups	23		23		23	
LR(chi-squared)	14.510***		33.140***		73.970***	
Eq. 3.7 (sig variables only)	-8.152		-7.175		-2.784	
Probability of Adoption (Eq 3.8)	0.030 or 3%		0.080 or 8%		0.582 or 58.2%	

Note: Absolute value of z statistics in parentheses; *** significant at 1%;** significant at 5%; LR = Long-run.

Finally, the non-convergence of the MLR results for the fragile African economies could be attributed to their poor infrastructural and financial development.

5. CONCLUSION AND POLICY IMPLICATIONS

This study examined both the probability and actual rates of fintech adoption in 32 African economies by means of MLR and descriptive analyses, respectively. These analyses were based on the information spillover and rank theories applied to emerging, frontier and fragile African economies. The results revealed that the overall average probability of fintech adoption in Africa to be 50.9%: 64.02%, 10.9% and 77.85% for ATM, INTB, and MPB, respectively. In particular, the average probability in the emerging economies was 83.1% compared with 23.1% in the frontier economies, indicating that a higher level of fintech adoption, mainly mobile phone banking will be witnessed in the emerging African economies. In fact, the mobile phone banking is widespread across Africa facilitating economic growth. Therefore, the adoption of fintech poses no economic challenges in Africa because it can be predicted and explored for its benefits.

These results further revealed that fintech adoption in Africa is driven by mobile phone banking and the emerging economies, whereas ATMs and fragile economies inhibited it. With 27% average rate of fintech adoption in Africa, it will be about 3.5 years for saturation point to be reached and financial exclusion resolved, if the adoption rate is maintained. However, the rate is below the global average of 33% (Ernest & Young, 2017); although this could be attributed to the low rate of adoption in fragile economies at 12% that weaken the predictors' effects on all economies, the rate of adoption in emerging African economies at 40% is above the global rate. The average adoption rates of 40% in emerging and 29% in frontier economies also implies that it will be 2.5 years emerging, 3.5 in frontier, but 9 years in fragile economies before fintech can end financial exclusion. These findings carry serious implications for not only Africa financial market development but also its macroeconomic stability.

Finally, the adoption of fintech across Africa is mainly influenced by information and the literacy rate, or quality of human capital, according to the levels of significance shown in the analyses; this is consistent with Khalifa (2016), who reported that these two predictors were the major determinants in whether firms adopted ICT. The odds ratio analysis emphasized the MLR results, because where it is below 1, Table 2, POPG, 0.6723, any change in this predictor will, over time, change the adoption rate. It is therefore inferred that with an overall average probability of 50.9%, the rate of fintech adoption in Africa will be higher in future than its current rate of 27%. Consequently, this study recommends improvements in literacy/education and ICT training should be the way forward.

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APPENDICES

Appendix A: Classification of African Economies.

Table-A.1. Classification of African economies in this study.

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

Source: World economic groupings under Standard & Poor (S&P) and FTSE (2017).

Appendix B. Principal component analysis and fintech indices.

Table-B.1. Principal component result: fintech index for the 32 African economies.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.9084	1.0686	0.6361	0.6361
Comp2	0.8398	0.5880	0.2799	0.9161
Comp3	0.2518	…..	0.0839	1.0000
Principal components (Eigenvectors)				
Variables	Component 1	Component 2	Component 3	Unexplained
ATM	0.6086	-0.4784	0.6330	0
INTB	0.6682	-0.1213	-0.7341	0
MPB	0.4279	0.8697	0.2458	0
Components: ATM, Internet Banking and Mobile Phone Banking				
Number of observations = 544; Number of components = 3; Trace = 3				

Table-B.2. Financial technology index for 32 African Economies.

