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Mobile Banking, Fintech Solutions and Poverty Alleviation in Rural Areas of Nigeria

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Abstract

This study examines the role of mobile banking in enhancing financial inclusion and its subsequent effects on poverty alleviation rural areas in Nigeria between 1999 and 2023 using data sourced from World Bank database and United Nations Development Programme (UNDP) and a technique of structural vector autocorrelation (SVAR) model. The results reveal that Fintech solutions in Nigeria, while positively impacting the Multidimensional Poverty Index, may also disrupt low-income areas and reduce demand for advanced solutions. The study proposes a practical approach to poverty alleviation through Fintech solutions, including infrastructure strengthening, digital literacy programmes, regulatory frameworks and tailored financial products, especially in the rural areas of Nigeria

Keywords: Mobile Banking, Financial Inclusion, Poverty Alleviation, Fintech Solutions and Nigeria
JEL Codes: O16, G21 and I38

INTRODUCTION

In recent years, mobile banking has emerged as a transformative phenomenon that is fundamentally altering the global financial architecture, particularly in developing nations. This transition is particularly noteworthy considering that over 70% of the world's unbanked demographic resides in rural locales, wherein achieving financial inclusion presents a considerable challenge. These areas frequently lack the requisite infrastructure to facilitate conventional banking services, thereby depriving numerous individuals of access to vital financial resources. In Nigeria, a country distinguished by a significant rural populace, mobile banking has become an indispensable instrument for addressing these challenges. It furnishes affordable, accessible, and convenient financial services to individuals who have traditionally been excluded from formal financial systems (CBN, 2020; Pew, 2021). The emergence of mobile banking has fundamentally transformed the modalities of conducting financial transactions, allowing users to oversee their financial affairs directly via their mobile devices.

The incorporation of Fintech solutions into mobile banking has markedly expedited this transformation. These pioneering technologies empower individuals in rural locales by affording them access to a varied spectrum of financial services, such as savings accounts, loan facilities, payment systems, and insurance products (Masinga & Dube, 2021 and World Bank, 2021). Such digital platforms have not only narrowed the divide between the banked and unbanked populations but also possess the potential to significantly contribute to the alleviation of poverty. It also enhances financial literacy, facilitates income-generating activities, and promotes economic resilience and as well creates opportunities for financial inclusion, especially for underrepresented populations in rural areas with limited traditional banking infrastructure (Jack & Suri, 2014).

The advent of mobile payment platforms and micro-loan services has unveiled new pathways for rural populations, enabling their participation in income-generating activities, investment in small enterprises, and mitigation of the impacts of income volatility. These financial services are especially vital for marginalized groups, such as women and smallholder farmers in rural communities, who often face substantial obstacles in accessing traditional banking services and financial products (Binns, Moore &

Cavanagh, 2019). Research indicates that mobile banking platforms have made a tangible difference in reducing poverty levels by enhancing access to credit and fostering financial security (Suri & Jack, 2016).

In Nigeria, for instance, a substantial segment of the population, especially in rural regions, remains unbanked and deprived of formal financial services. In response, mobile banking, bolstered by innovative Fintech solutions, has emerged as a powerful mechanism for delivering essential financial services, including savings accounts, loans, insurance, and payment systems, all without the necessity of physical bank branches. By harnessing mobile technology, individuals in rural Nigeria can now engage in a range of financial activities that were previously inaccessible to them. This shift not only promotes financial inclusion but also enhances financial literacy, as individuals gain the knowledge and skills necessary to navigate the financial landscape effectively (Munyegera & Matsumoto, 2016 and World Bank, 2021). These resources can empower users to better understand financial concepts, make informed decisions, and ultimately navigate the complexities of the financial system with confidence (Pew, 2021). By fostering both access and education, mobile banking not only facilitates immediate financial transactions but also lays the groundwork for long-term economic empowerment and resilience in underserved communities.

