Inoue *Journal of Economic Structures* (2024) 13:8
https://doi.org/10.1186/s40008-024-00328-z

Journal of Economic Structures

RESEARCH

Open Access

Digital financial inclusion, international remittances, and poverty reduction

Takeshi Inoue[1*]

*Correspondence:
takeinoue1@aol.com

[1] Graduate School of International Cooperation Studies, Kobe University, 8-1 Rokkodai Nada, Kobe, Hyogo 6578501, Japan

Abstract

Ensuring access to and usage of formal financial services through digital devices can be referred to as "digital financial inclusion" (DFI). In recent years, there has been a growing trend in the use of financial services, including money transfers through mobile phones. This study applies mobile phone subscriptions as a proxy to measure the degree of DFI and explores the individual effects of DFI and remittances and their interaction effects on poverty conditions in developing countries. Using panel data from 2000 to 2020 for 123 countries and employing the dynamic generalized method of moments estimation, the results reveal that DFI and remittance inflows help ameliorate poverty in developing countries. Furthermore, we find that the coefficient of the interaction term between DFI and remittances is statistically significant and positive, suggesting that the impact of DFI on poverty alleviation could weaken as remittance inflows increase in the remittance-receiving country and vice versa.

Keywords: Digital financial inclusion, International remittances, Mobile penetration, Poverty reduction

JEL Classification: E00, G20, I30, O33

1 Introduction

Financial inclusion is a new dimension of financial development, which is generally defined as the process of ensuring access to and usage of basic formal financial services for all people at an affordable cost. Governments in developing countries initially tended to emphasize the physical network expansion of financial intermediaries to promote financial inclusion. Accordingly, relevant empirical studies measured the degree of financial inclusion using conventional indicators, such as the number of bank branches and automated teller machines (ATMs), bank accounts opened, and borrowers from and depositors with financial intermediaries in demographic and geographic terms. Most of these studies have found that financial inclusion has a statistically significant poverty-reducing effect in developing countries (Burgess and Pande 2005; Honohan 2008; Guillaumont Jeanneney and Kpodar 2011; Neaime and Gaysset 2018; Park and Mercado 2018; Zhang and Ben Naceur 2019).

From the viewpoint of financial service providers, promoting financial inclusion through expanding the physical network is not profitable since opening new branches and installing ATMs are costly and sometimes not worth the expense in unbanked and less populous areas. Therefore, instead of brick-and-mortar outlets, digital devices typified by mobile phones have been adopted as a new critical tool to advance financial inclusion in several developing countries, especially in Africa, where traditional financial infrastructure was relatively less developed, and mobile banking was introduced at a relatively early stage. In practice, using digital devices, hitherto unbanked people in sub-Saharan Africa benefit from formal financial services by easily accessing and utilizing them without visiting bank branches or ATMs (Gosavi 2018). Subsequently, due to increased development and diffusion of mobile technology, financial inclusion through digital devices or "digital financial inclusion" (DFI) has received significant attention not only in Africa but also in other developing regions.

Considering the importance of this new phenomenon, this study empirically analyzes whether DFI exerts a significant impact on poverty reduction in developing countries. The current research differs from relevant previous studies in the following ways.

First, unlike previous studies using conventional indicators of financial inclusion, this study applies mobile phone subscriptions as a proxy to measure the degree of DFI. This indicator was chosen because the other relevant data on DFI provided by international organizations are not sufficiently accumulated for empirical analysis. To the best of the author's knowledge, no other studies have examined how mobile penetration proxied for DFI affects poverty using panel data from developing countries.

Second, for many years, the mobile phone has been extensively used to send and receive money within countries (International Fund for Agricultural Development, 2015), but more recently, mobile remittance transactions are expected to and are likely to expand exponentially across borders. Accordingly, by including the interaction term between mobile phone subscriptions and international remittances in the estimation models, this study examines the relationship between DFI and remittance inflows in alleviating poverty.

The remainder of this paper is organized as follows. Section 2 briefly reviews the relevant literature. Section 3 describes the model and data used to analyze the effects of DFI and international remittances on poverty. Section 4 provides the empirical results. Section 5 estimates alternative models to confirm the analysis results in Sect. 4. Finally, Sect. 6 summarizes the main findings.

2 Literature review

With the advancement of digital transformation, unbanked people can conduct financial transactions more easily using digital devices. Several international organizations have collected and provided data related to DFI to capture these developments.

For example, in 2009, the International Monetary Fund launched the Financial Access Survey based on information collected by central banks and financial regulators and published relevant data from 2004 onward, including the number of mobile accounts, mobile money transactions, mobile money agents, outstanding balances on mobile money accounts, and the value of mobile money transactions. In 2011, the World Bank released the Global Findex, which uses randomly selected nationally representative samples. This database provides information about the percentage of adults who have an account at a formal financial institution, those who have a loan from a financial institution, and those who use mobile phones to send money, receive money, and pay bills at roughly three-year intervals since 2011.

Despite insufficient data accumulation for quantitative analysis, recent studies (Banna and Alam 2021; Khera et al. 2021) have attempted to create a composite indicator of DFI based on these related variables. However, the sample size of these composite indicators is limited. Moreover, annual data on poverty status are unavailable every year in many countries, making it challenging to analyze the impact of DFI on poverty using these indicators. Therefore, empirical studies often resort to proxy indicators, with this study focusing on mobile phone subscriptions. This is because mobile phone subscribers benefit from digital financial services via a mobile phone and because extensive data on mobile phones are available.

This section reviews representative studies that demonstrate how the number of mobile phone subscriptions is used as a proxy of DFI and examine the impact of mobile penetration on economic development. Additionally, this section also considers another important explanatory variable in this study, that is, international remittances, and surveys relevant literature exploring the impact of remittance inflows on poverty.

2.1 Mobile phone penetration, growth, and inequality

Recently, the number of mobile phone subscribers has increased worldwide. By regional comparison, Europe and Central Asia have been leading in terms of the mobile phone subscription rate. However, since the early 2000s, mobile penetration has been rapidly increasing in other regions, with East Asia and the Pacific on par with Europe and Central Asia, followed by the Middle East and North Africa, Latin America and the Caribbean, South Asia, and sub-Saharan Africa. Even by income comparison, mobile penetration was initially higher in high-income countries, but since the early 2000s, the gap between high-income countries and other countries has narrowed, with upper middle-income countries now in line with the former.

Mobile phones, the use of which has been growing worldwide in recent years, serve not only as a telephone, but also as an internet access device. People have replaced fixed-line phones with mobile phones to communicate with others. People also use mobile phones to make financial transactions by accessing the internet. Of course, not all mobile phone subscribers benefit from digital financial services via a mobile phone. Materially, more people tend to access and utilize financial services and make payments and remittances via such devices in countries with less developed traditional financial infrastructure.[1] Previous studies have regarded mobile phones as the key driver of DFI and examined their impact on economic conditions. These studies can be broadly categorized into two groups.

