Asymmetric and threshold effects of FinTech on poverty in SSA countries

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Abstract

Purpose – The purpose of this paper is to analyze the dynamic asymmetric relationship between financial technology (FinTech) adoption and poverty alleviation on annual data for the Sub-Saharan Africa (SSA) region over the period from 2004 to 2020.

Design/methodology/approach – This study adopted the general method of moments (GMM) method on annual data for 127 countries including 45 countries from the SSA region over the period from 2004 to 2020.

Findings – The study's findings show that improvement in FinTech may initially decrease the rate of extreme poverty, leading to a decrease in total poverty as a percent of the population. While there is an initial decrease in the rate of extreme poverty with improvements of FinTech, once the FinTech index reaches its threshold level of 37.18 points, further improvement in FinTech tends to decrease as penetration increases, giving rise to an decrease in the rate of poverty alleviation.

Research limitations/implications – Policymakers should design more aggressive and comprehensive policies directed at recouping the maximum gains of FinTech adoption, with a reasonable threshold target.

Practical implications – Policymakers in the SSA region must be aware of a FinTech threshold level of 37.18 points. To ensure the highest reduction in extreme poverty, policymakers must keep investing in FinTech to reach this threshold level.

Social implications – FinTech improvement leads to poverty alleviation. Policymakers in the SSA region can fully recoup the benefits of FinTech by achieving a pre-set threshold level.

Originality/value – This paper addresses that gap in the literature by studying the impact of FinTech, instead of the traditional financial inclusion measures, on poverty in the 45 countries in the SSA region, exploring the potential dynamic asymmetry of this poverty-FinTech link, and testing the presence and statistical significance of the threshold level of FinTech.

Keywords FinTech, Nonlinear, Mobile cellular, Fixed broadband, Internet, Extreme poverty, SSA

Paper type Research paper

1. Introduction

Sub-Saharan Africa (SSA) is one of the poorest regions in the world. It consists of 48 countries, of which 27 are on the list of the world's 30 poorest countries, by virtue of having a poverty rate above 30%. For the overall region, the poverty rate decreased from 55.1% in 1990 to 40.4% in 2018, but due to population growth, the absolute number of poor people has risen, such that the percentage decrease translates to 155 million more people in poverty in 2018 than there were in 1990 (World Bank, 2021a, b). The region is also prone to destabilizing conflicts, weak institutions, and lack of resilience, and increased sensitivity to shocks. Extreme poverty remains prevalent. Over 30% of the world's food insecure population resides in Africa, and 33 African countries are in need of food aid (FAO, 2022). Lack of resources has made SSA's poor extremely vulnerable both to climate change and the coronavirus disease 2019 (COVID-19) pandemic, which creates a vicious cycle. A reversal of such cycles is vital if the world is to achieve the first Sustainable Development Goal (SDG): to eradicate extreme poverty by 2030.

The first SDG represents a continuation of a global effort to reduce the population of people living in extreme poverty that began with the Millennium Development Goals (MDGs)

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and its eight international development agendas. The first goal of the MDGs is related to the eradication of extreme poverty by the year 2015 (Emara and Moore, 2014; Emara, 2014) in which the SSA was the only developing region that did not meet this goal (Anyanwu and Anyanwu, 2017). In 2015, the SDGs succeeded the MDGs. This effort has found some success: East Asia and the Pacific and South Asia, hotspots of poverty in 1990, have seen significant progress. However, poverty rates in SSA have been far more elusive (see Figure 1). Climate change, population growth and the COVID-19 pandemic threaten even the modest gains in the region; for example, estimates say that in Africa the absolute number of people living in poverty is expected to rise through 2023 (United Nations, 2022). Climate change-induced temperature changes are disrupting agricultural production and worsening food insecurity. A temperature increase of 2 °C is expected to cause a loss of 40–80% of cropland in SSA by the 2040s (World Bank, 2013).

Financial technology (FinTech) has significant potential as a means to address extreme poverty in SSA. FinTech is a growing industry rapidly revolutionizing traditional financial and banking services. Software and algorithms include digital payments, crowdfunded micro-finance, cryptocurrency, blockchain-based identity and verification, and central bank digital currency, among others (Yermack, 2018). These nontraditional financial services are vital to the development of infrastructure in electrical power, telecommunications, Internet provision, and the overall efficiency of company and consumer financial operations.

FinTech could play an essential role in SSA by expediting the region's traditional banking methods, which currently struggle to provide sufficient services to the population. Bank penetration in the SSA region is currently below 35% leaving approximately 65% of the population without access to formal banking services. This shortage of financial services stems from an unstable currency exchange rate, an inadequate supply of financial products or services, limited public understanding, complicated processes of financial participation (i.e. opening accounts), and poor infrastructure (IFC, 2017).

Given the growing presence of mobile banking on the continent, FinTech has great market potential on the continent of Africa. Indeed, evidence suggests that much of SSA prefers online services to physical banking. According to data collected from 17 Sub-Saharan countries in the IMF Financial Access Survey, far more people have mobile money accounts

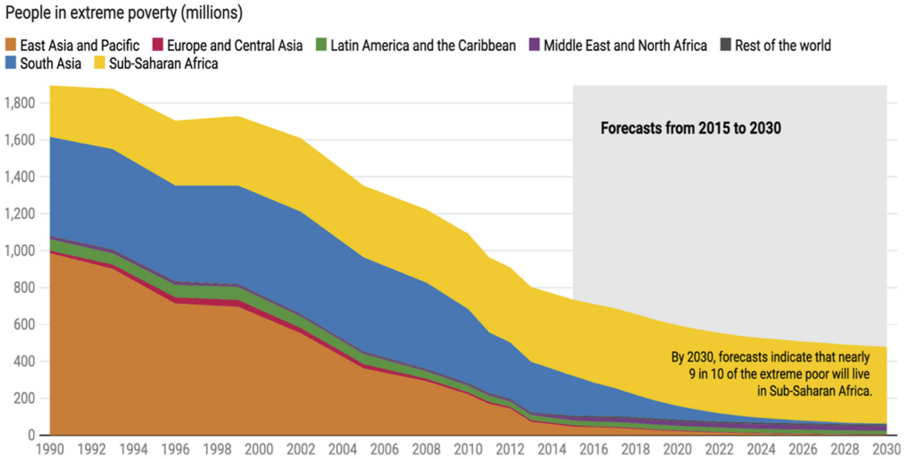


Figure 1.
World population of extreme poverty by region

Source(s): World Bank PovcalNet and Poverty and Equity Data Portal

than traditional bank accounts. In 2015, 49% of women and 41% of men used a form of "unique phone penetration" for banking, according to the Global System for Mobile Communications Association (IFC, 2017). People in SSA are already using FinTech to make payments, borrow and save money, initiate risk sharing, and allocate capital. This increased access to better and more efficient services opens up the financial value chain (Sy, 2019). Such developments have led to the notion that SSA could pave the way for completely mobile banking. However, FinTech has not fully penetrated SSA or reached its maximum potential in the region. High entry costs, lack of infrastructure, underinvestment, and low levels of financial literacy all pose barriers.