Literature Review

To substantiate the theoretical investigation of mobile banking and Fintech solutions as instrumental mechanisms for augmenting financial inclusion and mitigating poverty in the rural sectors of developing nations, this study specifically concentrates on Nigeria as a prototypical case. It leverages two seminal theoretical frameworks: Financial Inclusion Theory and the Technology Acceptance Model (TAM). Initially, Financial Inclusion Theory emphasizes the critical importance of access to formal financial services - including savings accounts, credit facilities, insurance products, and payment systems - as fundamental elements for enhancing the economic circumstances of individuals, particularly within marginalized communities. This theory asserts that financial inclusion transcends mere access; it serves as a crucial catalyst for economic empowerment, poverty alleviation, and equitable socio-economic progress (Munyegera & Matsumoto, 2016 and Demirgüç-Kunt, Klapper & Singer, 2018). The implications of this theory suggest that mobile banking platforms have the potential to augment financial participation among rural inhabitants, thereby enhancing household welfare and enabling individuals to partake in economic activities. Conversely, the Technology Acceptance Model (TAM), first articulated by Davis in 1989, offers a significant framework through which to comprehend the intricacies of technology adoption. TAM posits that the perceived ease of use and perceived usefulness of a technology serve as the principal determinants of its acceptance and subsequent utilization. Empirical research conducted by Munyegera and Matsumoto (2016) explores the transformative effects of mobile money services on household welfare in rural Uganda. The findings from this study highlight the favorable implications of mobile money, particularly for services designed for remittances, which have emerged as a vital support mechanism for families in these areas.

In a complementary examination, Jack and Suri (2024) investigated the role of mobile money in reducing transaction costs and enhancing risk management strategies, thereby contributing to poverty alleviation initiatives. Although their research predominantly concentrated on Kenya, the insights derived from their findings possess substantial relevance for comprehending the potential impacts of mobile banking within Nigeria's rural context. Services such as M-Pesa in Kenya and various Fintech innovations in Nigeria have significantly diminished transaction costs, thereby rendering financial services accessible to low-income and rural populations. This can reduce poverty levels and enhance financial resilience. Suri and Jack (2021) undertook a thorough investigation into the enduring impacts of mobile money adoption on poverty alleviation and gender equality within the Kenyan context. Their results underscore a significant correlation between mobile banking services and enhanced economic circumstances for disadvantaged rural households. This revelation provides a persuasive argument for the prospective implementation of analogous mobile money strategies in Nigeria, where the embrace of such technological advancements could function as a crucial mechanism for poverty alleviation. In Kenya, the emergence of mobile banking platforms such as M-Pesa has yielded a disproportionately beneficial effect on women, markedly augmenting their economic empowerment and facilitating advancements in gender equality.

In a related investigation, Olatokun and Igbinedion (2018) explored the determinants influencing the adoption of mobile banking services in Nigeria, with a specific focus on rural demographics. Their analysis uncovered several pivotal factors that shape the landscape of adoption, including trust, user-friendliness, and perceived advantages. Trust emerges as a significant concern in Nigeria, characterized by skepticism regarding security and the potential for fraud. The inquiry conducted by Aker & Mbiti (2020) investigates the transformative impact of mobile phones, particularly through the prism of mobile banking, on economic activities throughout Africa, with a notable focus on rural locales. Their findings highlight the significant manner in which mobile banking acts as a catalyst for economic empowerment, especially for rural farmers and small-scale entrepreneurs. The research provides compelling evidence that mobile banking not only broadens economic opportunities but also considerably reduces transaction costs and enhances market accessibility for these individuals. In the context of rural Nigeria, where agriculture remains a primary livelihood source, the implications of these findings are particularly pronounced.