The first relates to the link between mobile penetration and economic growth. For example, Andrianaivo and Kpodar (2012) investigated whether mobile phones providing mobile financial services could serve as a tool to overcome the financial infrastructure gap in African countries where the coverage of bank branches and ATMs was the lowest in the world. They estimated models in which per capita real gross

[1] M-Pesa in Kenya allows the unbanked to use their cell phones to open mobile accounts, through which they can make deposits and withdrawals, transfer money, make payments, and purchase goods.

domestic product (GDP) growth was explained by the mobile penetration rate (the number of mobile phone subscribers divided by the total population) and a set of control variables. Applying the generalized method of moments (GMM) and using panel data for 44 countries from 1988 to 2007, they found that mobile penetration had a statistically significant positive impact on African economic growth.

Using panel data on 14 Indian states from 2001 to 2012, Ghosh (2016) analyzed the impact of mobile penetration on economic growth. Mobile phone subscriptions in India increased dramatically from 6.5 million to 865 million during 2001–2012. Hence, in addition to banking outlets, the mobile phone was expected to serve as an alternative gateway into financial services in India. Following Andrianaivo and Kpodar (2012) and Lee et al. (2012), Ghosh (2016) estimated models in which the log difference of per capita real income was explained by the number of mobile phone subscribers per 100,000 people, as well as the control variables. The results from the system GMM indicated that mobile telephony had a positive and significant effect on economic growth and that this effect was larger in high mobile penetration states than in low ones.

The second group of literature analyzes the impact of mobile penetration on income distribution. For example, Asongu (2015) measured the degree of mobile penetration by the number of mobile phone subscribers as a percentage of the population and regarded it as the proxy for mobile banking activities. Asongu (2015) specified a model in which the dependent variable was the Gini coefficient, and the independent variables were the mobile penetration rate and a set of control variables such as exports plus imports as a percentage of GDP, inflation, and money supply as a percentage of GDP. Using cross-sectional data from 52 countries in Africa, Asongu (2015) found that mobile penetration had a statistically significant negative effect on income inequality, irrespective of which control variables were used. Therefore, it was concluded that mobile phones provided African countries with affordable and cost-effective means of attracting a large part of the population who had been excluded from formal finance, which enabled them to access basic financial services and eventually led to reduced income inequality.

Using the World Bank's Global Findex survey data for 2011, 2014, and 2017, Demir et al. (2022) examined the interrelationship between FinTech, financial inclusion, and income inequality in 140 countries. In their analysis, FinTech was proxied by the share of the adult population using mobile phones to pay bills. Financial inclusion was measured by the share of the adult population owning an account, and saving or borrowing from a formal financial institution. First, they regressed financial inclusion on FinTech and confirmed that FinTech had a statistically significant positive effect on financial inclusion in all indicators. Then, they estimated the model in which FinTech and financial inclusion explained income inequality measured by the Gini coefficient. The results of the pooled ordinary least squares (OLS) model indicated that the coefficients of FinTech and financial inclusion were significantly negative, suggesting that FinTech and financial inclusion reduced income inequality.

The aforementioned studies indicated that mobile penetration promotes economic growth and reduces income disparities. Referring to the literature, this study analyzes the potential impact of DFI proxied by mobile penetration on poverty conditions in developing countries.[2]

2.2 Remittance inflows and poverty

Remittance inflows are believed to contribute to poverty reduction in remittance-receiving countries through various channels. For example, the additional cash income generated through remittance transfers enables recipient households to smooth their consumption expenditures and promote productive activities, which is expected to raise the per capita income level in the recipient country. Remittances may also improve recipient households' living standards, especially the poor, by improving their sanitary conditions and financing their children's education.

Against the backdrop of the remarkable increase in remittance inflows, several empirical studies have investigated the poverty-reducing effect of remittances in recipient developing countries (e.g., Adams and Page 2005; Jongwanich 2007; Gupta et al. 2009; Portes 2009; Vargas-Silva, Jha, and Sugiyarto 2009; Anyanwu and Erhijakpor 2010; Serino and Kim 2011; Imai et al. 2014; Majeed 2015; Hassan et al. 2017; Masron and Subramaniam 2018; Abduvaliev and Bustillo 2020). These studies used multi-country panel data to estimate models with poverty indicators such as income level of the poorest, poverty ratio, poverty gap, and squared poverty gap as explained variables, and analyzed the existence and magnitude of the poverty reduction effect of remittance inflows to developing countries. With few exceptions, most found that remittances alleviated poverty conditions in sample countries.[3] However, there are differences as to which poverty indicators are statistically significant and the magnitude of the poverty-reducing effect of remittances.[4]

For example, Jongwanich (2007), Imai et al. (2014), and Masron and Subramaniam (2018) measured poverty conditions from the poverty ratio and found that remittances had the effect of alleviating poverty in the receiving countries. Adams and Page (2005), Anyanwu and Erhijakor (2010), Serino and Kim (2011), and Hassan et al. (2017) measured poverty status using multiple indicators and reported that remittance inflows to developing countries had negative and significant effects on poverty indicators, that is, poverty ratio, poverty gap, and squared poverty gap. In contrast, Gupta et al. (2009),

[2] Economic growth means an increase in average income levels. It can be largely categorized as either growth with rising income inequality and poverty or growth with falling income inequality and poverty. The differences between these two categories can alter the impact of growth on the poor. Theoretically, it is possible that in certain countries, the benefit of economic growth for the poor is undermined or even offset if growth is accompanied by an increase in income inequality (Guillaumont Jeanneney and Kpodar 2011). However, recent empirical evidence does not support the argument that economic growth affects income distribution (Roemer and Gugerty 1997; Li, Squire, and Zou 1998; Dollar and Kraay 2002), suggesting that economic growth benefits the poor as much as everyone else. In addition, related previous studies empirically indicated that mobile phone subscriptions promote economic growth and reduce income inequality. Based on these findings, this study hypothesizes that economic growth should help alleviate poverty and analyzes whether DFI proxied by mobile penetration improves poverty conditions through economic growth.

[3] Majeed (2015) examined the effect of international remittances on the poverty ratio for 65 developing countries applying OLS, two-stage least squares (2SLS), or GMM. The results indicated that remittances had a positive and significant effect on the poverty ratio, irrespective of which methods were used. Additionally, the analyses with 2SLS and GMM indicated that, when the interaction term between remittances and financial development measured by money supply and private credit relative to GDP was included in the model, the coefficient of the interaction term became negative and significant. Furthermore, when the sample countries were divided into financially developed and financially developing countries, the coefficient of remittances was not significant for the former. Majeed (2015) concluded that the effect of remittances on poverty status varied depending on the level of financial development and that remittances might cause detrimental effects on poverty only in countries with low levels of financial development.

[4] Some studies, such as Akobeng (2016) and Inoue (2018), highlighted that the poverty-reducing effect of remittances varies with the level of financial development in remittance-receiving countries.