Although the relationship between financial development [1] and poverty has been extensively studied (Jalilian and Kirkpatrick (2005), Beck *et al.* (2007), and Kappel (2010a, b), among many others [2]), the literature that examines the role of FinTech, as a booster of financial inclusion and a key driver for financial development, and its potential asymmetric impact on poverty is not as vast. In this paper, we aim to fill the gaps in the literature by estimating the dynamic asymmetric relationship between FinTech adoption and poverty alleviation in the SSA region by answering four main questions; first, what is the effect of FinTech on poverty alleviation? Second, is this relationship linear or nonlinear? Third, is the effect different in SSA compared with the full sample? Finally, what policy recommendations can be offered to policy-makers? The rest of this paper will be divided as follows. Section 2 reviews the literature and provides stylized facts, Section 3 describes the methodology and model specification, Section 4 describes the data used, Section 5 presents the results, Section 6 offers robustness checks, and Section 7 concludes. The Appendix includes detailed graphs and tables.

2. Literature review

Determinants of poverty have been widely debated, and may vary based on region. Haughton and Khandker (2009) utilized a theoretical approach to examine the causes of poverty at levels of individuals, households, communities, regions, and nations. They find that, at the individual and household levels, poverty is associated with factors including age, education level, gender of the household head, and labor force participation of household members. Community-level poverty is linked to infrastructure, human resource development, the employment rate, social mobility and representation, and land distribution. At the regional and national level, national isolation, natural resource availability, climate conditions, effectiveness of the government and judiciary, economic and political stability, and intellectual expression determine poverty.

Figure 1 shows a general decrease in extreme poverty from 1990 to 2030, the projected future, and the distribution of people living in extreme poverty across regions. This distribution is highly unequal, such that 90% of the world's people in extreme poverty will reside in SSA by 2030. In contrast, East Asia and the Pacific and South Asia are expected to continue to see improvement.

Poverty passes from a generation to the next, Viadero (2011) finds that the lag of poverty contributes to extreme poverty as people living in chronically poor areas tend to have low quality of human capital that prevent them from finding opportunities in the labor market, which further traps them in extreme poverty. The spell length of this poverty trap can be for years, where many panel datasets have shown that almost half of the population cannot exit it without a strong government intervention (Barrett and Swallow, 2006; Barrett and Carter, 2013).

There is no doubt that economic growth helps the poor to escape the poverty trap. Previous research work have proved that economic growth has a significant impact in improving the quality of life and reducing poverty in many regions such as the MENA region

(Emara and Moheildin, 2021), Africa (Fanta and Upadhyay, 2009), and Latin America (Cruces *et al.*, 2017), Eastern Europe (Nadori, 2010), India (Sehrawat and Giri, 2017) and Vietnam (World Bank, 2020).

Along the same lines, Tsai (2006) tested speculative theories on poverty in relation to data regarding 97 developing countries. He focused on four major aspects: economic development and openness; geographical and demographical disadvantages; regime characteristics and war; and social policy and human capital enhancement. He found that population growth and accessibility to secondary schooling are major factors affecting poverty, while political components such as democracy and military expenditures are less relevant factors. Ahlburg and Cassen (1993) find that the impact of population growth on poverty reduction is "neither obvious nor well-established". They claim that constraining population growth does not have a direct impact on reducing poverty. Along the same lines, Katoch (2022) shows the empirical evidence that the reduction in poverty leads to a fall in fertility rate; however, the converse relationship is not guaranteed without good governance models. Ali and Thorbecke (2000) find that income inequality resulting from population growth increases poverty in four SSA countries. Naschold's (2005) found that a higher level of inequality increases poverty levels in less developed countries even if consumption is held constant.

Continuing with the determinants of poverty, Sugema *et al.* (2010) examined the impact of inflation on poverty from national, urban and rural sectors in Indonesia. They found that rural, poor households are more sensitive to economic changes and shocks, like inflation, as they caused an increase in prices of food and other basic needs. Jefferson and Kim (2012) studied the effect of macroeconomic fluctuations on poverty. Using Granger predictive causality tests, they determined various representative indicators of the business cycle. They also determined the effects of inflation on poverty and unemployment. They emphasized the importance of considering determinants of poverty besides income, particularly inflation, which they found to have a greater effect on poverty than past research had suggested. Using a panel of 115 developing countries over the period 1980–2008, Talukdar (2012) found a negative correlation between poverty and inflation. She also found a more significant negative relationship between poverty and inflation in low-income countries than in higher-income countries. Easterly and Fischer (2001) further emphasize the negative effects of inflation on the poor. Their survey of 31,869 households in 38 countries shows inflation to be a top national concern for those below the poverty line. They also concluded that inflation has a negative relationship with well-being of the poorer classes, national income, minimum wage and decline in poverty.

Another factor that has a positive statistical effect on poverty is trade openness. Pradhan and Mahesh (2014) found that trade openness, measured by total trade (imports and exports), had a significant relationship with the lessening of poverty in 25 developing countries over three years. They also found that liberal trade policies negatively impacted growth and increased poverty levels. In a panel study of 54 developing countries, Figini and Santarelli (2006) found that trade openness, globalization and government size all contribute to lower levels of poverty. Agusalim (2017) studied the long-term effects of trade openness on poverty in Indonesia through forecast error decomposition analysis. Using error correction model, he found that openness did not have a significant effect on reducing poverty in the short run. More specifically, using impulse response function, he found that trade has poverty alleviation effects only after the third year. Carneiro and Arbache (2002) studied the effects of trade openness on poverty in Brazil. Using a general equilibrium model, they estimated the impact of trade openness on poverty and the distribution of income. They concluded that trade openness has some benefits and helps to alleviate poverty, but is insufficient to bring a significant number of Brazilians out of poverty.

Rising employment tends to lower poverty rates. Anyanwu and Augustine (2013) demonstrated that gender equality, as an engine of inclusiveness in the labor market,

contributes to economic success, social welfare and poverty reduction. Anyanwu and Anyanwu (2017) found that a higher level of education increases human capital and sequentially contributes to greater labor productivity and higher wages. Hughes and Irfan (2007) found that investment in human capital is not only related to economic growth, but is directly associated with poverty reduction. They also found that education and public health correlate with gross domestic product (GDP), continuing the virtuous cycle.