CtryN	Year	Fnth	CtryN	Year	Fnth	CtryN	Year	Fnth
Algeria	2002	-1.1753	Botswana	2002	-1.0980	Burundi	2002	-1.2477
Algeria	2003	-1.1307	Botswana	2003	-1.0978	Burundi	2003	-1.2438
Algeria	2004	-0.9116	Botswana	2004	-0.5175	Burundi	2004	-1.2346
Algeria	2005	-0.6913	Botswana	2005	-0.4755	Burundi	2005	-1.2252
Algeria	2006	-0.4574	Botswana	2006	-0.3087	Burundi	2006	-1.2193
Algeria	2007	-0.1956	Botswana	2007	0.2451	Burundi	2007	-1.2162
Algeria	2008	-0.1540	Botswana	2008	0.1774	Burundi	2008	-1.2068
Algeria	2009	0.0388	Botswana	2009	0.1306	Burundi	2009	-1.1867
Algeria	2010	0.1193	Botswana	2010	0.1931	Burundi	2010	-1.1594
Algeria	2011	0.2832	Botswana	2011	0.2419	Burundi	2011	-1.1431
Algeria	2012	0.4679	Botswana	2012	0.5292	Burundi	2012	-1.1216
Algeria	2013	0.7058	Botswana	2013	1.1951	Burundi	2013	-1.0926
Algeria	2014	1.1222	Botswana	2014	1.5324	Burundi	2014	-1.0774
Algeria	2015	1.5363	Botswana	2015	1.6840	Burundi	2015	-0.8937
Algeria	2016	1.8317	Botswana	2016	1.7640	Burundi	2016	-0.8738
Algeria	2017	2.0485	Botswana	2017	1.9182	Burundi	2017	-0.8234
Algeria	2018	1.9401	Botswana	2018	1.8411	Burundi	2018	-0.8486
Angola	2002	-1.2394	Burkina-F.	2002	-1.2430	Cameroon	2002	-1.2253
Angola	2003	-1.2312	Burkina-F.	2003	-1.2331	Cameroon	2003	-1.2085
Angola	2004	-1.1864	Burkina-F.	2004	-1.1648	Cameroon	2004	-1.1703
Angola	2005	-1.1172	Burkina-F.	2005	-1.1570	Cameroon	2005	-1.1276
Angola	2006	-1.0130	Burkina-F.	2006	-1.1440	Cameroon	2006	-1.0804
Angola	2007	-0.9161	Burkina-F.	2007	-1.1215	Cameroon	2007	-1.0074
Angola	2008	-0.8022	Burkina-F.	2008	-1.0974	Cameroon	2008	-0.9445
Angola	2009	-0.6771	Burkina-F.	2009	-1.0652	Cameroon	2009	-0.8790
Angola	2010	-0.5496	Burkina-F.	2010	-0.9923	Cameroon	2010	-0.8369
Angola	2011	-0.3976	Burkina-F.	2011	-0.8960	Cameroon	2011	-0.7509
Angola	2012	-0.1374	Burkina-F.	2012	-0.8194	Cameroon	2012	-0.5836
Angola	2013	0.0483	Burkina-F.	2013	-0.5450	Cameroon	2013	-0.4041
Angola	2014	0.1661	Burkina-F.	2014	-0.4875	Cameroon	2014	-0.0873
Angola	2015	0.2845	Burkina-F.	2015	-0.3546	Cameroon	2015	0.1220
Angola	2016	0.2832	Burkina-F.	2016	-0.2144	Cameroon	2016	0.2479
Angola	2017	0.3543	Burkina-F.	2017	-0.0730	Cameroon	2017	0.2712
Angola	2018	0.3187	Burkina-F.	2018	-0.1437	Cameroon	2018	0.2595
Chad	2002	-1.2459	Egypt	2002	-1.0528	Ghana	2002	-1.2102
Chad	2003	-1.2385	Egypt	2003	-0.9711	Ghana	2003	-1.1868
Chad	2004	-1.2338	Egypt	2004	-0.4875	Ghana	2004	-0.9958
Chad	2005	-1.2294	Egypt	2005	-0.3167	Ghana	2005	-0.9695
Chad	2006	-1.2168	Egypt	2006	-0.1558	Ghana	2006	-0.8883
Chad	2007	-1.1963	Egypt	2007	0.2039	Ghana	2007	-0.7951
Chad	2008	-1.1614	Egypt	2008	0.5325	Ghana	2008	-0.7062
Chad	2009	-1.1332	Egypt	2009	0.9195	Ghana	2009	-0.5892
Chad	2010	-1.1103	Egypt	2010	1.3016	Ghana	2010	-0.4413
Chad	2011	-1.0854	Egypt	2011	1.7301	Ghana	2011	-0.3160
Chad	2012	-1.0664	Egypt	2012	2.0480	Ghana	2012	-0.1106
Chad	2013	-1.0320	Egypt	2013	2.2580	Ghana	2013	0.2307
Chad	2014	-0.9952	Egypt	2014	2.4221	Ghana	2014	0.7400
Chad	2015	-0.9559	Egypt	2015	2.6353	Ghana	2015	1.1667
Chad	2016	-0.8770	Egypt	2016	2.9074	Ghana	2016	1.4060
Chad	2017	-0.7917	Egypt	2017	3.2470	Ghana	2017	1.5357
Chad	2018	-0.8344	Egypt	2018	3.0772	Ghana	2018	1.4708
Cote d'Iv	2002	-1.2134	Ethiopia	2002	-1.2498	Kenya	2002	-1.1791
Cote d'Iv	2003	-1.1973	Ethiopia	2003	-1.2483	Kenya	2003	-1.0951
Cote d'Iv	2004	-1.0299	Ethiopia	2004	-1.2434	Kenya	2004	-1.0103
Cote d'Iv	2005	-1.0089	Ethiopia	2005	-1.2360	Kenya	2005	-0.9711
Cote d'Iv	2006	-0.9576	Ethiopia	2006	-1.2234	Kenya	2006	-0.8466
Cote d'Iv	2007	-0.8824	Ethiopia	2007	-1.2142	Kenya	2007	-0.6703
Cote d'Iv	2008	-0.8284	Ethiopia	2008	-1.1962	Kenya	2008	-0.4955
Cote d'Iv	2009	-0.7672	Ethiopia	2009	-1.1534	Kenya	2009	-0.3505
Cote d'Iv	2010	-0.7083	Ethiopia	2010	-1.0860	Kenya	2010	-0.1369
Cote d'Iv	2011	-0.6373	Ethiopia	2011	-0.9393	Kenya	2011	-0.0026
Cote d'Iv	2012	-0.5367	Ethiopia	2012	-0.7393	Kenya	2012	0.1361
Cote d'Iv	2013	-0.1542	Ethiopia	2013	-0.5749	Kenya	2013	0.2700
Cote d'Iv	2014	0.2575	Ethiopia	2014	-0.3494	Kenya	2014	0.4632