Vargas-Silva et al. (2009), and Abduvaliev and Bustillo (2020) stated that the poverty reduction effect of remittances was not statistically significant when squared poverty gap, poverty ratio, and poverty gap were used as a poverty indicator, respectively.

Some previous studies have also noted that the effects of international remittances vary across income groups. For example, using panel data for 46 countries, Portes (2009) analyzed the effect of remittances on income levels by income decile and found that the effect of remittances on income was positive for the bottom 70% of the income distribution and diminishing as decile income increased, while it was negative and increasing for the top 20% of the income distribution, and this trend was more pronounced in low-income countries. Serino and Kim (2011) also used quantile regression analysis using panel data for 66 developing countries to examine how the effect of remittance inflows on poverty indicators varied through the poverty distribution strata. They demonstrated that international remittances improved poverty conditions more for the poorest stratum in developing countries.

As mentioned above, previous studies have empirically shown that DFI proxied by mobile penetration promotes economic growth and reduces income inequality. This implies that mobile penetration has a poverty-reducing effect. Although there are some differences in several respects, previous studies generally support the poverty-reducing effect of international remittances. This study examines the individual effects of mobile penetration and international remittances on poverty reduction and analyzes whether and how mobile penetration and remittances relate to each other in the poverty-reduction process.

In recent years, an increasing number of people have been using financial services, including money transfers through mobile phones. Therefore, it can be assumed that the widespread use of mobile phones has a synergistic effect with international remittances in promoting poverty reduction. On the other hand, mobile phones have thus far been used as primary tools for domestic remittances. If DFI is well developed and domestic money transfers already play an important role for people in that country, international remittances may not have a significant effect on the living conditions of people, including the poor. For this reason, this study analyzes the relationship between DFI proxied by mobile penetration and international remittances in the poverty-reduction process.

3 Model and data

The following model is estimated to analyze the individual effects of both DFI and international remittances and their interaction effect on poverty conditions in developing countries:

$$\mathrm{POV}_{i,t} = \beta_0 \mathrm{POV}_{i,t-1} + \beta_1 \mathrm{DFI}_{i,t} + \beta_2 \mathrm{REM}_{i,t} + \beta_3 \mathrm{DFI}_{i,t} \times \mathrm{REM}_{i,t} + \gamma\prime X_{i,t} + \alpha_i + u_{i,t} \tag{1}$$

where $\mathrm{POV}_{i,t}$ is the measure of poverty conditions in country i at time t, $\mathrm{DFI}_{i,t}$ is the measure of DFI in country i at time t, $\mathrm{REM}_{i,t}$ is remittance inflows to a country i at time t, $\mathrm{X}_{i,t}$ is the vector of control variables in country i at time t, α_i is a country-specific fixed effect, and $\mathrm{u}_{i,t}$ is the error term in country i at time t. i (=1, 2, …, N) is the number of cross-sections, and t (=1,2,…, T) is the number of time series.

In Eq. (1), the extent of poverty conditions (POV) is measured by the poverty headcount ratio. In this study, it is either the percentage of the population in a country living on less than US$1.90 per day at 2011 purchasing power parity (PPP) prices or the percentage of the population in a country living on less than US$3.20 per day at 2011 PPP prices. The former is named POV1 and the latter POV2. A higher poverty ratio means a more impoverished condition. In addition, the lagged value of the dependent variable is used as the independent variable. This is due to the persistence of poverty; that is, a poverty level is likely to be affected by the own past values.

The most important independent variable in this study is DFI. Following relevant studies such as Khera et al. (2021), this variable is measured by the number of mobile phone subscriptions per 100 people.[5] Those involuntarily excluded from formal finance tend to belong to the relatively low-income class. As mobile phones become widely used and financial transactions through digital device progress, unbanked people having mobile phones is thought to increase their economic activities and productive assets by improving access to and usage of basic formal financial services through their digital tools. Accordingly, the coefficient of DFI in Eq. (1) is expected to have a negative sign.

Remittance inflows (REM) are another important independent variable in this study. REM is the amount of personal remittances received divided by GDP. An increase in migrants' remittances is assumed to help lift their families out of poverty in their home countries by providing additional income for consumption, investment, and/or savings. Accordingly, the coefficient of REM in the equation is expected to be negative.

The interaction term (DFI $\times$ REM) indicates the combined effect of DFI and remittances in the poverty-alleviation process. The marginal effect of a change in DFI on poverty ($\partial POV/\partial DFI = \beta_1 + \beta_3 REM$) indicates how DFI influences the effect of remittances on poverty. Given that DFI and remittances have a poverty-reducing effect, a negative interaction term suggests that DFI can complement remittances. In this case, DFI and remittances support each other and have a synergistic effect on poverty reduction in developing countries. Conversely, if the coefficient of the interaction term has a positive sign, DFI can be regarded as a substitute for remittances in the poverty-alleviation process. In this case, the poverty-reducing effect of DFI becomes larger in developing countries with smaller amounts of remittances and vice versa.

Concerning the control variables, this study considers the regressors frequently used as determinants of poverty in representative literature. They are real GDP per capita (GDP), inflation rate (INF), government expenditure (GOV), economic openness (OPEN), and income inequality (GINI). Real GDP per capita is included to capture the average income level of a sample country. Previous studies indicate that a higher income level ameliorates the well-being of the poor (Ravallion and Chen 1997; Ravallion 2001; Dollar and Kraay 2002; Besley and Burgess 2003; Jalilian and Kirkpatrick 2005). Therefore, the coefficient of GDP in the equation is expected to be negative.

The inflation rate is calculated as the log difference of the consumer price index (CPI), where the value of the year 2010 is standardized to 100. Since low-income individuals tend to have a larger share of cash in their small portfolios and relatively limited access

[5] Khera et al. (2021) used the number of mobile phone subscription to create a composite indicator of DFI.

to financial instruments that hedge against inflation, high and unpredictable inflation is likely to have a disproportionately negative effect on them (Easterly and Fischer 2001; Holden and Prokopenko 2001). In line with these predictions, the coefficient of INF is expected to have a positive sign in Eq. (1).

Government expenditure is measured by the general government's final consumption expenditure as a percentage of GDP, which is a proxy for redistributive policies by a government in each country. The impact of such expenditure on the poor is ambiguous because it depends on whether and to what extent public resources are used for the poor (Cepparulo et al. 2017). If government expenditure benefits poor people, it will lead to poverty reduction; otherwise, it will not. Accordingly, we cannot a priori predict the sign of the government expenditure coefficient.

Economic openness is the sum of exports and imports of goods and services as a percentage of GDP. Its impact on the poor is also inconclusive because previous studies have not yet reached a quantitative consensus on this topic. For example, Dollar and Kraay (2004) observed that in a large sample of countries, economic openness measured in terms of trade integration alleviates poverty. However, some scholars have questioned whether international openness contributes to poverty reduction (e.g., Wade 2004; Milanovic 2005). Therefore, this study empirically investigates the signs and the statistical significance of the coefficient of economic openness.