Recently, several scholars have attempted to measure the impact of FinTech on various aspects of the economy, particularly economic growth and poverty alleviation. They have uncovered significant evidence that increases in FinTech have positive effects on economic growth, welfare measures and poverty alleviation (Gammage *et al.*, 2017; Gomber *et al.*, 2017; Jones, 2018; Lyons *et al.*, 2020).

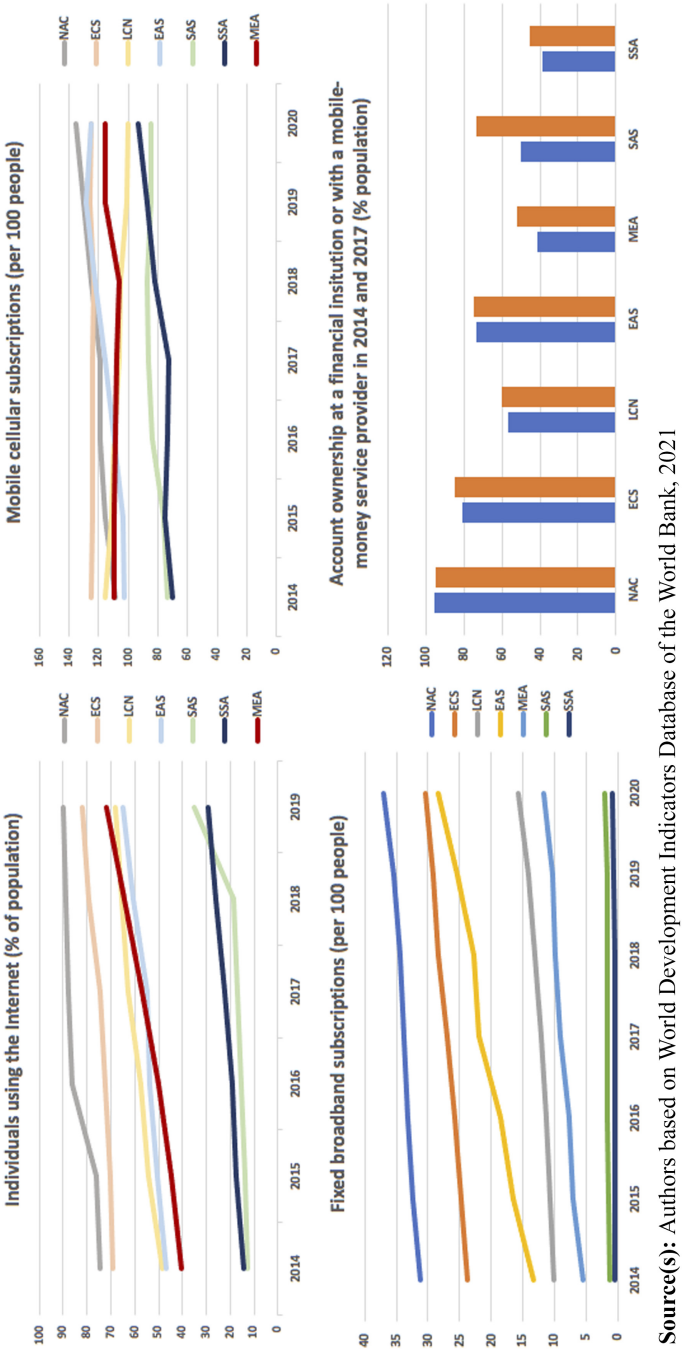
Figure 2 depicts FinTech usage and account ownership at a financial institution or with a mobile service provider in seven regions including North America (NAC), Europe and Central Asia (ECS), Latin America and Caribbean (LCN), East Asia and Pacific (EAS), Middle East and North Africa (MENA), South Asia (SAS), and SSA. As it shows, SSA ranks as one of the lowest in Internet consumption, in subscriptions for both mobile telephony and fixed broadband, and in account ownership at a financial institution or with a mobile money provider. These low rates of FinTech indicators provide some explanation of the poverty statistics shown in Figure 1.

Using a difference-in-difference approach with data from Kenya, Jack and Suri (2014) found that the mobile money system M-Pesa has enabled its users to fully absorb negative income shocks that reduced the consumption of nonusers by 7%. The same authors' work two years later confirms the long-run effects of M-Pesa on increasing the efficiency of the allocation of consumption and reducing extreme poverty by 2% (Suri and Jack, 2016). Similarly, using data from Tanzania, Riley (2018) estimated the impact of rainfall shocks on remittances received in rural areas for users and nonusers of mobile money. The study shows that in the presence of negative shocks, only the users of mobile money were able to fully avoid the drop in their consumption. Other studies demonstrate that digital money transfer had a significant advantage over other means in terms of improving the financial position of remittance recipients (Apiors and Suzuki, 2018; Aron, 2018; Riley, 2018; Suri and Jack, 2016).

Aker *et al.* (2016) found that a mobile cash transfer program significantly reduced transaction costs and enhanced households' nutrition in Niger. Sulastri and Kumar (2019) and Masino and Niño-Zarazúa (2019) reached similar conclusions regarding the positive impact of FinTech on the social assistance programs in Indonesia and Mexico, respectively. Studies of data from Uganda showed that mobile money technology facilitates monetary transfer among user households and improves the welfare of the rural population (Munyegera and Matsumoto, 2016; Wieser *et al.*, 2019).

Despite the evidence provided in the above research papers on the impact of FinTech on reducing poverty, some researchers have found that the link between the use of mobile money specifically and poverty alleviation is weak (Aron, 2018; Collins and Ng'weno, 2018). Others argue that historical successes of mobile technology in East Africa cannot be generalized to other regions since the adoption of technological innovation depends on institutional endowments and the pace of innovation depends on government regulations and its ability to spillover the benefits to other sectors (Barasa and Lugo, 2015; Mbiti and Weil, 2015; Arabéhéty, 2016; Johnson, 2016; Minto-Coy and McNaughton, 2016).

In examining the nonlinearity in the relationship between financial inclusion variables and poverty, using a dynamic panel model for African economies, Nsiah *et al.* (2021) confirmed the presence of a threshold level of financial inclusion beyond which poverty is reduced. Using panel data on African economies, Bolarinwa *et al.* (2021) reached the same conclusion on the presence of a threshold level. Five other studies on African economies also



Source(s): Authors based on World Development Indicators Database of the World Bank, 2021

Figure 2.
FinTech measurements by region

found nonlinearity (Batuo *et al.*, 2010; Asongu, 2013; Tita and Aziakpono, 2016; Nandelenga and Odour, 2020; Zungu and Grelying, 2021).

The above studies on nonlinearity have focused on different traditional measures of financial inclusion, with none focusing specifically on FinTech as a pivotal nontraditional booster of financial inclusion; as a one dimension of financial development. This paper addresses that gap by studying the impact of FinTech, instead of the traditional financial inclusion measures, on poverty in the 45 countries in the SSA region, exploring the potential dynamic asymmetry of this poverty-FinTech link, and testing the presence and statistical significance of the threshold level of FinTech.