Cote d'Iv	2015	1.1710	Ethiopia	2015	0.1344	Kenya	2015	0.5432
Cote d'Iv	2016	1.3326	Ethiopia	2016	0.3615	Kenya	2016	0.5447
Cote d'Iv	2017	1.5513	Ethiopia	2017	0.2967	Kenya	2017	0.7161
Cote d'Iv	2018	1.4419	Ethiopia	2018	0.3291	Kenya	2018	0.6304
Madagascar	2002	-1.2359	Mali	2002	-1.2430	Mauritius	2002	-0.7938
Madagascar	2003	-1.2300	Mali	2003	-1.2357	Mauritius	2003	-0.7061
Madagascar	2004	-1.2138	Mali	2004	-1.1139	Mauritius	2004	0.5780
Madagascar	2005	-1.1967	Mali	2005	-1.1039	Mauritius	2005	0.7608
Madagascar	2006	-1.1789	Mali	2006	-1.0813	Mauritius	2006	0.8729
Madagascar	2007	-1.1460	Mali	2007	-1.0582	Mauritius	2007	1.1900
Madagascar	2008	-1.0459	Mali	2008	-1.0108	Mauritius	2008	1.2269
Madagascar	2009	-1.0166	Mali	2009	-0.9772	Mauritius	2009	1.3157
Madagascar	2010	-0.9853	Mali	2010	-0.9251	Mauritius	2010	1.6291
Madagascar	2011	-0.9526	Mali	2011	-0.8351	Mauritius	2011	2.0241
Madagascar	2012	-0.9272	Mali	2012	-0.7350	Mauritius	2012	2.0836
Madagascar	2013	-0.8985	Mali	2013	-0.5875	Mauritius	2013	2.3140
Madagascar	2014	-0.8353	Mali	2014	-0.3536	Mauritius	2014	2.5300
Madagascar	2015	-0.7875	Mali	2015	-0.2144	Mauritius	2015	2.7900
Madagascar	2016	-0.8014	Mali	2016	-0.2150	Mauritius	2016	2.8390
Madagascar	2017	-0.5535	Mali	2017	-0.1159	Mauritius	2017	2.9490
Madagascar	2018	-0.6775	Mali	2018	-0.1654	Mauritius	2018	2.8940
Malawi	2002	-1.2428	Mauritania	2002	-1.2333	Morocco	2002	-1.0376
Malawi	2003	-1.2391	Mauritania	2003	-1.2288	Morocco	2003	-0.9734
Malawi	2004	-1.2053	Mauritania	2004	-1.0559	Morocco	2004	-0.2452
Malawi	2005	-1.1721	Mauritania	2005	-1.0437	Morocco	2005	0.2191
Malawi	2006	-1.1690	Mauritania	2006	-1.0241	Morocco	2006	0.4127
Malawi	2007	-1.1343	Mauritania	2007	-0.9982	Morocco	2007	0.6171
Malawi	2008	-1.1283	Mauritania	2008	-0.9657	Morocco	2008	1.2590
Malawi	2009	-1.0607	Mauritania	2009	-0.9481	Morocco	2009	1.7439
Malawi	2010	-0.9832	Mauritania	2010	-0.8569	Morocco	2010	2.3928
Malawi	2011	-0.8882	Mauritania	2011	-0.8338	Morocco	2011	2.2800
Malawi	2012	-0.8119	Mauritania	2012	-0.7816	Morocco	2012	2.7962
Malawi	2013	-0.7571	Mauritania	2013	-0.6610	Morocco	2013	2.9362