Income inequality is measured by the Gini coefficient. Previous studies state that a given rate of economic growth reduces poverty more in countries with low-income inequality than in those with high-income inequality (Ravallion 1997; Adams and Page 2005). Therefore, the coefficient of GINI is expected to be positive in Eq. (1).

For the empirical analysis, this study uses unbalanced panel data for 123 countries from 2000 to 2020. Appendix A presents the countries covered in this study. The sample consists of low-income, lower middle-income, and upper middle-income countries. All the countries for which data are available during the sample period are included in the analysis. Data are obtained from the World Development Indicators of the World Bank (2021). Among the variables, DFI, INF, and GDP are expressed in natural logarithms, whereas the other variables are not expressed in natural logarithms since they are expressed as a percentage of GDP. Data for variables such as POV are not available for all the years during the sample period. Therefore, the total number of observations

Table 1 Definition of the variables

Variable	Definition
POV1	Number of the population in a country living on less than US$1.90 per day at 2011 PPP prices (% of population)
POV2	Number of the population in a country living on less than US$3.20 per day at 2011 PPP prices (% of population)
DFI	Logarithm of mobile cellular subscriptions per 100 people
REM	Personal remittances, received (% of GDP)
GDPPC	Logarithm of GDP per capita (constant 2015 US$)
INF	Log difference of CPI (2010 = 100)
GOV	General government final consumption expenditure (% of GDP)
OPEN	Exports and imports of goods and services (% of GDP)
GINI	Gini index (%)

Table 2 Summary statistics

Variable	Average	Standard deviation	Maximum	Minimum
POV1	12.8890	18.3770	94.3000	0.0000
POV2	26.2133	25.8758	98.5000	0.0000
DFI	3.3516	1.6953	5.3363	− 4.0123
REM	5.8332	7.4168	53.8261	0.0000
GDPPC	7.7002	0.9306	9.5610	5.5553
INF	0.0691	0.1077	1.8146	− 0.1997
GOV	15.2606	9.8746	147.7333	0.9517
OPEN	76.7814	36.6636	347.9965	0.1674
GINI	40.8118	8.6276	64.8000	24.0000

ranges from 417 to 419. Table 1 provides the data definitions and Table 2 presents the summary statistics.

4 Empirical results

Table 3 provides information on the degree of correlation between the variables used in Eq. (1). The correlation between the variables is generally not strong. Kennedy (2008) argues that multicollinearity is problematic when the correlation is above 0.8. Although only the correlation between POV1 and POV2 exceeds this level, they are not used in the same model. Therefore, the multicollinearity problem seems to be not severe or non-existent in our analysis.

Conceptually, it is possible that changes in poverty conditions affect mobile phone subscriptions and international remittances. For example, a worsening poverty situation may cause households to struggle to make ends meet, leading to lower mobile penetration. Also, a worsening poverty situation may cause migrant workers to send more money to their family members in their home country for altruistic motives. For the estimations, therefore, this study uses the dynamic panel GMM developed by Arellano and Bond (1991) in order to deal with the potential endogeneity problem.[6,7]

Tables 4 and 5 show the empirical results using the GMM estimation for the model expressed by Eq. (1). In Table 4, POV1 is used as the dependent variable, whereas in Table 5, POV2 is used as the dependent variable. In each table, the estimation results are divided into ten cases. In Cases 1 and 2, only DFI and REM are used as the independent variable, respectively. In Case 3, both DFI and REM are used in estimating the equation, and in Case 4, the interaction term of DFI and REM is added. In Cases 5 to 9, the control

[6] Regarding the selection of the instrument variable, determining the variables that affect DFI and international remittances but do not directly affect poverty ratio except for the channels through DFI and international remittances was difficult. Accordingly, for each model, two lags of the dependent variable are used as the dynamic instrument variable and the lagged first difference of all explanatory variables as the standard instrument.

[7] To see if the use of different methods would affect the results, an analysis was also performed by applying the methods that do not take endogeneity into account. The results obtained from pooled OLS and the fixed effect model are presented in Appendix Tables 1 and 2, respectively. Appendix Table 1 indicates that both DFI and REM have a negative sign in all cases and become significant in several cases and that their interaction term becomes significant in several cases with a positive sign. Appendix Table 2 also indicates that DFI has a negative sign and becomes significant in all cases, while REM and the interaction term between DFI and REM do not become significant in almost all cases. Therefore, differences in methodology may affect the results, particularly with respect to REM and the interaction term between DFI and REM. The similar results were obtained when the dependent variable was POV2.

Table 3 Correlation matrix

	POV1	POV2	DFI	REM	GDPPC	INF	GOV	OPEN	GINI
POV1	1.0000								
POV2	0.9347	1.0000							
DFI	− 0.5034	− 0.5653	1.0000						
REM	− 0.1344	− 0.0709	0.0776	1.0000					
GDPPC	− 0.7217	− 0.7951	0.4979	− 0.2836	1.0000				
INF	0.0128	0.0299	− 0.1935	− 0.0759	− 0.0213	1.0000			
GOV	− 0.0431	− 0.0860	0.0730	0.0787	0.0332	− 0.0372	1.0000		
OPEN	− 0.1481	− 0.1652	0.0791	0.2711	− 0.0484	0.0954	0.1978	1.0000	
GINI	0.2130	0.1465	− 0.0727	− 0.2098	0.1738	− 0.1184	− 0.0554	− 0.2731	1.0000

variables (GDP, INF, GOV, OPEN, and GINI) are included individually. In Case 10, all control variables are considered together.

Table 4 reports the estimation results of the dynamic panel model when POV1 is used as the dependent variable. The main findings are as follows. First, the coefficients of DFI are estimated to be negative and are statistically significant at the 1% level in all cases. The empirical results also indicate that the coefficients of REM are negative and are statistically significant at the 1% level in all cases. Therefore, the coefficients of DFI and REM are statistically significant and have the expected sign, indicating that the increased coverage of mobile phone subscriptions and the increase in remittance inflows significantly reduce the poverty ratio in the sample of developing countries.

Furthermore, Table 4 indicates that the coefficients of the interaction term (DFI × REM) are estimated to be positive and are statistically significant at the 1% level in all cases. This result suggests that DFI is a substitute for international remittances in the poverty-alleviation process, considering the positive impacts of DFI and remittances on poverty reduction. In other words, the impact of DFI on poverty alleviation could weaken as remittance inflows increase in the remittance-receiving country and vice versa.

Regarding the control variables, the coefficients of GDP, GOV, and OPEN are estimated to be negative and are statistically significant at the 1% level. Therefore, an increase in average income, government expenditure, or economic openness contributes to poverty reduction. Meanwhile, the coefficients of INF and GINI are positive, as expected, and are statistically significant, implying that an increase in inflation or income inequality worsens poverty conditions.