In a complementary investigation, Osei-Assibey and Tetteh (2020) scrutinized the adoption of mobile banking in rural Ghana and its ramifications for financial inclusion. Their findings indicate that mobile banking has substantially enhanced access to financial services, including savings and credit, which subsequently exerts a positive influence on poverty alleviation. This research is particularly relevant for understanding the dynamics of mobile banking in Nigeria, as it highlights the critical role mobile banking plays in enhancing financial literacy and expanding access to credit within rural communities. The ability for rural residents to conduct banking transactions directly from their mobile devices represents a paradigm shift in financial management. It empowers individuals to take control of their finances and make informed investments. Furthermore, mobile banking plays a vital role in promoting financial inclusion by enhancing access to credit, thereby enabling rural households to invest in agriculture, entrepreneurial ventures, or educational opportunities. This access can spur entrepreneurship and drive economic growth within rural communities (Evans & Schmalensee, 2021). By improving access to essential financial services such as savings accounts, credit, and insurance, mobile banking not only empowers individuals but also stimulates local economies. Increased financial literacy and resource accessibility foster sustainable development, creating a more resilient and prosperous future for these communities. In their insightful analysis, Abor & Quartey (2020) delve into the significant role that mobile banking and Fintech solutions play in financing Small and Medium Enterprises (SMEs) in Ghana. The research underscores the transformative potential of digital finance in empowering entrepreneurs, a concept that holds great relevance for Nigeria's rural entrepreneurs and farmers as well. It suggests mobile banking and Fintech innovations can help overcome these obstacles, especially in rural areas with limited financial literacy.

Complementing the work of Ayo, Adewoye, and Oni (2016) provides a thorough examination of the mobile banking landscape in Nigeria. The study highlights the growth of mobile banking, driven by factors like mobile phone usage, telecommunications infrastructure, and innovative practices. Key factors include user-friendliness, accessibility, cost-effectiveness, and government policies. However, infrastructure deficiencies and trust issues hinder its expansion. Mobile banking enhances financial inclusion for rural populations, improves cash flow, empowers women, and aids poverty alleviation by creating income opportunities and streamlining remittance processes.

METHODS

The paper employs a Structural VAR model which relies on Financial Inclusion Theory and the Technology Acceptance Model **(**TAM**)** to sort out the contemporaneous link among the variables in our model by using a system of equations as

$$\begin{bmatrix} FIN \\ MPI \\ MBK \end{bmatrix} = A_0 + A_1[FIN_{-1}] + A_2[MPI_{-1}] + A_3[MBK_{-1}] + u_t \qquad 1$$

Where:

MPI is the Multidimensional Poverty Index

FIN is the Fintech Index which measures the overall level of Fintech innovation and adoption.

MBK is the Mobile banking adoption rate (which represents Financial Inclusion)

The study is limited to a 3-variable Structural Vector Autoregression (SVAR) model. This is as result of the fact that SVARs, especially with multiple variables can consume degrees of freedom, leading to imprecise estimates and unreliable inference and misleading conclusions (Munyegera & Matsumoto, 2016 and Demirgüç-Kunt, Klapper & Singer 2018).

In an attempt to ensure stationarity of the variables, the model in equation I is log-linearised as follows

$$\begin{bmatrix} lnFIN \\ lnMPI \\ lnMBK \end{bmatrix} = A_0 + A_1[lnFIN_{-1}] + A_2[lnMPI_{-1}] + A_3[lnMBK_{-1}] + u_t \qquad 2$$

The variables are in log form and we impose the following Cholesky identification:

$$A = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & 0 \\ b_{31} & b_{32} & b_{33} \end{bmatrix}; \text{ and } B = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \qquad 3$$

With these structural restrictions as indicated in the matrices A and B, it is assumed that the percentage change in Fintech innovation (FIN) is not contemporaneously affected by the percentage changes in either Multidimensional Poverty Index (MPI) or financial inclusion rate (MBK). It is also assumed that the percentage change Fintech innovation (FIN) is affected by contemporaneous changes in MPI but not financial inclusion rate. Finally, we assume that changes in Fintech innovation (FIN) are affected by contemporaneous changes in both MPI and MBK. The structural equations represent the relationships between these variables, and identification restrictions are imposed to ensure that the model reflects the true structural relationships (Chen & Ravallion, 2022). Moreover, after estimating the model, Impulse Response Functions (IRFs) are also investigated in order to examine the dynamic effects of shocks to the Fintech innovation on the financial inclusion rate and poverty alleviation nexus**.** Then, some model diagnostic tests are also performed.