3. Dataset

Our dataset is constructed as a panel of country observations from the World Development Indicators (WDI) of the World Bank's database (World Bank, 2021a), and it covers 125 countries from NAC, EAS, ECS, LCN, MENA, and SSA over the period 2004–2020. The focus of our study is however on 45 SSA countries, where a list of these countries is reported in Tables A1 of Appendix.

The dependent variable in the model is the poverty headcount ratio at $1.90 a day as a percentage of the population. The set of explanatory variables contains common determinants of poverty, including real GDP per capita growth rate, inflation rate, trade openness as a percentage of GDP, population growth and FinTech indicators. The measures of FinTech include mobile cellular subscriptions (per 100 people), fixed broadband subscriptions (per 100 people) and individuals using the Internet (% of population). Table A2 of Appendix provides a detailed list of the macroeconomic and FinTech variables used, their definitions, units of measurement, abbreviations and data sources. And Tables A3 and A4 of Appendix report the descriptive statistics of the macroeconomic and FinTech variables for the full and SSA samples, respectively.

4. Estimation methodology

The poverty model is estimated using system general method of moments (GMM) panel estimation methodology proposed by Arellano and Bover (1995), Blundell and Bond (1998), and Blundell *et al.* (2001) [3] to examine the impact of changes in the macroeconomic variables and Fintech levels on poverty alleviation. Our main model is as follows,

$$pov_{i,t} = \alpha + \rho pov_{i,t-1} + \beta X_{i,t} + \delta fintech_{i,t} + \varepsilon_{i,t} \quad i = 1, 2, \ldots N, t = 2004, \ldots 2020 \tag{1}$$

where pov_{it} denotes the poverty headcount ratio at $1.90 a day as a percent of the population of country i, at time t, pov_{it-1} is the lagged poverty variable, and X_{it-1} is the vector of explanatory variables. These include the annual GDP growth rate, inflation rate, trade openness as a percentage of GDP and the annual population growth rate. The variable $fintech_{it}$ is the financial technology index that cover the number of mobile cellular subscriptions (per 100 people), the number of fixed broadband subscriptions (per 100 people), the percentage of people in the population who use the Internet in country i at time t, and ε_{it} is the error term. Following the literature on financial sector, we use the principal component analysis (PCA) to estimate the $fintech_{it}$ index (Driesson *et al.*, 2003; Chamberlain and Rothschild, 1983; Connor and Korajczyk, 1986). This method transforms our three observables of FinTech into a smaller set of observable composite dimensions that can be used to represent their interrelationships. Most studies performed on the financial sector use the PCA to estimate the evolving correlation structures of financial systems; it is considered an established method

(Podobnik *et al.*, 2010; Wang *et al.*, 2011; Kritzman *et al.*, 2011; Zheng *et al.*, 2012; Nobi and Lee, 2016).

Next, to estimate the impact of FinTech on poverty alleviation in the SSA region versus other countries in our sample, we add a dummy for SSA countries along with an interaction term of this dummy with the FinTech variable to the model as follows,

$$pov_{i,t} = \alpha + \rho pov_{i,t-1} + \beta X_{i,t} + \delta fintech_{i,t} + \theta SSA_{i,t} + \vartheta(SSA_i * fintech_{i,t}) + \varepsilon_{i,t} \quad (2)$$

where SSA_i represents the dummy variable, which takes 1 if country i is in the SSA region and zero if not. The total effect of the different areas of FinTech is estimated by adding the coefficient δ to the coefficient φ and the statistical significance of the effect is estimated using the standard errors of these two coefficients. To avoid the pitfalls documented by Brambor *et al.* (2006) for interactive regressions, net effects are computed as in contemporary literature (Tchamyou and Asongu (2017), Tchamyou (2019), Asongu *et al.* (2017)) which is equal to $\delta + \varphi$*$\overline{\text{fintech}}$, where $\overline{\text{fintech}}$ is the average of the fintech variable as presented in the descriptive statistics Tables A3 and A4 of Appendix.

Further, to examine the potential nonlinear effect of digitization on inflation, the squared term of the FinTech index is added to the model as follows,

$$pov_{i,t} = \alpha + \rho pov_{i,t-1} + \beta X_{i,t} + \delta fintech_{i,t} + \gamma fintech^2_{i,t} + \theta SSA_{i,t} + \vartheta(SSA_i * fintech_{i,t}) + \varphi\left(SSA_i * fintech^2_{i,\,t,}\right) + \varepsilon_{i,t} \quad (3)$$

Following the literature on quadratic regressions on computing net effects (Asongu and Odhiambo, 2020a, b), and to avoid the pitfalls documented by Brambor *et al.* (2006), the net effect of FinTech on poverty is equal to $\delta + 2\gamma\overline{fintech}$. We do expect a negative δ coefficient and a positive γ coefficient, which implies that a one-unit increase in the FinTech index decreases poverty by a magnitude of δ; however, this effect is decreasing at an increasing rate of "2γ". Additionally, the cut-off point (or threshold level) of the FinTech index, or $fintech^*_{i,t}$, is equal to $\left|\frac{\delta}{2\gamma}\right|$ where any level of $fintech_{i,t}$ below $fintech^*_{i,t}$ will result in a decrease in poverty and any level above it results in a rate increase. Additionally, the total effect of the FinTech index on poverty is estimated by adding the coefficient δ to the coefficient γ, and the statistical significance of the effect is estimated using the standard errors of these two coefficients.

It is important to note three fundamental points about the GMM methodology; identification, simultaneity, and exclusion restrictions. First, identification refers to the choice of the dependent, endogenous variables, and strictly exogenous variables. Second, the simultaneity refers to an endogeneity problem that occurs when the explanatory variable is jointly determined with the dependent variable. This issue has been taken care of by using the lagged explanatory variables as instruments. Finally, for the exclusion restrictions requires that the dependent variable to be exclusively affected by the strictly exogenous variables through the endogenous variables. Following Boateng *et al.* (2018), Asongu and Nwachukwu (2016), all explanatory variables are treated as endogenous and only time-invariant variables are considered to be strictly exogenous. Finally, the simultaneity is an endogeneity problem that refers to explanatory variable is jointly determined with the dependent variable. We take care of this issue by using the lagged explanatory variables as instruments.