Next, Table 5 reports the estimation results of the dynamic panel model when POV2 is used as the dependent variable. Empirically, the results in Table 5 are mostly consistent with those in Table 4. First, the coefficients of DFI and REM are estimated to be negative and are statistically significant at the 1% level in all cases. The empirical results also reveal that the coefficients of the interaction term are positive and are statistically significant at the 1% level in all cases. Therefore, these results suggest that DFI and remittance inflows have a positive effect on poverty reduction and that there is substitutability between DFI and remittances in the poverty-reduction process.

Concerning the control variables, in line with Table 4, the coefficients of GDP, GOV, and OPEN have a negative sign, and the coefficients of INF and GINI have a positive

Table 4 Empirical result 1

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
POV1(−1)	0.5103	0.7606	0.5056	0.5054	0.4850	0.5104	0.4976	0.5067	0.5045	0.4952
	(2.8E-05)***	(0.0003)***	(0.0001)***	(0.0002)***	(0.0025)***	(0.0010)***	(0.0017)***	(0.0011)***	(0.0028)***	(0.0030)***
DFI	−1.9924		−1.9149	−2.0000	−1.6641	−1.7363	−1.9471	−1.9627	−2.0095	−1.3995
	(0.0001)***		(0.0013)***	(0.0020)***	(0.0091)***	(0.0033)***	(0.0066)***	(0.0222)***	(0.0217)***	(0.0773)***
REM		−0.1620	−0.0723	−0.1251	−0.1902	−0.1329	−0.1299	−0.0983	−0.3049	−0.2496
		(0.0010)***	(0.0004)***	(0.0009)***	(0.0112)***	(0.0033)***	(0.0107)***	(0.0030)***	(0.0207)***	(0.0191)***
DFI × REM				0.0126	0.0215	0.0102	0.0145	0.0087	0.0504	0.0375
				(0.0006)***	(0.0018)***	(0.0020)***	(0.0025)***	(0.0016)***	(0.0020)***	(0.0078)***
GDPPC					−2.8532					−2.1722
					(0.1168)***					(0.5114)***
INF						5.2591				5.8585
						(0.0377)***				(0.6082)***
GOV							−0.1208			−0.1571
							(0.0051)***			(0.0533)***
OPEN								−0.0108		−0.0215
								(0.0003)***		(0.0026)***
GINI									0.1728	0.1426
									(0.0018)***	(0.0128)***
J-Statistics (Prob.)	0.4792	0.6229	0.4907	0.6322	0.4503	0.5723	0.6236	0.4384	0.4620	0.5045
AR(1) (Prob.)	0.0132	0.0096	0.0121	0.0123	0.0133	0.0125	0.0125	0.0119	0.0181	0.0161
AR(2) (Prob.)	0.7490	0.7349	0.7466	0.7762	0.8344	0.7549	0.8453	0.7222	0.8627	0.8623
Observations	417	419	417	417	417	417	417	417	417	417

Standard errors are reported in parentheses

The dependent variable is the poverty headcount ratio (POV1). DFI is equal to the logarithm of mobile cellular subscriptions per 100 people. REM is equal to personal remittances relative to GDP. GDPPC is equal to the logarithm of per capita real GDP. INF is equal to the log difference of the CPI. GOV is government expenditure relative to GDP. OPEN is equal to the sum of exports and imports relative to GDP. GINI is equal to the Gini index

*** indicates statistical significance at the 1% level

Table 5 Empirical result 2

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
POV2(−1)	0.6204	0.8608	0.6122	0.6225	0.5196	0.6249	0.6271	0.6249	0.6297	0.5491
	(2.4E-07)***	(0.0009)***	(0.0029)***	(0.0046)***	(0.0079)***	(0.0068)***	(0.0058)***	(0.0048)***	(0.0152)***	(0.0276)***
DFI	−3.0477		−2.8996	−3.2110	−2.4036	−3.1080	−3.2260	−3.2380	−3.3181	−2.7300
	(1.1E-06)***		(0.0081)***	(0.0269)***	(0.1121)***	(0.0922)***	(0.0891)***	(0.0357)***	(0.0255)***	(0.2831)***
REM		−0.2411	−0.1382	−0.3688	−0.5943	−0.3631	−0.3646	−0.3386	−0.6117	−0.6504
		(0.0019)***	(0.0047)***	(0.0115)***	(0.0238)***	(0.0161)***	(0.0273)***	(0.0114)***	(0.0456)***	(0.0934)***
DFI × REM				0.0589	0.0713	0.0580	0.0611	0.0588	0.1166	0.1088
				(0.0020)***	(0.0035)***	(0.0061)***	(0.0082)***	(0.0033)***	(0.0128)***	(0.0182)***
GDPPC					−11.1844					−7.0450
					(1.4951)***					(2.8086)**
INF						3.7304				3.5827
						(0.1309)***				(0.5154)***
GOV							−0.1978			−0.1099
							(0.0302)***			(0.1077)
OPEN								−0.0131		−0.0071
								(0.0024)***		(0.0104)
GINI									0.2319	0.0712
									(0.0220)***	(0.0347)**
J-Statistics (Prob.)	0.6416	0.7912	0.4874	0.5530	0.4918	0.5811	0.5817	0.5408	0.4997	0.3016
AR(1) (Prob.)	0.0191	0.0153	0.0184	0.0187	0.0194	0.0191	0.0177	0.0182	0.0223	0.0165
AR(2) (Prob.)	0.6333	0.5119	0.6342	0.5588	0.5115	0.5356	0.4736	0.5680	0.5182	0.4171
Observations	417	419	417	417	417	417	417	417	417	417

Standard errors are reported in parentheses

The dependent variable is the poverty headcount ratio (POV2). DFI is equal to the logarithm of mobile cellular subscriptions per 100 people. REM is equal to personal remittances relative to GDP. GDPPC is equal to the logarithm of per capita real GDP. INF is equal to the log difference of the CPI. GOV is government expenditure relative to GDP. OPEN is equal to the sum of exports and imports relative to GDP. GINI is equal to the Gini index

*** and ** indicate statistical significance at the 1% and 5% levels, respectively sign. Additionally, all coefficients are statistically significant when they are included separately. Unlike Table 4, the coefficients of GOV and OPEN in Table 5 lose their statistical significance in Case 10, where all control variables are considered together.

Finally, to confirm the validity of the set of instrumental variables, this study performs both the Hansen test for over-identifying restrictions and the Arellano–Bond serial correlation test. As indicated by *J*-statistics in Tables 4 and 5, the Hansen tests for over-identifying restrictions do not reject the null hypothesis that the instruments are valid in all cases. Tables 4 and 5 also report the Arellano–Bond tests for autocorrelation. The null hypothesis of no serial correlation in the first differenced residuals is rejected for the AR (1) process but is not rejected for the AR (2) process. These diagnostic test results imply that the instruments are valid and that the model is correctly specified.

