Abstract

Mobile phones have been widely adopted in developing countries with potential to enhance opportunities for employment and entrepreneur. Although the effects of mobile phones on income have been documented by many studies, the potential to increase income diversification has not been studied as much. To fill this gap, we investigate the link between mobile phone ownership, income diversification, and poverty reduction. We use nationally representative panel data and fixed-effect models to control confounding factors and unobserved heterogeneity. We find that mobile phone ownership increases income diversification, especially on-farm enterprises, off-farm enterprises, and non-earned income. This association is larger in less educated households and households in deprived areas. Furthermore, mobile phone ownership reduces poverty channeled through income diversification. Therefore, a policy to improve access to mobile technologies could create resilient income portfolio by reducing transaction cost and improving market efficiency, which subsequently alleviate poverty in rural areas.

Keywords: ICT, Mobile phones, Income diversification, Poverty reduction, Bangladesh

JEL code: C23, I32, Q12

1. Introduction

Mobile phones (MP) have been widely adopted in developing countries, contributing to economic development. Bangladesh also has experienced expansion of mobile phone subscription, which become almost 100% in 2019 while it was less than 50% in 2010 as shown in Figure 1. Mobile technologies are believed to lead economic growth by driving productivity and efficiency gains in other sectors of the economy. For example, mobile phone ownership (MP ownership) is positively associated with the likelihood of participating in various types of off-farm work through reduction of transaction cost (Rajkhowa & Qaim, 2022) and may generate income gains by facilitating job market participation, expanding social networks and reducing households' exposure to risks (Aker & Mbiti, 2010). It also improves smallholder farmers' productivity by providing access to vital information on weather, cultivation techniques and market prices (Sekabira & Qaim, 2017; GSM Association, 2021). Furthermore, mobile platforms lead to human capital development by enabling remote delivery of academic lessons, reading materials and diffusion of knowledge (Asongu & Nwachukwu, 2016; GSM Association, 2021). However, little is known whether mobile phone ownership enhances income diversification, which is a possible economic channel to affect poverty and vulnerability (Yang et al., 2023). Given that the importance of mobile phone technologies has been acknowledged, understanding the link between mobile phone ownership, income diversification, and poverty reduction would provide important policy implications, especially for developing countries.

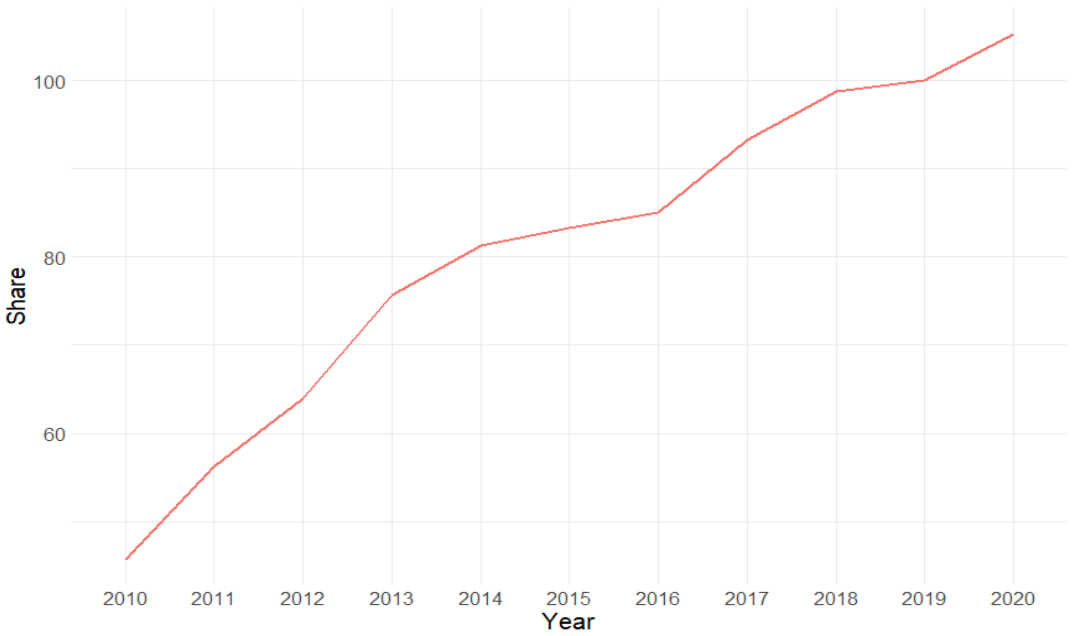

Figure 1 Expansion of Mobile phone subscription in Bangladesh last 10 years

Source: World Bank (2023)

Note: Mobile cellular subscriptions (per 100 people)

In this paper, first, we investigate whether mobile phone ownership increases income diversification, and contributes to monetary and non-monetary poverty reduction in the context of rural Bangladesh. Second, in addition to the average effect of mobile phone ownership, we investigate the heterogeneous effect of mobile phone ownership for several types of households, differentiating by educational level, geographical inequality, and gender. To achieve these goals, we use a most recently collected nationally representative panel dataset, spanning eight years and two data points from 2011 to 2019 of Bangladeshi rural households.