Data

The table provides the sources and measurement of the variables used in this work.

Table 1: Data sources and measurement

Variable	Definition/Measurement	Sources
Fintech Solution (FIN)	Fintech Index, which is a composite score that combine the standardized values of variables such as: Mobile Payment Volume, Number of Fintech Startups, Investment in Fintech, Number of Banked Population, Internet Penetration Rate, Mobile Penetration Rate, Regulatory Environment and FinTech Adoption Rate	World Bank's Global Findex database, (2023)
Poverty (MPI)	Multidimensional Poverty Index which reflects various deprivations people face. These factors include: Education, Health and Living Standards	UNDP, (2023)
Financial Inclusion	Mobile Banking Adoption rate which represents Financial Inclusion (the % of the population with access to financial services).	World Bank, (2023)

RESULTS

Stationarity Test

The paper employed an Augmented Dickey-Fuller Unit Root Test to determine the stationarity or otherwise of the variables used. The Table 2 presents ADF test statistics for MPI, FIN, and MBK, tested at level and at first difference, and compared to critical values at 1%, 5%, and 10% significance levels.

Table 2: Augmented Dickey-Fuller Unit Root Test Results

Variable	Test Stat	1% critical value	5% critical value	10% critical value
At Levels				
MPI	2.9180	-3.750	-3.000	-2.630
FIN	-3.827			
MBK	-2.891			
At First Difference				
MPI	-3.499	-3.750	-3.000	-2.630
FIN	-3.108			
MBK	-4.147			

Source: Authors' estimation

From the result, the test statistic for MPI at levels is 2.9180, which is greater than critical values, indicating non-stationarity. FIN is stationary at levels, with a test statistic of -3.827, more negative than the 1% critical value. MBK is stationary at the 5% level, with a test statistic of -2.891, more negative than the 5% critical value but not the 1% critical value. Also, the test statistic for MPI at first difference is -3.499, indicating it is stationary after first differencing. FIN's test statistic is -3.108, more negative than the 5% critical value but not the 1% critical value. MBK's test statistic is -4.147, more negative than the 1% critical value, indicating it is stationary after first differencing. Therefore, the variables used are stationary.

Selection-Order Criteria

The Table 2 presents selection-order criteria results for the model used with varying lag lengths, using key statistical measures like Log-Likelihood (LL), Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC) and Schwarz Bayesian Information Criterion (SBIC).

Table 3: Selection-Order Criteria Results

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	119.2				3.1e-09	11.07	-11.04	-10.92
1	255.4	272.2	9	0.000	1.7e-14	-23.18	-23.05	-22.58*
2	263.9	17.13	9	0.047	1.9e-14	-23.14	-22.91	-22.09
3	273.1	18.41	9	0.031	2.3e-14	-23.16	-22.83	-21.66
4	291.7	37.18*	9	0.0000	1.3e-14*	-24.07*	-23.65*	-22.13

Source: Authors' estimation

From the results in the Table 2, it is clear that Lag 4 is the optimal model for a model due to its low AIC, HQIC, and SBIC values, strong out-of-sample prediction ability, and significant LR test statistic. Lag 1 also performs well, but slightly underperforms compared to Lag 4. Lag 2 and Lag 3 show improvement, but their AIC, HQIC, and SBIC values are worse than Lag 4 and Lag 1.

SVAR Short Run Estimates

Two matrices A and B provide estimates for the relationships among variables lnFIN, lnMPI, and lnMBK in the short run. The variables are analyzed in percentage terms using log-transformed versions.

Matrix A =

	lnMPI	**lnFIN**	**lnMBK**
lnMPI	1	0	0
lnFIN	1.607	1	0
lnMBK	-0.531	-0.244	1

Matrix B =

	lnMPI	**lnFIN**	**lnMBK**
lnMPI	0.003	0	0
lnFIN	0	0.009	0
lnMBK	0	0	0.004

Source: Authors' estimation

The results show that a 1% increase in lnFIN (Fintech solution) leads to a 1.607% increase in lnMPI (Multidimensional poverty Index). This suggests that Fintech solution has a strong positive impact on Multidimensional poverty Index in Nigeria in the short run.