5 Alternative empirical result

This section examines the impacts of DFI and international remittances on poverty using an alternative method. Specifically, how DFI and remittances affect the average income for different income groups in developing countries is empirically analyzed. The findings are expected to reveal the impacts of DFI and remittances not only on poverty conditions, but also on income distribution. The analysis is based on the following model:

$$\mathrm{INCOME}_{j,i,t} = \beta_0 \mathrm{INCOME}_{j,i,t-1} + \beta_1 \mathrm{DFI}_{i,t} + \beta_2 \mathrm{REM}_{i,t} + \beta_3 \mathrm{DFI}_{i,t} \times \mathrm{REM}_{i,t} + \gamma\prime X_{i,t} + \alpha_i + \nu_{i,t} \qquad (2)$$

where $\mathrm{INCOME}_{j,i,t}$ is the *j*th quintile income of country *i* at time *t*, and $\mathrm{v}_{i,t}$ is the error term in country *i* at time *t*. INCOME represents the average income of five income classes from the bottom 20% to the top 20% of the population.[8] The other variables, except for GDP in a set of control variables, are the same as those in Eq. (1). In Eq. (2), GDP is defined as the logarithm of GDP per capita measured in current US dollars.

Table 6 indicates the empirical results using the GMM estimation for the model expressed by Eq. (2). DFI, the most important explanatory variable, has a statistically significant positive impact on average income for all income groups. From the values of the coefficients, it is found that the impact is the largest for the poorest group, followed by the second and the third quintiles, and the smallest for the top 20 richest group. Therefore, DFI, proxied by the number of mobile phone subscriptions, is considered to contribute to reducing poverty and income inequality by increasing the incomes of relatively poor people.

Regarding another important regressor, REM impacts average income across quintile groups differently. In Cases 2 to 4, the coefficient of REM is statistically significant with a positive sign, and its impact becomes larger as the income level is higher. In contrast, in Case 1, the coefficient is statistically insignificant, whereas in Case 5, it is statistically significant with a negative sign. Accordingly, international remittances are thought to raise the incomes of the poor, albeit worsening income inequality. This finding is partially consistent with Portes (2009), who reported that the impact of

[8] Referring to Dollar and Kraay (2002) and Portes (2009), the average income of each income quintile is calculated. For example, INCOME1 is the average income of the first (poorest) quintile and INCOME5 is the average income of the fifth (richest) quintile. Where s1 and Y represent the income share of the first quintile and total income, respectively, INCOME1 can be computed as follows:
INCOME1 = (s1/0.2)*(Y/population).

Table 6 Alternative empirical result

	Case 1 INCOME1	Case 2 INCOME2	Case 3 INCOME3	Case 4 INCOME4	Case 5 INCOME5
$INCOME_j(-1)$	0.0556 (0.0160)***	−0.0040 (0.0024)*	−0.0109 (0.0019)***	−0.0197 (0.0047)***	−0.0055 (0.0024)**
DFI	0.0252 (0.0069)***	0.0041 (0.0009)***	0.0031 (0.0009)***	0.0038 (0.0006)***	0.0019 (0.0011)*
REM	−0.0026 (0.0016)	0.0008 (0.0004)*	0.0014 (0.0007)*	0.0019 (0.0002)***	−0.0013 (0.0003)***
DFI × REM	−0.0002 (0.0009)	−0.0008 (0.0001)***	−0.0009 (0.0002)***	−0.0008 (0.0001)***	6.9E-05 (0.0001)
GDPPC	0.9476 (0.0261)***	1.0084 (0.0027)***	1.0196 (0.0060)***	1.0209 (0.0067)***	1.0063 (0.0029)***
INF	0.0364 (0.0314)	0.0119 (0.0022)***	0.0058 (0.0022)**	0.0043 (0.0044)	0.0016 (0.0032)
GOV	−0.0018 (0.0026)	0.0002 (0.0003)	0.0004 (0.0009)	0.0022 (0.0010)**	0.0003 (0.0004)
OPEN	0.0004 (0.0001)***	0.0002 (7E-05)***	−0.0001 (2E-05)***	−0.0001 (6E-05)**	−1.4E-05 (1.6E-05)
GINI	−0.0339 (0.0030)***	−0.0251 (0.0001)***	−0.0162 (0.0003)***	−0.0068 (0.0008)***	0.0173 (0.0003)***
J-statistic (Prob.)	0.9075	0.1642	0.0068	0.9614	0.5052
AR (1) (Prob.)	0.0416	0.0016	0.0385	0.0024	0.0036
AR (2) (Prob.)	0.6362	0.0713	0.5028	0.1173	0.6305
Observations	417	417	417	417	417

Standard errors are reported in parentheses

The dependent variable is the *j*th quintile average income ($INCOME_j$, $j = 1,2,3,4,5$). DFI is equal to the logarithm of mobile cellular subscriptions per 100 people. REM is equal to personal remittances relative to GDP. GDPPC is equal to the logarithm of per capita nominal GDP. INF is equal to the log difference of the CPI. GOV is government expenditure relative to GDP. OPEN is equal to the sum of exports and imports relative to GDP. GINI is equal to the Gini index

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

remittances is negative and increasing in income for the top 20% of the population but is positive and decreasing in income for the bottom 70% of the population.

Finally, the interaction term between DFI and REM becomes statistically significant in Cases 2 to 4 and has a negative sign. In these cases, as previously mentioned, both DFI and REM have a positive impact on income levels. This implies that, while both DFI and REM raise income levels, at least for the second through fourth quintiles, their combined term has the opposite effect on the income levels of these income groups. Therefore, this alternative analysis also reveals the substitutability of DFI and REM.

6 Conclusions

The widespread use of mobile phones leads to economic growth (Andrianaivo and Kpodar 2012; Ghosh 2016) and a reduction in income inequality (Asongu 2015; Demir et al. 2022). Additionally, international remittances reduce poverty reduction

(Adams and Page 2005; Jongwanich 2007; Gupta et al. 2009; Portes 2009; Vargas-Silva et al. 2009; Anyanwu and Erhijakpor 2010; Serino and Kim 2011; Imai et al. 2014; Hassan et al. 2017; Masron and Subramaniam 2018; Abduvaliev and Bustillo 2020).

Based on previous studies, this study examines whether and how mobile penetration and international remittances affect poverty separately and interactively in developing countries. Models in which the poverty headcount ratio is explained by mobile phone subscriptions, remittance inflows, their interaction term, and other standard control variables used in the literature are estimated. The poverty ratio is alternatively measured by a poverty line of either US$1.90 or US$3.20. The number of mobile phone subscriptions is used as the proxy to measure the degree of DFI.

By applying the GMM to panel data from 123 developing countries during 2000–2020, this study first finds that the coefficients of mobile penetration and remittances are estimated to have significant negative values, irrespective of which poverty indicator is used. Therefore, advances in DFI and increased remittance inflows could reduce poverty in developing countries. Several related studies have noted the poverty-reducing effect of international remittances, and this study confirms these results. In contrast, regarding the effect of DFI, existing studies have demonstrated that mobile penetration promotes economic growth and reduces income inequality, but none have analyzed the effect on poverty conditions, and in this respect, this study is a new contribution.