5. Estimation results

Prior to the estimation of the model, multiple econometric tests were performed, checking for heteroskedasticity, multicollinearity, endogeneity and serial correlation. The model is confirmed to be heteroskedastic using the Breusch–Pagan test; therefore, a robust standard

error is used. There are no issues of multicollinearity in our model as the mean of the model's variance inflation factor (VIF) is only 1.42 points. As indicated in the previous section, simultaneous causality could be a major econometric issue in our model, since economic growth affects poverty and is also affected by it, hence Arellano–Bond system GMM has been chosen for our estimation methodology. The Hansen test is used to test for overidentification restrictions in the set of instruments. In other words, the validity to the exclusion restriction assumption depends on the rejection of the Hansen's null hypothesis on instruments' exogeneity. Additionally, due to the structure of our panel dataset, the cross-sections may suffer from a serial correlation issue; thus, we performed the Arellano–Bond's test for first and second order of autocorrelation. Furthermore, to test the overall validity of the model the Wald test is performed. The estimation tables display the results of the three tests where the Arellano–Bond test confirms the absence of serial correlation, the Hansen test confirms the exogeneity of the chosen set of instruments, and the Wald test confirms that the model is overall valid.

The estimation of Equation (1) for the full model is presented in Table A5. The poverty variable ("*pov*" in our dataset) is regressed on the set of explanatory variables, namely GDP growth rate ("*gr*" in our dataset), inflation rate ("*inf*" in our dataset), openness ("*op*" in our dataset), population growth rate ("*popgr*" in our dataset), the lagged poverty variable ("*L.pov*" in our dataset), and the set of financial variables including mobile cellular subscription measured per 100 people ("*mob*" in our dataset), individuals using the Internet as a percent of the population ("*net*" in our dataset), and fixed broadband subscription measured per 100 people ("*fbb*" in our dataset), and the FinTech index ("*fintech*" in our dataset). All FinTech variables are measured logarithmically.

As shown in columns 1 to 5 of Table A5, the poverty lag has a positive statistically significant impact, in the range of 0.91–1.66% of the population. These results are consistent with empirical evidence found in Viadero (2011). Additionally, the table shows that the effect of the GDP growth rate on poverty is as expected, negative and statistically significant, where a 1% increase in economic growth reduces poverty head count ratio in the range of 0.05–0.30% of the population. This result is accordant with the empirical evidence provided in Emara and Moheildin (2020, 2021) and is parallel with findings of similar studies conducted in other regions (Sehrawat and Giri, 2017; World Bank, 2020; Fanta and Upadhyay, 2009; Cruces *et al.*, 2017).

Additionally, as confirmed by the results, a 1% increase in inflation leads to a decrease in poverty head count ratio in the range of 0.02–0.11% of the population. This result is congruous with the empirical findings of Talukdar (2012), who finds that the relationship between inflation and poverty could be negative for low-income developing countries. Furthermore, the trade openness measure had a positive and statistically significant effect on the increase of poverty. As per the table results, a 10% increase in trade openness increases poverty in the range of 0.01–0.8%, as a percent of the population. This result is consistent with the findings of Neaime and Gaysset (2018) and Emara and Moheildin (2020) who find that, in the MENA region, trade openness increases poverty.

Next, column 1 also shows that a 1% increase in population growth results in an increase in poverty head count ratio 0.04% of the population. These results are in line with the empirical evidence provided by Birdsall (1980) and Ahlburg (1996), who find that population growth increases incidences of poverty. It is important to note that we could not detect statistical significant impact of population growth on poverty in the remaining regression of the same table confirming the results of Ahlburg and Cassen (1993) and Katoch (2022).

Moving to the FinTech variables, the results in column 2 show that a 10% increase in mobile cellular subscription results in a decrease in poverty head count ratio by roughly 0.16% of the population, all else equal. Column 3 shows that a 10% increase in individuals using the Internet leads to a drop in poverty by about 0.18% of the population, which is statistically significant. Likewise, column 4 shows that a 10% increase in fixed broadband

subscription results in a decrease in poverty by about 0.18% of the population. Lastly, column 5 confirms that a 10% increase in the index of FinTech reduces poverty rate by about 0.16% of the population. The result is consistent with the empirical finding of Berkmen *et al.* (2019), who find that FinTech reduces poverty through supporting economic growth and financial inclusion.

Moreover, we analyze the effect of the improvement in FinTech measures on poverty alleviation in the SSA region [4]. Equation (2) is estimated by including a dummy variable for the SSA region, as well as an interaction term of that dummy with the FinTech measures, each one in a turn, as displayed in Table A6. The table shows the calculations of the total effects of *mob, net, fbb,* and the *fintech* index on the poverty head count ratio within the SSA region, as explained in Equation (3). Column 2 shows that the total effects of *mob*, *net*, *fbb*, and the *fintech* index on poverty reduction are negative and statistically significant, where a 10% increase in each of these four variables decrease poverty by about 0.21%, 0.38%, 0.28% and 0.40% of the population, respectively. These findings are consistent with the findings of Haftu (2019) and Donou-Adonsou *et al.* (2016), all of which show that an increase in the use of mobile phones and Internet effectively reduce extreme poverty rates.

Next, we test the nonlinearity hypothesis for the full sample, as explained in Equation (3), and the estimation results are shown in Table A7. The results of the computation of the total effects in column 2 confirm that the nonlinear impact of *fintech* is mainly derived from the impact of the *mob*, followed by *net*, and then *fbb*, where a 1% increase in each of these sub-indices leads to a decrease in poverty by about 0.35%, 0.17% and 0.01% of the population, respectively.

Furthermore, the last row of the table shows that a 1% increase in the *fintech* decreases poverty by about 0.20% with an increasing rate of two times 0.026, or 0.052%, with a threshold level of about 58.69 points [5], which is on the 75th percentile of the index, and a total poverty alleviation effect of 0.17% of the population. These results imply that the marginal effect of FinTech on poverty alleviation is dependent on the degree of *fintech* penetration; as penetration increases beyond the threshold point, marginal effect decreases by about 13%. These findings are consistent with the evidence provided in Lang (2009), Hawash and Lang (2010), Vu (2011), and Albiman and Sulong (2017) on the presence of nonlinear effects on productivity, economic growth and poverty using different ICT measures Nsiah *et al.* (2021), Bolarinwa *et al.* (2021).

Next, we test the nonlinearity hypothesis for the SSA region by adding the region's dummy variable to Equation (3). Similar to our findings for the full sample, column 3 of Table A8 confirms that within the SSA region, the three sub-indices have negative significant nonlinear effects on poverty alleviation, where a 1% increase in *mob*, *net*, and *fbb* leads to decrease in poverty by about 0.11%, 0.07%, and 0.04% of the population, respectively. Additionally, a 1% increase in the *fintech* index leads to a decrease in poverty of about 0.08%. However, the absolute value of this effect is decreasing at an increasing rate of two times 0.014, or 0.028%, with a total effect of 0.07% and a threshold level of about 37.18 points [6], which falls under the 50th percentile of the index. In other words, the impact of FinTech on poverty decreases by about 17% after the threshold level. Given that the average level of FinTech of 21.48 points (i.e. about 16 points below the threshold level), there are a lot of opportunities to maximize the benefit of FinTech proliferation. These results are consistent with the empirical evidence on the nonlinear impact of the traditional measures of financial inclusion on poverty alleviation in the African economies (Batuo *et al.*, 2010; Asongu, 2013; Tita and Aziakpono, 2016; Nandelenga and Odour, 2020; Zungu and Grelying, 2021).