There is substantial literature looking at the relationship between mobile phone ownership and household income. Many studies found that mobile phone ownership increases household income (Asongu S., 2015; Ma et al., 2018; Miyajima, 2022; Munyegera & Matsumoto , 2016; Rajkhowa & Qaim, 2022; Sekabira & Qaim, 2017). However, there is scant literature on the effect of mobile phone on income diversification, to the best of our knowledge, only Leng, Ma , Tang, & Zhu, 2020; Ma et al., (2020); Rajkhowa & Qaim (2022) examine the effects of mobile phones or ICT adoption on income diversification or off-farm employment with established econometric methods. In addition, the effect of mobile phone ownership on monetary and non-monetary poverty have been documented but the mechanism through income diverisification is not. Furthermore, even though there is evidence on reduction in income inequality due to off-farm employment in developing countries (Adams Jr., 1994; Adams Jr., 2002), there are only a few studies exploring reduction in income inequality as a result of income diversification through mobile phone adoption. This is important because the poor often lack access to assets which has been identified as a barrier to entry to employment (Reardon et al., 2000).

The contribution of this paper is threefold. First, we provide the first empirical micro-econometric evidence on the effect of mobile phone expansion on income diversification and poverty in the context of rural Bangladesh. Second, we use a first and new nationally representative panel household dataset allowing us to use fixed effect models to account for time-invariant unobserved heterogeneity at the household level to generate evidence in South

Asia settings. Third, we investigate the heterogeneous impact of mobile phone ownership, in terms of human capital, geographical inequality, and gender. To this end, we use interaction terms in models to find who benefits more from owning mobile phones, thus providing more appropriate policy implications.

We find that mobile phone ownership accelerates income diversification as well as alleviates monetary and non-monetary poverty. Mobile phone ownership is positively associated with farm income, off-farm self-employment income, off-farm employment income and non-earned income. Moreover, farm income, off-farm self-employment income, and non-earned income contribute to poverty reduction, suggesting that the income diversification of rural households with mobile phone ownership improves the overall welfare of the rural society. Furthermore, heterogeneous analysis reveals that mobile phones are particularly beneficial for households led by individuals with lower levels of education and households located in relatively poverty-stricken areas.

The rest of this article is organized as follows. In section 2, the data, key variables, and empirical framework including the identification strategy and model specifications are presented. Section 3 presents the empirical results and discussion. In Section 4, the results of robustness checks are discussed. Section 5 concludes with policy implication and suggestions for future research.

2. Materials and methods

2.1 Data

We use data from a nationally representative household panel survey conducted in 2011/2012 and 2018/2019 titled the Bangladesh Integrated Household Survey (BIHS) designed and supervised by International Food Policy research Institute. The sample is representative of rural Bangladesh as well as of the seven administrative division of the country (Islam et al., 2018; Ahmed & Tauseef, 2022). The sample design of the BIHS followed a two staged stratified sampling method. Following the sampling framework developed from the community series of the 2001 Population and Housing Census of Bangladesh, primary sampling units (PSUs) were randomly selected in the first stage and random selection of households within each PSU constitute the second stage (Ahmed & Tauseef, 2022)[1]. The original sample size in the first wave is 6503 households in 325 PSUs which are allocated among seven divisions. In addition, the original sample size in the third wave is 5604 households. For this study, we use the balanced subsample of rural households included in both survey rounds, resulting in 7,636 observations from 3,818 households as shown in Table 1 and Table 2[2]. Since our analysis uses panel data, our estimates would be biased if the attrition is related to some household

[1] Using a sampling frame created from the community series of Bangladesh's 2001 population census, the BIHS sample design used a stratified sampling in two stages—selection of PSUs and selection of homes within each PSU. The 325 PSUs from the entire BIHS sample were divided into the 8 strata (seven divisions and the FTF zone) in the first stage of sampling, with probability proportional to size. From each PSU, 20 households were chosen at random for the second stage (Ahmed, et al., 2013).

[2] Due to the attrition of the households and split households because of marriage etc. in round 3 of BIHS, the number of observations is decreased from the original sample size. We do not take into its households who are split into several households. We follow the original household head to create a balanced panel dataset.

characteristics. However, Ahmed & Tauseef (2022) shows that the attrition between 2011/12 and 2018/19 is random. Therefore, the estimates presented in this paper are not adjusted for attrition. Descriptive statistics of the whole sample are presented in Table 3.

Table 1 shows the number of households owning and not owning mobile phones in our sample. In 2011/12, about 23% households in our sample did not own a mobile phone which dropped to 2% in 2019. Table 1 depicts that mobile phones have been widely adopted in rural Bangaldesh from 2012 to 2019. Figure 2 shows the poverty rate of seven divisions of Bangladesh. The poverty rate is found to be most severe in Rangpur Division compared to other six divisions, which is consistent with Khandker (2012). In the subsection 3.4, we examine how much mobile phone ownership increased income resilience through diversification, especially in the poor division, Rangpur.

Table 1 Number of households in the sample owning and not owning a mobile phone

	2012	**2019**
Non-ownership	877 (23%)	58 (2%)
Ownership	2,941 (77%)	3.760(98%)
Total	3,818	3,818

Source: BIHS 2011/12 and 2018/19. Note: Calculated by authors.