Second, the interaction term between DFI and international remittances has a positive sign for the poverty indicator and is statistically significant in all cases for both poverty indicators. Assuming that DFI and international remittances have a negative sign on the poverty indicator, this result implies that DFI and international remittances are substitutive in the poverty-reduction process. In other words, the poverty-reducing effect of international remittances is interpreted as being low in countries with high levels of DFI. Conversely, the poverty-reducing effect of DFI is low in countries with high remittance inflows. This study uses mobile phone subscriptions as a proxy variable for DFI. It is known that mobile phones are already being used as a tool for remittances in some developing countries, but until now, they have been used mainly for money transfers within a country. If there is relatively little demand for international remittances in regions where domestic remittances predominate, the results of the interaction term will support this phenomenon.

Third, regarding the control variables, income level, government spending, and economic openness are found to alleviate poverty in developing countries. In contrast, inflation and income inequality have an exacerbating effect on poverty. Therefore, to achieve poverty alleviation, governments in developing countries are required to curb rising inflation, lower income inequality, increase government spending, and promote economic growth and trade openness.

Appendix A: List of sample countries

Albania, Algeria, Angola, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, China, Colombia, Comoros, Congo (Democratic Republic), Congo (Republic), Costa Rica, Côte d'Ivoire, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Eswatini, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, Kosovo, Kyrgyz, Lao PDR, Lebanon, Lesotho, Liberia, Madagascar, Malawi, Malaysia, Maldives, Mali, Mauritania, Mexico, Micronesia, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, North Macedonia, Pakistan, Papua New Guinea, Paraguay, Peru, Philippines, Russia Federation, Rwanda, Samoa, Sao Tome and Principe, Senegal, Serbia, Sierra Leone, Solomon Islands, Somalia, South Africa, South Sudan, Sri Lanka, St. Lucia, Sudan, Suriname, Syria, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Tonga, Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, Uzbekistan, Vanuatu, Venezuela, Vietnam, West Bank and Gaza, Yemen, Zambia, Zimbabwe.

Appendix

See Table 7

Appendix

See Table 8

Table 7 Empirical result from pooled OLS estimation

POV1	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
Constant	38.8330	16.2601	39.9659	43.2377	152.6984	42.9831	44.9368	47.3432	28.1284	137.6564
	(3.4027)***	(2.1308)***	(3.8630)***	(5.1535)***	(11.4924)***	(5.0950)***	(5.2838)***	(5.4235)***	(7.2620)***	(10.7835)***
DFI	− 6.9195		− 6.8855	− 7.7396	− 0.9780	− 7.4613	− 8.1091	− 8.2512	− 7.8180	− 1.0115
	(0.6541)***		(0.6959)***	(1.0179)***	(0.7894)	(0.9898)***	(1.0700)***	(1.0528)***	(0.9746)***	(0.6585)
REM		− 0.3209	− 0.2309	− 0.9537	− 0.5502	− 0.7244	− 1.3554	− 1.5251	− 1.0484	− 1.1025
		(0.1597)**	(0.1337)*	(0.6587)	(0.5252)	(0.6788)	(0.5140)***	(0.5151)***	(0.6231)*	(0.3744)***
DFI × REM				0.1844	− 0.0633	0.1280	0.2784	0.3247	0.2308	0.0973
				(0.1424)	(0.1199)	(0.1458)	(0.1110)**	(0.1114)***	(0.1341)*	(0.0841)
GDPPC					− 16.3298					− 17.4279
					(1.4274)***					(1.3529)***
INF						− 13.5059				0.3042
						(16.9639)				(6.6311)
GOV							− 0.0316			0.0893
							(0.1675)			(0.0992)
OPEN								− 0.0303		− 0.0133
								(0.0343)		(0.0217)
GINI									0.3635	0.5572
									(0.1182)***	(0.1031)***
R-squared	0.2726	0.0180	0.2702	0.2771	0.6642	0.2677	0.2896	0.2967	0.3067	0.7331
Observations	772	770	759	759	750	724	730	739	759	697

White period standard errors are reported in parentheses

The dependent variable is the poverty headcount ratio (POV1). DFI is equal to the logarithm of mobile cellular subscriptions per 100 people. REM is equal to personal remittances relative to GDP. GDPPC is equal to the logarithm of per capita real GDP. INF is equal to the log difference of the CPI. GOV is government expenditure relative to GDP. OPEN is equal to the sum of exports and imports relative to GDP. GINI is equal to the Gini index

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table 8 Empirical result from fixed effect estimation

POV1	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
Constant	25.9750	16.1278	26.8653	25.3012	73.1227	24.6984	27.4995	26.3288	12.2340	57.2235
	(1.4962)***	(1.1770)***	(1.4640)***	(1.9717)***	(28.2717)**	(2.0434)***	(2.7442)***	(2.9969)***	(7.1025)*	(34.0920)*
DFI	− 3.4903		− 3.6059	− 3.2112	− 2.3827	− 3.0962	− 3.3876	− 3.4194	− 3.0086	− 2.4312
	(0.3990)***		(0.4185)***	(0.5175)***	(0.6807)***	(0.5342)***	(0.5500)***	(0.5452)***	(0.5868)***	(0.7417)***
REM		− 0.6312	− 0.1287	0.2090	0.1141	0.2703	0.0427	− 0.0044	0.0735	− 0.2092
		(0.1956)***	(0.1334)	(0.3050)	(0.3357)	(0.3120)	(0.3323)	(0.3218)	(0.3219)	(0.3662)
DFI × REM				− 0.0839	− 0.0750	− 0.0991	− 0.0514	− 0.0415	− 0.0563	− 0.0160
				(0.0666)	(0.0700)	(0.0682)	(0.0750)	(0.0725)	(0.0678)	(0.0792)
GDPPC					− 6.2655					− 5.3777
					(3.6656)*					(3.9057)
INF						1.6284				− 0.7663
						(0.6481)				(6.5551)
GOV							− 0.1189			− 0.1196
							(0.1574)			(0.1858)
OPEN								− 0.0043		− 0.0035
								(0.0347)		(0.0360)
GINI									0.3040	0.2691
									(0.1449)**	(0.1757)
R-squared	0.9545	0.9110	0.9556	0.9566	0.9585	0.9561	0.9568	0.9564	0.9585	0.9585
Observations	772	770	759	759	750	724	730	739	759	697

White period standard errors are reported in parentheses

The dependent variable is the poverty headcount ratio (POV1). DFI is equal to the logarithm of mobile cellular subscriptions per 100 people. REM is equal to personal remittances relative to GDP. GDPPC is equal to the logarithm of per capita real GDP. INF is equal to the log difference of the CPI. GOV is government expenditure relative to GDP. OPEN is equal to the sum of exports and imports relative to GDP. GINI is equal to the Gini index

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Acknowledgements
The author would like to thank the editor and the anonymous referees for their helpful comments and suggestions. This research was supported by Zengin Foundation for Studies on Economics and Finance and JSPS KAKENHI Grant Number JP20K01655.