6. Robustness check

To confirm the relevance of our results, we have applied robustness checks using various methods of estimation methodologies. First, we started with ordinary least squares (OLS),

basic regression encompassing only poverty (in log) and the *fintech* index (in log). The regression provides negative and significant coefficient (−0.114) at the 99% confidence level, which is in line with theoretical predictions and correlations in Table A5. Next, we control for other explanatory variables by adding the annual GDP growth rate, inflation rate, trade openness as a percentage of GDP, and the annual population growth rate, the point estimate of the effect of *fintech* falls – in absolute value – but keeps the negative and significant sign (−0.124). The nonlinear effect is also confirmed, where the negative impact FinTech on poverty tends to decrease as penetration increases, with a negative statistically significant total effect at the 1% (−0.184).

Next, to deal with endogeneity effectively, we use the instrumental variables (IV) method to estimate the elasticity of poverty with respect to FinTech. The estimation provides a significant and negative coefficient that is comparable to the one obtained using OLS (−0.114), which confirms the effect of FinTech policies on poverty alleviation. This effect still holds after adding the four control variables, and the coefficient has the same sign as the one obtained with OLS regressions (−0.124). Similarly, the total nonlinear effect on FinTech on poverty is also confirmed with a negative statistically significant at the 1% (−0.184).

Finally, we use the panel data regressions with fixed effects (FE) to test the poverty and FinTech nexus, the elasticity is negative and significant (−0.036) at the 1% significance level. The effect also holds when adding our four control variables (−0.046), maintaining the same sign and statistical significance. This confirms the outcome of previous regressions (OLS and IV) and corroborates the effect of the proliferation of financial technology on poverty reduction. This negative effect holds even with our set of control variables. Lastly, the total negative nonlinear effect of FinTech on poverty is also confirmed (−0.088) at the 1% significance level [7].

7. Conclusion

The United Nations has established 17 SDGs, to promote prosperity while protecting the planet, which they hope to achieve by 2030. While many countries may have little to no issues tackling these goals, other less developed countries may lack the resources and technology needed to fully attain these goals by the ideal year. As a result of this, it is important to understand how such resources and technology play a role in achieving one of the important SDGs; eradication of poverty. As FinTech grows in popularity, it is critical to measure its impact on the aforementioned goal. Hence, the purpose of this study is to analyze the impact of FinTech on the achievability of the SDGs with respect to extreme poverty by 2030.

By using the system GMM on annual data from 127 emerging and developing economies including 45 countries in SSA over the period from 2004 to 2020, the study analyzes the dynamic asymmetric impact of the level of FinTech adoption on poverty alleviation. This paper measures the level of FinTech adoption through three key indicators: the number of mobile cellular subscriptions (per 100 people), the number of fixed broadband subscriptions (per 100 people) and the percentage of the population who use the Internet. From these three indicators, we create a composite index of the level of FinTech adoption for all of the countries in our sample.

We conclude that wider access to FinTech, measured either by its composite index or its three sub-indices, has a statistically significant impact on poverty alleviation. Empirical analysis also suggests a statistically significant nonlinear relationship between the improvement in FinTech measures and poverty alleviation with an exact threshold level. More specifically, our results of the SSA sample show that the impact of FinTech proliferation on poverty alleviation lessens with more penetration. The study defines threshold point of 37.18 point, beyond which the impact of FinTech on poverty falls by about 17%. For the SSA region, with an average level of FinTech index of 21.48 points (i.e. about 16 points below the

threshold level), policy-makers should apply more aggressive and comprehensive policies to recoup the maximum gains of FinTech adoption, with a reasonable threshold target.

Our policy implications for the majority of developing countries in our sample are directed towards creating the enabling environment for the expansion of FinTech services, which includes, first, promoting cross-functional coordination within existing organizational structures such as adding mobile, web engineering, cyber security or data science units within existing departments. Second, building capacity and FinTech skills by offering training courses and boot camps for the workforce, empowering consumers by providing financial literacy campaigns and offering incentives for promoting digital innovations among government officials and financial regulators. Finally, formulating the necessary guidelines to ensure a well-defined regulatory framework required for the proper supervision and stability of FinTech development, especially in light of its renewed utility due to a variety of implications from the COVID-19 pandemic.

Notes

1. According to the World Bank (2021b), financial development has four dimensions; financial stability, financial efficiency, financial depth and financial access (or financial inclusion).
2. De Haan *et al.* (2022) have a full list of previous studies on the relationship between financial development and poverty alleviation.
3. For more details on the estimation methodology, please check Emara and Kasa (2020) and Emara and El Said (2021).
4. Due to data limitation on the poverty variable, we interpolated the data using linear interpolation technique.
5. The FinTech index ranges from 0.099 points to 139.489 points check Table A3 of Appendix for descriptive statistics.
6. The FinTech index for the SSA region ranges from 0.118 points to 76.525 points, check Table A4 of Appendix for descriptive statistics.
7. The robustness checks are also confirmed for the SSA sample.

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(The Appendix follows overleaf)

Appendix

Table A1.
List of SSA included in the sample

Country ID	Country	Code	IMF classification	World Bank classification
1	Angola	AGO	EM	Lower middle income
2	Benin	BEN	LIDC	Lower middle income
3	Botswana	BWA	EM	Upper middle income
4	Burkina Faso	BFA	LIDC	Low income
5	Burundi	BDI	LIDC	Low income
6	Cabo Verde	CPV	EM	Lower middle income
7	Cameroon	CMR	LIDC	Lower middle income
8	Central African Republic	CAF	LIDC	Low income
9	Chad	TCD	LIDC	Low income
10	Comoros	COM	LIDC	Lower middle income
11	Congo, Dem. Rep	COD	LIDC	Low income
12	Congo, Rep	COG	LIDC	Lower middle income
13	Côte d'Ivoire	CIV	LIDC	Lower middle income
14	Eswatini	SWZ	EM	Lower middle income
15	Ethiopia	ETH	LIDC	Low income
16	Gabon	GAB	EM	Upper middle income
17	The Gambia	GMB	LIDC	Low income
18	Ghana	GHA	LIDC	Lower middle income
19	Guinea	GIN	LIDC	Low income
20	Guinea-Bissau	GNB	LIDC	Low income
21	Kenya	KEN	LIDC	Lower middle income
22	Lesotho	LSO	LIDC	Lower middle income
23	Liberia	LBR	LIDC	Low income
24	Madagascar	MDG	LIDC	Low income
25	Malawi	MWI	LIDC	Low income
26	MAli	MLI	LIDC	Low income
27	Mauritania	MRT	LIDC	Lower middle income
28	Mauritius	MUS	EM	High income
29	Mozambique	MOZ	LIDC	Low income
30	Namibia	NAM	EM	Upper middle income
31	Niger	NER	LIDC	Low income
32	Nigeria	NGA	LIDC	Lower middle income
33	Rwanda	RWA	LIDC	Low income
34	São Tomé and Príncipe	STP	LIDC	Lower middle income
35	Senegal	SEN	LIDC	Lower middle income
36	Seychelles	SYC	EM	High income
37	Sierra Leone	SLE	LIDC	Low income
38	South Africa	ZAF	EM	Upper middle income
39	South Sudan	SSD	LIDC	Low income
40	Sudan	SDN	LIDC	Low income
41	Tanzania	TZA	LIDC	Lower middle income
42	Togo	TGO	LIDC	Low income
43	Uganda	UGA	LIDC	Low income
44	Zambia	ZMB	LIDC	Lower middle income
45	Zimbabwe	ZWE	LIDC	Lower middle income