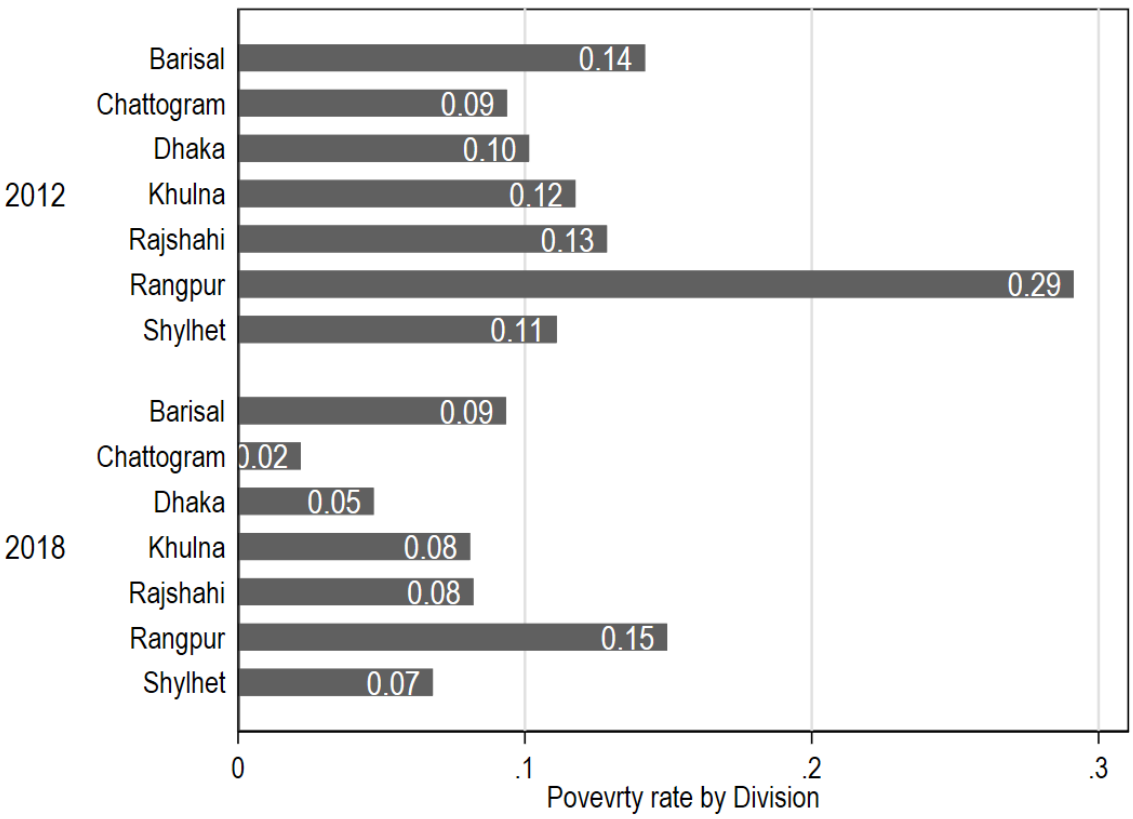

Figure 2 Poverty rate of Division by year

Source: BIHS2011/12 and 2018/19. Note: Calculated by authors.

2.2 Measurement of key variables

Our main explanatory variable of interest is mobile phone ownership[3]. We consider a household to be a mobile phone owner if at least one adult household member owns a mobile phone during a particular survey year. Mobile phone ownership is captured through a binary variable at the household level.

In terms of outcome variables, we are particularly interested in income diversification, measures of monetary and non-monetary poverty. Moreover, we introduce an income

[3] Due to the data availability, we cannot distinguish mobile phones with or without internet access. They include cellular phones and smartphones.

diversification index that is transformed from the Simpson index usually used to indicate the degree of diversity (Asfaw et al., 2019; Matsuura, Luh, & Islam, 2023)

$$Simpson = 1 - \sum_{k=1}^{n} \left[\frac{s_k}{S}\right]^2$$

where s_k is income for income k, and S is total income. A highly diversified household has an index close to 1, while a fully specialized one has an index of 0. We divide 12-month income sources into farm income, farm wage, non-farm wage, non-farm self-employment, and non-earned income including remittance and social network program transfer, etc., following Khandker (2012). Table 2 shows the breakdown of each income source of households. It indicates that the share of non-farm income including non-farm wage, and non-farm self-employment is more than 50% of the total income of households. For monetary indicators of poverty, we use two measures from the Foster-Greer-Thorbecke (FGT) class of poverty indicators (Foster et al., 1984), namely the poverty headcount and poverty gap measure. Let be $x = (x_1, x_2, \dots, x_n)$ the income distribution among n households, where $x_i \geq 0$ is the income of the household i. The poverty line is denoted by z ($1.90 per person per day). For any income distribution, household i is poor if $x_i < z$. The normalized deprivation of household i who is poor with respect to z is given by the relative shortfall from the poverty line:

$$d_i^{\alpha} = \left(\frac{z - x_i}{z}\right)^{\alpha}$$

where α is a parameter. When $\alpha = 0$, we get the incidence or headcount measure of poverty since the normalized deprivation is always set equal to 1 for all of the poor. When $\alpha =$

1, normalized deprivation reflects the poverty gap or depth of poverty, with a higher value of d_i being assigned to poorer households. We used the US$1.90/per person per day international poverty line, which is the standard for low-income countries (World Bank, 2020)[4]. The normalized deprivation score for the rich, i.e., those whose income weakly exceeds z, is set equal to 0 (Tauseef, 2022).