Author Contributions
Conceptualization, Takeshi Inoue; Methodology, Takeshi Inoue; Data Curation, Takeshi Inoue; Writing – Original Draft Preparation, Takeshi Inoue; Writing – Review & Editing, Takeshi inoue; Funding Acquisition, Takeshi Inoue.

Funding
Zengin Foundation For Studies On Economics And Finance, Japan Society for the Promotion of Science JP20K01655, Takeshi Inoue

Availability of data and materials
The dataset used is available from the corresponding author on reasonable request.

Declarations

Competing interests
The author declares that I have no competing interests.

Received: 11 September 2023 Revised: 14 March 2024 Accepted: 6 April 2024
Published online: 03 May 2024

References

Abduvaliev M, Bustillo R (2020) Impact of remittances on economic growth and poverty reduction amongst CIS countries. Post-Communist Econ 32:525–546
Adams RH Jr, Page J (2005) Do international migration and remittances reduce poverty in developing countries? World Dev 33:1645–1669
Akobeng E (2016) Out of inequality and poverty: evidence for the effectiveness of remittances in sub-Saharan Africa. Q Rev Econ Finance 60:207–223
Andrianaivo M, Kpodar K (2012) Mobile phones, financial inclusion, and growth. Rev Econ Inst 3:1–30
Anyanwu JC, Erhijakpor AEO (2010) Do international remittances affect poverty in Africa? Afr Dev Rev 22:51–91
Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev Econ Stud 58:277–297
Asongu SA (2015) The impact of mobile phone penetration on African inequality. Int J Soc Econ 42:706–716
Banna H, Alam MR (2021) Impact of digital financial inclusion on ASEAN banking stability: Implications for the post-Covid 19 era. Stud Econ Financ 38:504–523
Besley T, Burgess R (2003) Halving global poverty. J Econ Perspect 17:3–22
Burgess R, Pande R (2005) Do rural banks matter? Evidence from the Indian social banking experiment. Am Econ Rev 95:780–795
Cepparulo A, Cuestas JC, Intartaglia M (2017) Financial development, institutions, and poverty alleviation: an empirical analysis. Appl Econ 49:3611–3622
Demir A, Pesqué-Cela V, Altunbaş Y, Murinde V (2022) Fintech, financial inclusion and income inequality: a quantile regression approach. The European Journal of Finance 28:86–107
Dollar D, Kraay A (2002) Growth is good for the poor. J Econ Growth 7:195–225
Dollar D, Kraay A (2004) Trade, growth, and poverty. Econ J 114:F22–F49
Easterly W, Fischer S (2001) Inflation and the poor. J Money, Credit, Bank 33:160–178
Ghosh S (2016) Does mobile telephony spur growth? Evidence from Indian states. Telecommun Policy 40:1020–1031
Gosavi A (2018) Can mobile money help firms mitigate the problem of access to finance in eastern sub-Saharan Africa? J Afr Bus 19:343–360
Guillaumont Jeanneney G, Kpodar K (2011) Financial development and poverty reduction: can there be a benefit without a cost? J Dev Stud 47:143–163
Gupta S, Pattillo CA, Wagh S (2009) Effect of remittances on poverty and financial development in sub-Saharan Africa. World Dev 37:104–115
Hassan GM, Chowdhury M, Shakur S (2017) Remittances, human capital and poverty: a system approach. J Dev Areas 51:177–192
Holden P, Prokopenko V (2001) Financial development and poverty alleviation: Issues and policy implications for developing and transition countries. IMF Working Paper WP/01/160.
Honohan P (2008) Cross-country variation in household access to financial services. J Bank Financ 32:2493–2500
Imai KS, Gaiha R, Ali A, Kaicker N (2014) Remittances, growth and poverty: new evidence from Asian countries. J Policy Model 36:524–538
Inoue T (2018) Financial development, remittances, and poverty reduction: empirical evidence from a macroeconomic viewpoint. J Econ Bus 96:59–68
International Fund for Agricultural Development, 2015. Remittances and mobile banking: The potential to leapfrog traditional challenges. In Brief.
Jalilian H, Kirkpatrick C (2005) Does financial development contribute to poverty reduction? J Dev Stud 41:636–656
Jongwanich J (2007) Workers' remittances, economic growth and poverty in developing Asia and the Pacific countries. UNESCAP Working Paper WP/07/01.

Kennedy P (2008) A Guide to Econometrics, 6th edn. Blackwell Publishing, Malden
Khera P, Ng S, Ogawa S, Sahay R (2021) Measuring digital financial inclusion in emerging market and developing economies: A new index. IMF Working Paper WP/21/90.
Lee SH, Levendis J, Gutierrez L (2012) Telecommunications and economic growth: an empirical analysis of sub-Saharan Africa. Appl Econ 44:461–469
Li H, Squire L, Zou H-F (1998) Explaining international and intertemporal variations in income inequality. Econ J 108:26–43
Majeed MT (2015) Poverty effects of remittances: a comparative analysis. J Int Dev 27:1–14
Masron TA, Subramaniam Y (2018) Remittance and poverty in developing countries. Int J Dev Issues 17:305–325
Milanovic B (2005) Can we discern the effect of globalization on income distribution? Evidence from household surveys. World Bank Econ Rev 19:21–44
Neaime S, Gaysset I (2018) Financial inclusion and stability in MENA: evidence from poverty and inequality. Financ Res Lett 24:230–237
Park C-Y, Mercado R Jr (2018) Financial inclusion, poverty, and income inequality. Singap Econ Rev 63:185–206
Portes LSV (2009) Remittances, poverty and inequality. J Econ Dev 34:127–140
Ravallion M (1997) Can high-inequality developing countries escape absolute poverty? Econ Lett 56:51–57
Ravallion M (2001) Growth, inequality and poverty: looking beyond averages. World Dev 29:1803–1815
Ravallion M, Chen S (1997) What can new survey data tell us about recent changes in distribution and poverty? World Bank Econ Rev 11:357–382
Roemer M, Gugerty MK (1997) Does economic growth reduce poverty? CAER II Discussion Paper 4.
Serino MNV, Kim D (2011) How do international remittances affect poverty in developing countries? A quantile regression analysis. J Econ Dev 36:17–40
Vargas-Silva C, Jha S, Sugiyarto G (2009) Remittances in Asia: implications for the fight against poverty and the pursuit of economic growth. ADB Economics Working Paper Series 182.
Wade RH (2004) Is globalization reducing poverty and inequality? World Dev 32:567–589
World Bank (2021) World Development Indicators. World Bank, Washington DC
Zhang R, Ben Naceur S (2019) Financial development, inequality, and poverty: some international evidence. Int Rev Econ Financ 61:1–16

Publisher's Note