Malawi	2014	-0.7068	Mauritania	2014	-0.4123	Morocco	2014	3.0410
Malawi	2015	-0.5308	Mauritania	2015	-0.1586	Morocco	2015	3.0652
Malawi	2016	-0.4266	Mauritania	2016	-0.0107	Morocco	2016	3.1199
Malawi	2017	-0.3122	Mauritania	2017	0.1093	Morocco	2017	3.3286
Malawi	2018	-0.3694	Mauritania	2018	0.0493	Morocco	2018	3.2243
Mozambique	2002	-1.2378	Niger	2002	-1.2472	Rwanda	2002	-1.2394
Mozambique	2003	-1.2275	Niger	2003	-1.2455	Rwanda	2003	-1.2357
Mozambique	2004	-1.1368	Niger	2004	-1.2151	Rwanda	2004	-1.2308
Mozambique	2005	-1.1031	Niger	2005	-1.2108	Rwanda	2005	-1.2162
Mozambique	2006	-1.0479	Niger	2006	-1.2051	Rwanda	2006	-1.1532
Mozambique	2007	-1.0175	Niger	2007	-1.1926	Rwanda	2007	-1.1374
Mozambique	2008	-0.9426	Niger	2008	-1.1626	Rwanda	2008	-1.0157
Mozambique	2009	-0.8471	Niger	2009	-1.1441	Rwanda	2009	-0.8376
Mozambique	2010	-0.7204	Niger	2010	-1.1284	Rwanda	2010	-0.7807
Mozambique	2011	-0.6749	Niger	2011	-1.0929	Rwanda	2011	-0.7571
Mozambique	2012	-0.5626	Niger	2012	-1.0741	Rwanda	2012	-0.6144
Mozambique	2013	-0.4141	Niger	2013	-1.0280	Rwanda	2013	-0.5331
Mozambique	2014	-0.1645	Niger	2014	-1.0009	Rwanda	2014	-0.4287
Mozambique	2015	0.2606	Niger	2015	-0.9260	Rwanda	2015	-0.0829
Mozambique	2016	0.2075	Niger	2016	-0.8681	Rwanda	2016	0.0132
Mozambique	2017	0.2299	Niger	2017	-0.5849	Rwanda	2017	0.0863
Mozambique	2018	0.2187	Niger	2018	-0.7265	Rwanda	2018	0.0497
Namibia	2002	-1.1346	Nigeria	2002	-1.2115	Senegal	2002	-1.1994
Namibia	2003	-1.1011	Nigeria	2003	-1.1726	Senegal	2003	-1.1468
Namibia	2004	-0.7093	Nigeria	2004	-1.0329	Senegal	2004	-0.8777
Namibia	2005	-0.6933	Nigeria	2005	-0.7366	Senegal	2005	-0.8487
Namibia	2006	-0.6811	Nigeria	2006	-0.3587	Senegal	2006	-0.7905
Namibia	2007	-0.6426	Nigeria	2007	-0.0537	Senegal	2007	-0.7207
Namibia	2008	0.1599	Nigeria	2008	0.5697	Senegal	2008	-0.6822
Namibia	2009	0.6951	Nigeria	2009	0.9450	Senegal	2009	-0.6318
Namibia	2010	1.2284	Nigeria	2010	1.2623	Senegal	2010	-0.5967
Namibia	2011	1.3020	Nigeria	2011	1.5334	Senegal	2011	-0.4732
Namibia	2012	1.2657	Nigeria	2012	1.9334	Senegal	2012	-0.3796
Namibia	2013	1.4578	Nigeria	2013	2.3972	Senegal	2013	-0.2497