To capture a more holistic view of household wellbeing, we further look at non-monetary aspects of deprivation such as education, health, and living standards. We used the Alkire and Foster (AF) counting approach to construct a multidimensional poverty index (MPI) score which is similar to the global MPI published by the Oxford Poverty and Human Development Initiative (OPHI) and adopted by the United Nations Development Program (UNDP) (Alkire et al., 2018). The MPI score is calculated using three dimensions of welfare which includes health, education, and living standards. The indicators used for health are the nutrition status of the household members and dietary diversity in the household, for education, years of schooling of household members and school attendance for school-aged children, and for living standards, cooking fuel, sanitation, drinking water, electricity, housing condition, and assets[5]. Table A 2 shows the description and dimensions of MPI score.

[4] Bangladesh was a low-income country in 2011/12 when the first round survey was conducted.
[5] The dataset is available at https://www.ifpri.org/blog/ifpris-bangladesh-integrated-household-survey-bihs-second-round-dataset-now-available.

Table 2 Breakdown of household income

	2011/12					2018/19				
Income sources	MP ownership		Non-ownership		Dif	MP ownership		Non-ownership		Dif
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Farm self-income (taka)	23,955	89,814	12,730	34,032	***	44,765	368,607	13,252	35,186	
Farm wage (taka)	7,049	22,072	14,323	24,506	***	10,835	44,919	7,003	25,774	
Off-farm self-income (taka)	61,044	97,809	33,038	42,920	***	96,007	123,689	40,198	55,814	***
Off-farm wage (taka)	13,728	33,609	9,332	29,345	***	29,741	71,833	11,079	34,585	**
Non-earned (taka)	7,620	120,845	2,278	16,690		4,441	22,669	2,277	7,911	

Source: BIHS 2011/12 and 2018/19.

Note: Calculation by authors. Taka is a nominal value and the currency of Bangladesh. Mean values are shown with standard deviations in parentheses. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level of the results of t-test detecting the difference between ownership and non-ownership.

2.3 Conceptual framework

Mobile phones have a function to reduce the transaction costs and improve communication with potential employers and business partners and provide better access to relevant market information (Leng, Ma , Tang, & Zhu, 2020; Rajkhowa & Qaim, 2022). As a result, households have more options to diversify their income sources, which reduces poverty, indicating improving household welfare. The conceptual model is specified as

$$W = f(D(M, \boldsymbol{X}), \boldsymbol{X}; \boldsymbol{Z}) \tag{1}$$

Where W is poverty status of households, D is decision of income diversification, M is the mobile phone ownership, $\boldsymbol{X}$ is the vector of covariates, and $\boldsymbol{Z}$ is the vector of unobserved characteristics. The impact of mobile phone ownership and income diversification are described as follows:

$$\frac{\partial f(D(M, \boldsymbol{X}), \boldsymbol{X}; \boldsymbol{Z})}{\partial D} < 0 \tag{2}$$

Mobile phones are hypothesized to affect income diversification decisions, denoted by $D(M, \boldsymbol{X})$, as Leng, Ma , Tang, & Zhu (2020) show that ICT adoption enhances income diversification. In our conceptual framework, income diversification plays a role in "push" factors that reduce transaction cost at labor market and uncertainties of agricultural marketing (Leng, Ma , Tang, & Zhu, 2020). We thus hypothesize $\frac{\partial W}{\partial D} < 0$ in Equation (2). The conceptual framework is also depicted in Figure 3.

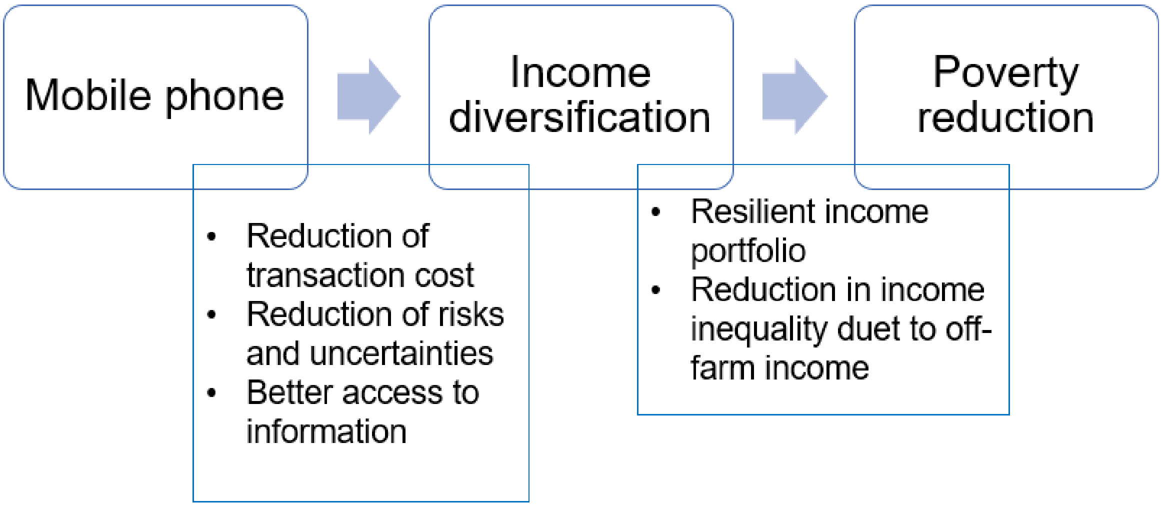

Figure 3 Conceptual framework
Source: Authors' design

2.4 Empirical strategy

2.4.1. Association among mobile phone ownership, income diversification, and poverty

Given the above preliminaries, we estimate the following panel data models to examine the effect of mobile phone ownership on income diversification and household poverty:

$$ID_{it} = \beta_o + \beta_1 M_{it} + \beta_2 X_{it} + a_i + t_t + \varepsilon_{it} \tag{1}$$

$$Y_{it} = \gamma_o + \gamma_1 M_{it} + \gamma_2 X_{it} + a_i + t_t + \varepsilon_{it} \tag{2}$$

where ID_{it} is income diversification and each income source shown in Table 2, Y_{it} is the outcome variables we use are, namely poverty headcount, depth of poverty, and MPI score, and estimate a regression for each of them. X_{it} presents covariate such as household characteristics. a_i and t_t are household Fixed Effect (FE) and year FE, respectively. ε_{it} is an error term. Both Equation (1) and (2) are estimated by Fixed Effect OLS. We are particularly interested in the estimates for β_1 and γ_1. For β_1, positive and significant estimates would imply that mobile phone ownership significantly accelerates the income diversification, after controlling other factors that are included in the vector X_{it} while negative γ_1 would imply that mobile phone ownership significantly reduces the monetary and non-monetary poverty. In the regression analysis, we do not differentiate between farm households and non-farm households, but we control the farmland size, as this may influence the likelihood of employment opportunities (Rajkhowa & Qaim, 2022).

Moreover, mobile phones can be negatively associated with poverty through various mechanisms, of which income diversification is a path. Mobile phone expansion is associated with farm incomes, off-farm income, and non-earned income (Aker & Ksoll, 2016; Fu & Akter, 2016; Rajkhowa & Qaim, 2022). To assess whether income diversification is a relevant mechanism and which income sources play an important role, we additionally estimate the following model:

$$Y_{it} = \theta_o + \theta_1 M_{it} + \theta_2 ID_{it} + \theta_3 X_{it} + a_i + t_t + \varepsilon_{it} \tag{3}$$

In this regression, θ_2 should be negative and significant when ID_{it} is the income diversification index, which would mean that income diversification reduces monetary and non-monetary poverty. Comparing the estimates in Equation (2) and (3), $|\theta_1| < |\gamma_1|$ would support our hypothesis that mobile phones are negatively associated with monetary and non-monetary poverty at least partly through the income diversification mechanism.

The main variable of interest, mobile phone adoption, is itself a decision variable. Hence, it may be correlated with the error term in the outcome equation because of possible self-selection into mobile phone ownership. Rural households can decide on the adoption of mobile phones on their own, thus, unobserved factors and attributes would affect their decision making. Systematic differences among households might affect their decision, such as socioeconomic and demographic factors. Given these conditions, the fixed effects (FE) estimator is a better choice because it controls time-invariant unobserved heterogeneity (Cameron & Trivedi, 2005)[6].

We do not expect reverse causality to be a major issue in our context, as mobile phones are nowadays used widely even among the very poor households in rural Bangladesh, including households with and without income diversification and poverty status (Rajkhowa & Qaim, 2022). However, there is another concern about dynamic causal relationships between past treatment and current outcome (Imai & Kim, 2019). There are two important identification assumptions of fixed effects model; Past treatments do not directly influence current outcome, and past outcomes do not affect current treatment (Imai & Kim, 2019). Imai & Kim (2019)

6 To address the unobserved time-variant characteristics, instrumental variable (IV) approach can be used. However, the use of IV requires that IV affects an endogenous variable but do not affect outcome variables (Angrist et al.,1996). Based on economic literature on the important role of peer effect in the decision to adopt mobile phone, the instrumental variable used in some studies is the share of household owning mobile phones within a local community (Ma et al. 2020; Zheng, Zhou, & Rahut 2022). However, our falsification test cannot reject the null hypothesis of the exclusion restriction of the social network IV in Table A 1, violating the important condition for instrument validity. Hence, we do not use IV approach in this paper.

suggests that lagged outcomes can be included in an outcome equation to address the correlation between past outcomes and current treatment. Unfortunately, since we use only two round data, we cannot follow the reaonable test. We emphasize that our interpretation of empirical results are association rather than causality.

In a robustness check, we use a doubly robust (DR) method and Propensity Score Matching-Difference in Difference (PSM-DID) to further reduce potential bias due to time-varying differences between adopters and non-adopters of mobile phones. One potential source of endogeneity that neither the FE estimator, the DR, the PSM-DID can control reverse causality[7].

2.4.2. Heterogeneous associations

The association between mobile phone ownership and income diversification may change depending on household characteristics. Aside from the mean association evaluated with Equation (1), we also analyze heterogeneous associations with respect to some household characteristics, which are educational of household head, a place where they live, gender of gender, and distance to the nearest town. We estimate heterogeneous associations using FE models as follows:

$$ID_{it} = \alpha_o + \alpha_1 M_{it} + \alpha_2 X_{it} + \alpha_3 M_{it} \times H_{it} + a_i + t_t + \varepsilon_{it} \quad (4)$$

where H_{it} is one of the household characteristics mentioned that is interacted with M_{it}

[7] We conduct the PSM-DiD as follows. First, we match the observations from sub-samples of the two groups "obtained phones between the two waves" and "never own phones". After matching, we estimate an ordinary difference in differences so that we can account for unobserved time-invariant characteristics and observed characteristics.