The coefficient is 1, indicating that MPI does not directly influence Fintech solution in the short run. This suggests that MPI does not immediately affect the Fintech solution in the same way that the latter impacts the former. This is an indication that the Multidimensional Poverty Index (MPI) does not directly impact the adoption of Fintech solutions, such as mobile banking and digital payments, as they are primarily supply-driven and may take time to penetrate poor communities due to infrastructure, user education, and barriers to entry. The results corroborate the findings of Masinga & Dube, (2021) which show that there exist disparities in Fintech access and outcomes. Also, it is revealed that a 1% increase in MBK (financial inclusion) – as a result of rise in Fintech solution - results in a 0.531% decrease in MPI **(**Multidimensional poverty Index). This indicates a negative relationship between MBK and MPI in the short run, meaning that an increase in MBK is associated with a decline in MPI.

A 1% increase in financial inclusion (lnMBK) leads to a 0.244% decrease in Fintech solution (lnFIN)**.** This suggests that there is a negative relationship between MBK and FIN, indicating that an increase in financial inclusion may harm Fintech solution in Nigeria in the short run.

SVAR Long Run Estimates

Matrix A =

	lnMPI	**lnFIN**	**lnMBK**
lnMPI	0.133	0	0
lnFIN	0	0.211	0
lnMBK	0	0	0.286

Source: Authors' estimation

The study reveals that each variable (lnMPI, lnFIN, and lnMBK) has a positive long-run self-impact, with MBK having the strongest self-reinforcement effect. However, there are no direct long-run effects of one variable on the other, indicating that these variables evolve independently in the long run, based on their own past values, rather than the past values of the other variable

Impulse Response Functions

The IRF graph in Figure 1 shows the dynamic response of variables like Fintech Innovation, Multidimensional Poverty Index, and Financial Inclusion Rate to shocks from 1999 to 2023 in Nigeria. It demonstrates the interaction and persistence of these effects, with the graph's height indicating change, significance indicating statistical significance, and duration indicating lasting impact.

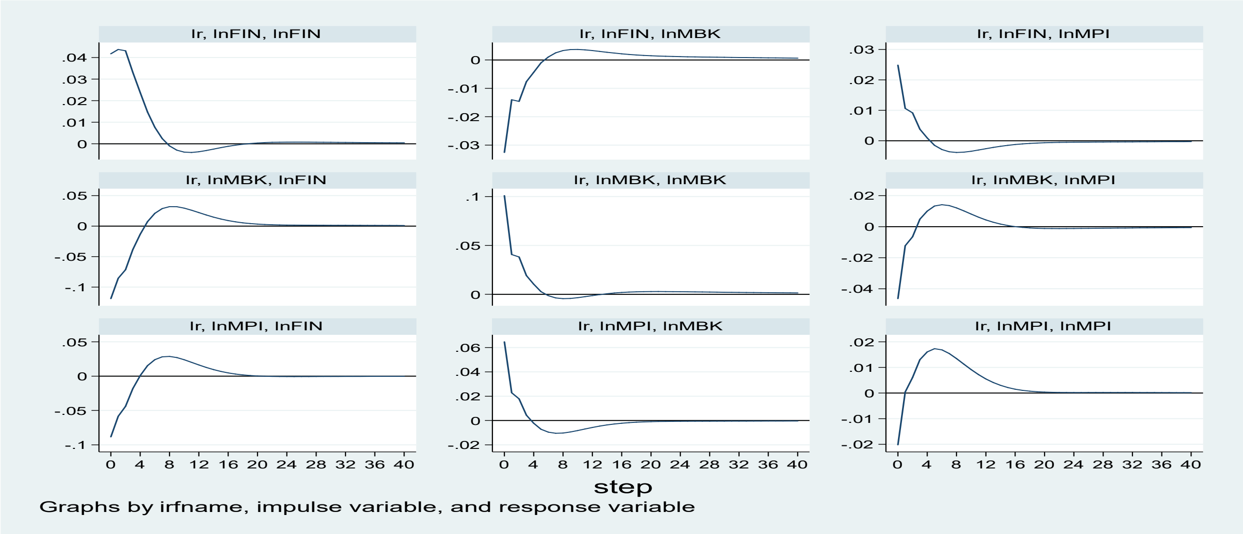

Figure 1: The dynamic effects of shocks to Fintech innovation (FIN), Multidimensional Poverty Index (MPI) and Financial Inclusion Rate (MBK) in Nigeria (1999 -2023)