Variable name	WDI definition	Unit of measurement	Abbreviation	Data source
Poverty	Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population). Increase in poverty gap at $1.90 ($ 2011 PPP) poverty line due to out-of-pocket health care expenditure, as a percentage of the $1.90 poverty line	Percent	*pov*	WDI
Growth	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U S dollars. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources	Percent	*gr*	WDI
Inflation	Change in the log of consumer price index (2010 = 100) (Authors computation). Consumer price index reflects changes in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used. Data are period averages	Percent	*inf*	WDI
Openness	The sum of net exports of goods and services, net primary income, and net secondary income	Percent of GDP	*op*	WDI
Population Growth	Change in the log of population (total). Annual population growth rate for year t is the exponential rate of growth of midyear population from year $t-1$ to t, expressed as a percentage. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship	Percent	*popgr*	WDI
Mobile cellular subscriptions	Mobile cellular telephone subscriptions are subscriptions to a public mobile telephone service that provide access to the PSTN using cellular technology. The indicator includes (and is split into) the number of post-paid subscriptions, and the number of active prepaid accounts (i.e. that have been used during the last three months). The indicator applies to all mobile cellular subscriptions that offer voice communications. It excludes subscriptions via data cards or USB modems, subscriptions to public mobile data services, private trunked mobile radio, telepoint, radio paging and telemetry services	Per 100 people	*mob*	WDI
Individuals using the internet	Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc.	Percent of population	*net*	WDI
Fixed broadband subscriptions	Fixed broadband subscriptions refer to fixed subscriptions to high-speed access to the public Internet (a TCP/IP connection), at downstream speeds equal to, or greater than, 256 kbit/s. This includes cable modem, DSL, fiber-to-the-home/building, other fixed (wired)-broadband subscriptions, satellite broadband and terrestrial fixed wireless broadband. This total is measured irrespective of the method of payment. It excludes subscriptions that have access to data communications (including the Internet) via mobile-cellular networks. It should include fixed WiMAX and any other fixed wireless technologies. It includes both residential subscriptions and subscriptions for organizations	Per 100 people	*fbb*	WDI
Mobile cellular subscriptions	Mobile cellular telephone subscriptions are subscriptions to a public mobile telephone service that provide access to the PSTN using cellular technology. The indicator includes (and is split into) the number of post paid subscriptions, and the number of active prepaid accounts (i.e. that have been used during the last three months). The indicator applies to all mobile cellular subscriptions that offer voice communications. It excludes subscriptions via data cards or USB modems, subscriptions to public mobile data services, private trunked mobile radio, telepoint, radio paging and telemetry services	Per 100 people	*mob*	WDI

Source(s): Author

Table A2. Definitions of economic and FinTech variables

Table A3.
Descriptive statistic – full sample

Variable	Obs	Mean	Std. dev.	Min	Max
pov	1,158	0.064	0.140	0.000	0.943
gr	3,000	0.015	0.058	−0.978	0.797
inf	2,813	0.049	0.073	−0.106	1.569
op	2,591	0.919	0.570	0.007	4.345
popgr	3,272	0.014	0.015	−0.045	0.175
mob	2,986	86.718	47.171	0.190	345.325
net	2,771	36.547	29.726	0.000	99.702
fbb	2,779	9.826	11.919	0.000	56.244
fintech	2,558	43.659	25.424	0.099	139.489

Source(s): Author

Table A4.
Descriptive statistic – SSA sample

Variable	Obs	Mean	Std. dev.	Min	Max
pov	373	0.397	0.228	0.002	0.943
gr	734	0.013	0.053	−0.646	0.166
inf	699	0.072	0.104	−0.094	1.569
op	669	0.730	0.310	0.007	2.019
popgr	807	0.025	0.009	−0.026	0.050
mob	743	56.091	41.144	0.210	198.152
net	659	10.372	12.538	0.031	64.000
fbb	628	0.853	2.842	0.000	27.598
fintech	552	21.478	15.835	0.118	76.525

Source(s): Author

Table A5. Extreme poverty and FinTech measures – full sample

Regressors	(1)	(2)	(3)	(4)	(5)
L.pov	0.914*** (0.013)	1.567*** (0.306)	1.360*** (0.243)	0.498*** (0.182)	1.662*** (0.378)
gr	−0.046*** (0.011)	−0.246*** (0.092)	−0.293*** (0.111)	−0.186** (0.087)	−0.304** (0.128)
inf	−0.019*' (0.013)	−0.079 (0.068)	−0.105*' (0.075)	−0.100* (0.059)	−0.082 (0.070)
op	0.001*** (0.000)	0.072** (0.031)	0.081** (0.039)	0.064*** (0.021)	0.066** (0.029)
popgr	0.042*' (0.027)	−0.831 (0.831)	−1.424 (1.059)	−1.100 (0.864)	−0.698 (0.787)
mob		−0.016** (0.006)			
net			−0.018** (0.008)		
fbb				−0.018*** (0.006)	
fintech					−0.016** (0.007)
Observations	803	794	776	786	768
Number of countries	66	66	66	65	65
Number of instruments	28	11	11	14	11
AB Test order 1 *p*-value	0.0117	0.0274	0.0235	0.0123	0.0326
AB Test order 2 *p*-value	0.449	0.959	0.813	0.525	0.733
Hansen test *p*-value	0.477	0.427	0.398	0.162	0.370
Wald Test	3844.78***	6815.37***	11227.13***	1491.98***	4614.01***

Note(s): ***, ** * and * denotes statistical significance at the 1%, 5%, 10% and 15% levels, respectively
Numbers in round parentheses (.) are the robust standard errors
Dependent variable: Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population)
Estimation Method: Arellano-Bover/Blundell–Bond dynamic panel system GMM