(note that H_{it} is also included in X_{it}). The other variables are defined as above. We estimate separate models for each household characteristic of interest with a particular focus on the interaction term estimate α_3.

3. Results and discussion

3.1 Descriptive statistics

Table 3 shows the mean comparison of outcome variables between households who own a mobile phone and those who do not as well as test on the statistical significance of difference in mean between mobile phone owners and non-owners. We find that mobile phone owners are more likely to diversify income sources, have higher total household income as well as higher per capita income than non-owners. These observed differences are consistent with Sekabira & Qaim (2017); Rajkhowa & Qaim (2022). Furthermore, the incidence of poverty of households owning mobile phones is lower than households not owning mobile phones. At the same time, the poverty gap and MPI score of households not owning mobile phones are worse than mobile phone owners. The results are reasonable that non-poverty households can afford to own mobile phones and utilize them.

Moreover, Table 3 presents descriptive statistics for the socioeconomic characteristics that we use as explanatory variables in the econometric models, differentiating between mobile phone users and non-users. In most of the variables, we observe significant differences. Mobile phone owners are likely to be male, younger, have more family members, with better educated household head. Furthermore, households who own mobile phones have larger farmland than households not owning mobile phones. The description of the variables is shown in Table A 3. The covariates are chosen based on relevant literature such as Leng, Ma , Tang, & Zhu (2020); Rajkhowa & Qaim (2022); Fowowe (2023); Amber & Chichaibelu (2023).

Table 3 Summary statistics by MP ownership

	2011/12					2018/19				
Outcome Variables	MP ownership		Non-ownership			MP ownership		Non-ownership		
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Income diversification	0.444	0.273	0.408	0.268	***	0.407	0.261	0.278	0.267	***
Poverty headcount	8.637	28.095	26.910	44.374	***	6.702	25.009	6.897	25.561	
Poverty gap	1.316	5.505	4.979	10.686	***	0.867	4.242	0.831	4.575	
MPI score	38.131	17.486	55.118	16.342	***	27.326	15.293	40.310	13.118	***
Socioeconomic variables										
Female household head	0.154	0.361	0.141	0.349	***	0.182	0.386	0.483	0.504	***
Age of HH	44.200	13.267	43.926	13.539	***	47.566	12.847	55.5	13.6937	***
Household size	4.523	1.669	4.011	1.490	***	5.672	2.157	4.759	1.967	***
Schooling year of HH	3.917	4.089	1.725	2.941	***	3.787	4.076	1.276	2.441	***
Farm Size	116.497	169.791	65.269	104.016	***	104.142	143.890	71.836	116.991	*
Livestock ownership	0.929	0.256	0.921	0.269		0.246	0.431	0.172	0.381	
Distance to the nearest town	0.010	0.009	0.009	0.008		0.011	0.021	0.009	0.006	

Source: BIHS 2011/12 and 2018/19.

Note: Calculation by authors. Mean values are shown with standard deviations in parentheses. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level of the results of t-test detecting the difference between ownership and non-ownership. 100 decimals are equal to 0.4 ha. Table A 3 explains the description of the variables and units of them.

3.2 Association between mobile phone ownership and income diversification

Table 4 shows the regression results of Equation (1) from Section 2.3.2. First, we find that mobile phone ownership is positively and significantly associated with income diversification in Column (1). Ownership of mobile phone is associated with a 3.1% higher probability of income diversification[8]. It indicates that mobile phone ownership enriches an income portfolio of rural households for building livelihood resilience.

As Column (1) shows that mobile phone ownership increase income diversification, we decompose the relationship between mobile phone ownership and income diversification with five income sources. Column (2) shows that mobile phone ownership increases income of those in farm self-employment, i.e. income from agricultural production, while it decreases income of those in farm wage employment in Column (3). The result is similar to (Jensen, 2007). In general, non-farm sectors have higher wage than on-farm employment has. The plausible explanation is that rural people are more likely to have off-farm employment rather than on-farm employment, due to the better access to labor market information through using mobile phones. Furthermore, Column (4) and (5) show that mobile phone ownership increases off-farm income by both employment and self-employment. This is consistent with the findings of Rajkhowa & Qaim (2022). Non-earned income is also positively and significantly associated with mobile phone ownership. It indicates that mobile phone ownership increases non-earned income. The plausible explanation is that mobile phone expansion enables households to receive non-earned income easily (Lee, Morduch, Ravindran, Shonchoy, & Zaman, 2021).

To summarize, mobile phone ownership generally increases income diversification. Specifically, mobile phone ownerhsip increases income from on-farm self employment, off-farm self employment, off-farm employment, and non-earned. We hypothesize that the increase

[8] In Table 4, we use year-division interaction terms to control for possible unequal regional developments over time.

in such sources of income would reduce poverty. We test this hypothesis in the following section.