Source: Authors' graphical illustration

The Figure 1 illustrates how the Multidimensional Poverty Index (MPI) and Financial Inclusion Rate (MBK) respond to a shock to Fintech Innovation (FIN). A positive shock to FIN could indicate improvements in financial technology or policies, reducing poverty while a negative shock to FIN could result in higher poverty levels or lower financial inclusion. The duration of the response depends on the shock's nature and the system's characteristics. A negative shock to MPI could result in a positive response in FIN, while a shock to the Financial Inclusion Rate (MBK) could have direct effects on MPI and FIN.

Model Diagnostics

After estimation, we check for issues such as normality of residuals using the Jarque-Bera test and test for stability using Eigenvalue stability condition and the results are presented in the Tables 4 and 5.

Table 4: Jarque-Bera Normality Test Results

Equation	Chi^2	df	Prob. > Chi^2
lnFIN	0.406	2	0.81630
lnMPI	0.664	2	0.71746
lnMBK	0.580	2	0.74843
ALL	1.650	6	0.94895

Source: Authors' estimation

The Jarque-Bera (JB) normality test is a statistical method used to determine if a dataset follows a normal distribution, using the Chi-squared value and p-value to reject the null hypothesis. The study reveals that the data for lnFIN, lnMPI, and lnMBK, as well as the combined dataset, follow a normal distribution, as indicated by the p-values. These values are significantly higher than the 0.05 threshold, indicating that they do not reject the null hypothesis. The combined dataset also shows a high p-value, indicating that the entire dataset is also normally distributed. Thus, the data for these variables, along with the combined dataset, are all normal, indicating no evidence of non-normality

Stability Test

The stability test results are based on the eigenvalues of a system, likely related to a Vector Autoregressive or Structural Vector Autoregressive model. The modulus of each eigenvalue indicates its stability, with a modulus of less than or equal to 1 indicating stability or a modulus of exactly 1.

Table 5: Stability Test Results

Eigenvalue	Modulus
0.9636	0.9636
0.73169+ 0.1521i	0.7473
0.7316 - 0.1521i	0.7473
0.68001	0.6800
-0.3182 + 0.0307i	0.3197
-0.3182 - 0.03076i	0.3197

Source: Authors' estimation

The system's stability test results show that all eigenvalues have a modulus less than 1, indicating no instability. The presence of complex eigenvalues with real and imaginary parts indicates some oscillatory behaviour, but these do not affect the overall stability of the system. The system's stability test results indicate that all eigenvalues lie inside the unit circle, indicating no indication of instability.

Discussion

By implication, the lack of direct influence from MPI on Fintech adoption in the short run can be attributed to non-responsive financial infrastructure, financial inclusion policy gap, and the lack of access to financial products targeted at reducing multidimensional poverty. The financial infrastructure required for Fintech solutions is typically influenced by policy decisions, technology availability, and investment, rather than directly by the poverty index. Fintech solutions may not immediately address all dimensions of poverty, such as education, living standards, and health, which are part of the MPI. As claimed by Binns, Moore & Cavanagh, (2019) that Fintech development affects financial inclusion and poverty alleviation. Therefore, poverty alleviation through Fintech is likely a long-term process. The results also imply that rapid growth of mobile banking in Nigeria may decrease the demand for Fintech solutions in the short term due to market saturation, competition, and regulatory priorities. As mobile banking becomes more widespread, there may be less demand for advanced Fintech solutions like peer-to-peer lending or blockchain-based services as claimed by Binns, Moore, & Cavanagh, (2019). However, as users gain financial literacy, the market may open up for specialized Fintech solutions like digital lending and wealth management platforms.