Namibia	2014	1.6000	Nigeria	2014	2.8045	Senegal	2014	-0.0180
Namibia	2015	2.1222	Nigeria	2015	3.1732	Senegal	2015	0.1844
Namibia	2016	2.7005	Nigeria	2016	3.3088	Senegal	2016	0.3712
Namibia	2017	2.7879	Nigeria	2017	3.2127	Senegal	2017	0.5541
Namibia	2018	2.7442	Nigeria	2018	3.2607	Senegal	2018	0.4627
Seychelles	2002	-0.6199	Sudan	2002	-1.2310	Tanzania	2002	-1.2331
Seychelles	2003	-0.6071	Sudan	2003	-1.2206	Tanzania	2003	-1.2006
Seychelles	2004	1.1664	Sudan	2004	-1.2000	Tanzania	2004	-1.0757
Seychelles	2005	1.2000	Sudan	2005	-1.1639	Tanzania	2005	-1.0454
Seychelles	2006	1.7152	Sudan	2006	-1.0049	Tanzania	2006	-0.9933
Seychelles	2007	1.9142	Sudan	2007	-0.6801	Tanzania	2007	-0.9241
Seychelles	2008	2.2013	Sudan	2008	-0.4683	Tanzania	2008	-0.8426
Seychelles	2009	2.2982	Sudan	2009	-0.2815	Tanzania	2009	-0.7064
Seychelles	2010	2.3216	Sudan	2010	-0.0535	Tanzania	2010	-0.5941
Seychelles	2011	2.4558	Sudan	2011	0.1140	Tanzania	2011	-0.4707
Seychelles	2012	2.8337	Sudan	2012	0.3331	Tanzania	2012	-0.3915
Seychelles	2013	3.4997	Sudan	2013	0.4141	Tanzania	2013	-0.3502
Seychelles	2014	3.6053	Sudan	2014	0.5092	Tanzania	2014	-0.1510
Seychelles	2015	3.7324	Sudan	2015	0.6119	Tanzania	2015	0.1361
Seychelles	2016	4.0739	Sudan	2016	0.6853	Tanzania	2016	0.2685
Seychelles	2017	4.4635	Sudan	2017	0.8397	Tanzania	2017	0.4033
Seychelles	2018	4.2687	Sudan	2018	0.7625	Tanzania	2018	0.3359
South Afr.	2002	-0.7111	Swaziland	2002	-1.1722	Togo	2002	-1.2066
South Afr.	2003	-0.6412	Swaziland	2003	-1.1445	Togo	2003	-1.1964
South Afr.	2004	0.6311	Swaziland	2004	-0.8334	Togo	2004	-1.0677
South Afr.	2005	0.6467	Swaziland	2005	-0.6257	Togo	2005	-1.0524
South Afr.	2006	0.8142	Swaziland	2006	-0.5273	Togo	2006	-1.0390
South Afr.	2007	1.0359	Swaziland	2007	-0.4743	Togo	2007	-1.0207
South Afr.	2008	1.6089	Swaziland	2008	-0.2173	Togo	2008	-1.0071
South Afr.	2009	2.0285	Swaziland	2009	-0.1196	Togo	2009	-0.9834
South Afr.	2010	2.8954	Swaziland	2010	0.0796	Togo	2010	-0.9650
South Afr.	2011	3.6571	Swaziland	2011	0.4157	Togo	2011	-0.9277
South Afr.	2012	4.0400	Swaziland	2012	0.6667	Togo	2012	-0.8511
South Afr.	2013	4.4731	Swaziland	2013	0.8828	Togo	2013	-0.7932
South Afr.	2014	4.9207	Swaziland	2014	1.1639	Togo	2014	-0.7625
South Afr.	2015	5.3347	Swaziland	2015	1.1269	Togo	2015	-0.7329
South Afr.	2016	5.3342	Swaziland	2016	1.2540	Togo	2016	-0.5082
South Afr.	2017	5.4910	Swaziland	2017	1.1904	Togo	2017	-0.4434
South Afr.	2018	5.4126	Swaziland	2018	1.2222	Togo	2018	-0.4758
Tunisia	2002	-1.0110	Zambia	2002	-1.2302			
Tunisia	2003	-0.9322	Zambia	2003	-1.2061			
Tunisia	2004	-0.4801	Zambia	2004	-1.1223			
Tunisia	2005	-0.3448	Zambia	2005	-1.0589			
Tunisia	2006	-0.1203	Zambia	2006	-0.9602			
Tunisia	2007	0.1928	Zambia	2007	-0.8825			
Tunisia	2008	0.7242	Zambia	2008	-0.7775			
Tunisia	2009	1.1276	Zambia	2009	-0.6584			
Tunisia	2010	1.3790	Zambia	2010	-0.4527			
Tunisia	2011	1.5456	Zambia	2011	-0.3297			
Tunisia	2012	1.6854	Zambia	2012	-0.1487			
Tunisia	2013	1.8230	Zambia	2013	-0.0281			
Tunisia	2014	2.0078	Zambia	2014	0.1687			
Tunisia	2015	2.1029	Zambia	2015	0.3131			
Tunisia	2016	2.2769	Zambia	2016	0.5293			
Tunisia	2017	2.5178	Zambia	2017	0.6641			
Tunisia	2018	2.3973	Zambia	2018	0.5967			