Table 4 Association between MP ownership and income diversification

	(1)	(2)	(3)	(4)	(5)	(6)
				Income source		
	Income diversification	Farm self	Farm wage	Off-farm self	Off-farm wage	Non-earned
MP ownership	0.031**	0.348*	-0.491**	0.431***	0.736***	0.613***
	(0.013)	(0.204)	(0.200)	(0.159)	(0.207)	(0.210)
Female household head	-0.152***	-1.170***	-1.584***	-2.830***	-1.648***	3.976***
	(0.016)	(0.258)	(0.200)	(0.227)	(0.267)	(0.270)
Age of HH	0.001	0.024***	-0.018**	0.014*	-0.003	0.039***
	(0.001)	(0.009)	(0.008)	(0.008)	(0.010)	(0.011)
Household size	0.007*	-0.106*	0.013	0.103**	0.106	-0.130*
	(0.004)	(0.062)	(0.049)	(0.049)	(0.071)	(0.070)
Schooling year of HH	0.001	0.024	-0.086**	-0.011	-0.009	0.050
	(0.003)	(0.048)	(0.035)	(0.039)	(0.047)	(0.047)
Farm Size(decimal)	0.000***	0.010***	-0.003***	0.005***	-0.001	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Livestock ownership (=1)	0.036***	0.749***	-0.331**	0.784***	0.096	0.180
	(0.010)	(0.182)	(0.148)	(0.119)	(0.178)	(0.194)
Distance to nearest town (km)	-0.437***	-2.191	-7.398***	1.093	-3.820	9.469**
	(0.157)	(5.821)	(2.550)	(2.391)	(3.843)	(4.293)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,582	7,636	7,636	7,636	7,636	7,636

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. Outcome variables in from Column (2) to (6) are logarithm of income. Robust standard errors clustered by households in parenthesis.

3.3 Association between mobile phone ownership and household poverty

Table 5 presents the association between mobile phone ownership and poverty, estimated using a FE model to account for the endogeneity of mobile phone ownership. Mobile phone ownership decreases the prevalence of poverty as depicted by the statistically significant negative coefficient presented in Column (1). The probabilty of being poor decreased by 8.3% as a result of mobile phone ownership. The poverty reduction effect of mobile phone adoption is consistent with Asongu (2015). Moreover, Column (2) shows that mobile phone ownership reduces the depth of poverty as seen by the statistically significant negative impact on the poverty gap measure, decreasing 2.0% of poverty depth as seen in Column (3). The magnitude of the coefficients are similar to another setting by Beuermann et al., (2012). Furthermore, mobile phone ownership has an impact on non-monetary aspects of poverty, reducing the multidimensional poverty score by 7.9%, as seen in Column (4). The results, thus, indicate that mobile phone adoption not only contributes to reduction in monetary poverty but has a holistic impact on other non-monetary dimensions of poverty as well.

These significant associations may be channelled through higher resilience of income sources due to income diversification. Table 6 shows results of the channel analysis by additionally controlling income diversification. The first important result is that inocme diversification has a negative association with povery headcount in Column (1) while coefficients of income diversificatoin in Column (2) and (3) are insignificant. It indicates that income diversification reduces the probability of being poor. Moreover, an absolute value of the coefficient of mobile phone ownership in Column (1), which is $|\theta_1|$ in Equation (3), is smaller than the one in Column (1) of Table 5, which is $|\gamma_1|$ in Equation (2). The results confirm that mobile phone ownership is negatively associated with monetary poverty, at least partly through the income diversification mechanism, as hypothesized. Our results are consistent with the findings about welfare enhancing effects of mobile phones by Munyegera and Matsumoto (2016); Sekabira and Qaim (2017); Ma et al., (2018); Rajkhowa and Qaim (2022); and Miyajima (2022).

Furthermore, we investigate which income sources contribute to poverty reduction rather than just income diversification. In Column (4), income of farm self employment, off-farm self employment, non-earned are negatively associated with poverty headcount, indicating that they reduce the incidence of poverty. In column (5), income of farm self employment and non-earned are negatively associated with depth of poverty while off-farm self employment is significantly associated with MPI. The results confirm that a more detailed income diversification mechamism are related to farm self employment, off-farm self employment,and non-earned income.

Table 5 Association between MP ownership and poverty (FE model)

	(1) Poverty Headcount	(2) Depth of poverty	(3) MPI score
MP ownership	-8.343***	-1.967***	-5.845***
	(1.775)	(0.366)	(0.637)
Female household head	3.590**	0.727*	0.413
	(1.808)	(0.404)	(0.813)
Age of HH	-0.010	-0.000	0.059*
	(0.065)	(0.016)	(0.032)
Household size	3.435***	0.493***	1.063***
	(0.441)	(0.087)	(0.204)
Schooling year of HH	-0.417	-0.050	-0.350**
	(0.260)	(0.062)	(0.149)
Farm Size(decimal)	-0.012***	-0.002***	-0.003
	(0.004)	(0.001)	(0.003)
Livestock ownership (=1)	-0.252	-0.090	-1.458***
	(1.209)	(0.225)	(0.539)
Distance to the nearest town (km)	14.039	3.565	37.730***
	(15.333)	(2.879)	(7.207)
Individual FE	Yes	Yes	Yes
Year×Division FE	Yes	Yes	Yes
Observations	7,636	7,636	6,972

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. Robust standard errors clustered by households in parenthesis.