Thus, in the short run, the results indicate that the rapid adoption of Fintech solutions may cause short-term disruptions, particularly in low-income areas where people lack the necessary infrastructure to fully benefit from these services. This could widen inequalities, with wealthier individuals or businesses gaining more access to financial services while those in extreme poverty remain excluded. This is in line with the findings of Aker & Mbiti, (2020) which reveal that disparities in access to technology can lead to uneven benefits. In the long run, Fintech solutions are expected to promote financial inclusion, reduce transaction costs, and support economic opportunities for marginalized groups. However, the short-term effects may not be as evident if the population is still adapting to these technologies or if Fintech platforms fail to cater adequately to the needs of the poor.

In the long run analysis, the results imply that the positive long-run self-impact of the three variables- Multidimensional Poverty Index (MPI), Fintech Solutions (FIN), and Mobile Banking (MBK) - indicates that these variables evolve based on their historical trends. MPI suggests that poverty levels remain persistent or gradually improve depending on past trends, suggesting that if high, low living standards, education, and income would lead to continuing poverty unless external interventions are introduced. Fintech Solutions (FIN) suggest that the adoption and development of Fintech services reinforce itself over time, leading to increased institutional investments and technological advancements. Mobile Banking (MBK) shows the strongest self-reinforcement effect, suggesting that its use and effectiveness reinforce themselves over time, particularly in low-income countries like Nigeria where mobile phone penetration is rapidly increasing. This is the claim of Chen & Ravallion, (2022) that multidimensional poverty tends to persist over time due to structural factors beyond just income.

The study reveals that poverty levels do not directly influence the growth or adoption of Fintech solutions or mobile banking, suggesting that these variables evolve independently over time. The absence of direct long-run effects between these variables suggests that each variable evolves based on its own internal dynamics, with no significant spillover effects from the other variables in the long run. This is in line with the findings of Evans & Schmalensee, (2021) that Fintech and mobile banking grow through network effects. This is due to the complex nature of each variable, including factors beyond the availability of Fintech solutions or mobile banking. The results imply that poverty alleviation and financial inclusion policies should consider a multi-faceted approach, focusing on infrastructure, regulatory frameworks, and digital literacy. These solutions may evolve, but poverty reduction requires broader socio-economic improvements beyond financial inclusion. Structural factors like education, health, and basic living standards may require targeted interventions.

Conclusion

The study reveals that changes in Fintech solutions affect the Multidimensional Poverty Index in Nigeria, indicating a positive impact on the Index in the short run. However, this could cause disruptions in low-income areas where infrastructure is lacking, potentially widening inequalities. In the long run, Fintech solutions are expected to promote financial inclusion, reduce transaction costs, and support economic opportunities for marginalized groups. This is in line with Financial inclusion theory which emphasizes the importance of access to formal financial services, particularly in marginalized communities, for improving economic conditions. The Multidimensional Poverty Index does not directly influence Fintech solutions in the short run, as they are primarily supply-driven and may take time to penetrate poor communities due to infrastructure, user education, and barriers to entry. Also, an increase in financial inclusion may harm Fintech solutions in Nigeria in the short run, potentially reducing demand for advanced Fintech solutions. This also affirms the Technology Acceptance Model (TAM) which suggests that technology acceptance and utilization are influenced by perceived ease of use and usefulness, particularly in mobile banking and Fintech solutions. The study concludes that three variables - Multidimensional Poverty Index, Fintech Solutions, and Mobile Banking - have a positive long-run self-impact, with Fintech solutions having the strongest self-reinforcement effect, especially in low-income countries like Nigeria.

The study suggests a practical approach to poverty alleviation through Fintech solutions, including infrastructure strengthening, digital literacy programs, regulatory frameworks, and tailored financial products. It recommends integrating Fintech with education, healthcare, and living standards, diversifying offerings, and ensuring regulatory flexibility.

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