Regressors	(1) Coefficient and interaction	(2) Total effect	(3) Net effect	(4) Number of countries/ instruments/ observations	(5) AB test order 1 and 2 *p*-values	(6) Hansen test *p*-value	(7) Wald test
ssa	0.063*						
	(0.032)						
mob	−0.016**	−0.021***	−0.0349***	134/16/1,374	0.012	0.192	11861.07***
	(0.008)	(0.006)			0.793		
mob_ssa	−0.005						
	(0.007)						
ssa	0.197***						
	(0.061)						
net	0.003	−0.038***	−0.123***	134/20/1,372	0.039	0.253	2521.63***
	(0.003)	(0.012)			0.538		
net_ssa	−0.040***						
	(0.014)						
ssa	0.081**						
	(0.036)						
fbb	−0.013*	−0.028***	−0.044***	131/19/1,329	0.936	0.137	943.57***
	(0.007)	(0.008)			0.0822		
fbb_ssa	−0.016**						
	(0.007)						
ssa	0.475**						
	(0.191)						
fintech	−0.022	−0.040**	−0.081**	132/19/1,302	0.795	0.395	525.20***
	(0.017)	(0.019)			0.735		
fintech_ssa	−0.018						
	(0.012)						

Table A6.
Extreme poverty and FinTech measures –linear model – SSA sample

Note(s): ***, ** * and * denotes statistical significance at the 1%, 5%, 10% and 15% levels, respectively
Numbers in round parentheses (.) are the robust standard errors
Dependent variable: Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population)
Estimation Method: Arellano-Bover/Blundell–Bond dynamic panel system GMM

Table A7. Extreme poverty and FinTech measures – nonlinear model – full sample

Regressors	(1) Coefficient and interaction	(2) Total effect	(3) Threshold point	(4) Net effect	(5) Number of countries/ instruments/observations	(6) AB test order 1 and 2 p-values	(7) Hansen test p-value	(8) Wald test
mob	−0.397***	−0.348***	95.445	−0.208***	66/11/794	0.098	0.245	60.41***
	(0.142)	(0.124)				0.671		
mob^2	0.049***							
	(0.018)							
net	−0.199***	−0.171***	59.428	−0.111***	66/11/776	0.151	0.326	197.09***
	(0.064)	(0.055)				0.428		
net^2	0.028***							
	(0.009)							
fbb	−0.014**	−0.010**	20.433	−0.006**	65/12/786	0.026	0.155	253.68***
	(0.006)	(0.008)				0.647		
fbb^2	0.004**							
	(0.002)							
fintech	−0.195***	−0.169***	58.693	−0.110***	65/18/768	0.020	0.170	592.21***
	(0.057)	(0.051)				0.680		
$fintech^2$	0.026***							
	(0.008)							

Note(s): ***, **, * and * denotes statistical significance at the 1%, 5%, 10% and 15% levels, respectively
Numbers in round parentheses (.) are the robust standard errors
Dependent variable: Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population)
Estimation method: Arellano-Bover/Blundell–Bond dynamic panel system GMM

Table A8.
Extreme poverty and FinTech measures – nonlinear model – SSA sample

Regressors	(1) Coefficient and interaction	(2) Linear and non-linear total effects	(3) Total effect	(4) Threshold point	(5) Total effect	(6) Number of countries/ instruments/ observations	(7) AB test order 1 and 2 *p*-values	(8) Hansen test *p*-value	(9) Wald test
SSA	0.217**								
	(0.085)								
mob	−0.010					134/12/1,374	0.0602	0.355	7181.38***
	(0.016)						0.452		
*mob***SSA*	−0.113**	−0.123**							
	(0.051)	(0.049)							
mob^2	0.001								
	(0.003)								
mob^2**SSA*	0.017**	0.018	−0.105**	68.401	−0.053**				
	(0.008)	(0.008)	(0.042)						
SSA	0.237***								
	(0.063)								
net	0.042**					134/19/1,342	0.496	0.330	1011.46***
	(0.016)						0.127		
*net***SSA*	−0.136**	−094**							
	(0.059)	(0.046)							
net^2	−0.011***								
	(0.004)								
net^2**SSA*	0.033*	0.023*’	−0.071**	21.149	−0.023**				
	(0.018)	(0.015)	(0.032)						
SSA	0.091***								
	(0.031)								
fbb	−0.005					131/21/1,329	0.0514	0.174	1862.86
	(0.005)						0.820		
*fbb***SSA*	−0.031***	−0.036***							
	(0.009)	(0.010)							
fbb^2	0.001								
	(0.001)								

(*continued*)

Table A8.

Regressors	(1) Coefficient and interaction	(2) Linear and non-linear total effects	(3) Total effect	(4) Threshold point	(5) Total effect	(6) Number of countries/ instruments/ observations	(7) AB test order 1 and 2 *p*-values	(8) Hansen test *p*-value	(9) Wald test
fbb^2*SSA	−0.003*	−0.002*	−0.037***	10.653	−0.039***				
	(0.001)	(0.001)	(0.011)						
SSA	0.992**								
	(0.396)								
fintech	0.021					132/19/1,302	0.478	0.907	320.57***
	(0.020)						0.707		
*fintech**SSA	−0.104**	−0.083**							
	(0.051)	(0.036)							
fintech^2	−0.007*'								
	(0.004)								
fintech^2*SSA	0.020*	0.014*	−0.069**	37.178	−0.037**				
	(0.011)	(0.008)	(0.029)						

Note(s): ***, **, * and * denotes statistical significance at the 1%, 5%, 10% and 15% levels, respectively
Numbers in round parentheses (.) are the robust standard errors
Dependent variable: Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population)
Estimation Method: Arellano-Bover/Blundell–Bond dynamic panel system GMM

About the author

Dr Noha Emara received her MA and her PhD in economics from Rutgers University, The State University of New Jersey, New Brunswick. Upon finishing her PhD. Dr. Emara served as a Term Assistant Professor of Economics at Barnard College, Columbia University, where she has taught economic reasoning, econometrics, money and banking, labor economics, and development economics. Dr. Emara also taught courses at Drew University, Rutgers University–New Brunswick, and Helwan University. Among the course she has taught at the three universities are Econometrics, Mathematical Economics, Economic Fluctuations, Money and Banking, and Intermediate Macro. Her current research program includes five streams of research suitable for peer-review: (1) explorations of the impact of governance and economic freedom on economic growth; (2) explorations of development in developing countries; (3) examinations of monetary and financial issues; (4) papers related to predictions and forecasting; and (5) co-authored microeconomics papers in which she supplied the econometrics part. Noha Emara can be contacted at: nemara@camden.rutgers.edu