Table 6 Possible mechanisms underlying the effects of MP ownership on poverty (FE model)

	(1)	(2)	(3)
Panel A	Poverty Headcount	Depth of poverty	MPI score
Income diversification index	-4.066**	-0.531	-0.593
	(2.025)	(0.423)	(0.908)
MP ownership	-8.238***	-1.942***	-5.771***
	(1.776)	(0.368)	(0.640)
Individual FE	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	7,582	7,582	6,918
	(4)	(5)	(6)
Panel B	Poverty Headcount	Depth of poverty	MPI score
Farm self	-0.202*	-0.038*	-0.038
	(0.110)	(0.022)	(0.052)
Farm wage	0.480***	0.082**	0.084
	(0.169)	(0.034)	(0.066)
Off-farm self	-0.431**	-0.029	-0.217***
	(0.167)	(0.037)	(0.073)
Off-farm wage	-0.067	-0.004	-0.069
	(0.124)	(0.025)	(0.055)

Non-earned	-0.269***	-0.047***	-0.035
	(0.093)	(0.018)	(0.048)
MP ownership	-7.638***	-1.870***	-5.640***
	(1.765)	(0.367)	(0.641)
Individual FE	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	7,636	7,636	6,972

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. Robust standard errors clustered by households in parenthesis. Control variables used in regression models are gender of household head, age of household head, household size, schooling year of household head, farm size, livestock ownership, distance to the nearest town. A full regression table is available in

Variables	**Description of variables**
Outcome Variables	
Income diversification	Measured by income diversification index from 0 to 1
Poverty headcount	100 if household is poor, 0 otherwise
Poverty gap	Measures depth of poverty and takes 0 to 100
MPI score	Measures multidimensional poverty and takes 0 to 100
Socioeconomic variables	
Female household head	1 if households is female, 0 otherwise
Age of HH	Age of household head
Household size	Number of household member
Schooling year of HH	Years that household head attend a school
Farm Size	Farm size that household owns, and the unit is decimal
Livestock ownership	1 if household owns livestock, 0 otherwise

Distance to the nearest town	Distance to the nearest town from homestead (km)

Note: 100 decimal is equivalent to 0.4 ha

Table A 4 and Table A 5.

3.4 Who benefits more from mobile phones?

In this section, we disentangle the relationship between mobile phone ownership and characteristics of households to the outcome variables. Using the models explained in Equation (4) above, we interact mobile phone ownership with education of household head, place of residence, gender, and distance to the nearest town.

The results summarized in Table 7 show the estimated coefficients on the interaction between the household characteristics and mobile phone ownership. In Column (1), the coefficient of the interaction term for income diversification is negatively significant. It indicates that less educated households are more likely to engage in income diversification when the households own mobile phones. This is a welcome result that mobile phone ownership can enhance income diversification which improves livelihood, especially for less educated households.

Moreover, we find that households living in Rangpur Division, which is the poorest Division in Bangladesh (see Figure 2), benefit more from mobile phones than households in other Divisions as shown in Column (2). This highlights the potential of mobile phones in reducing geographical inequality and having a pro-poor effect. It is an encouraging finding from a social development perspective.

The coefficients for the interaction term between mobile phone ownership and female household head is insignificant. In column (4), we look at the role of distance to the nearest town, as it may be an alternative to mobile phones for accessing information on job opportunities. Note that a longer distance to a town indicates worse access to information. Contrary to our expectation, the coefficient of the interaction term between the distance and mobile phone ownership is statistically insignificant.

Table 7 Heterogeneous associations based on various household characteristics (summary results)

	(1) Income diversification	(2) Income diversification	(3) Income diversification	(4) Income diversification
MP ownership	0.052***	0.017	0.034**	0.031*
	(0.014)	(0.014)	(0.014)	(0.017)
Schooling year of HH×MP ownership	-0.012***			
	(0.004)			
Rangpur Division×MP ownership		0.113***		
		(0.037)		
Female of HH ×MP ownership			-0.016	
			(0.032)	
Distance to the nearest town ×MP ownership				0.025
				(1.171)
Household FE	Yes	Yes	Yes	Yes
Year×Division FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	7,582	7,582	7,582	7,582

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. Robust standard errors clustered by household in parenthesis. Control variables used in regression models are gender of household head, age of household head, household size, schooling year of household head, farm size, livestock ownership, distance to the nearest town. The full regression table is in Table A 6.

4. Robustness check

In this section, we carry a robustness check to see whether the results change when we use different estimation methods. We use the DR method and PSM-DID method instead of FE model to estimate the association among mobile phone ownership, income diversification, and poverty. The DR method, or more precisely, an inverse-probability weighted regression adjustment, combines the regression and propensity score weighting. It is more robust than the PSM estimator and the inverse-probability-weighting estimator (Mano et al., 2022). The PSM-DID overcomes limitations of PSM using cross-sectional data, which are systematic differences between mobile phone owners and non-owners even after controlling on household's observed characteristics (Imai & Azam, 2012). Table A 7 by the DR and Table A 8 by the PSM-DID show similar results to those in Table 4 and Table 5, but the association between mobile phone ownership and income diversification index is insignificant. It indicates that mobile phone ownership enhances off-farm income, farm income from self-employment, and non-earned income but reduces wage of on-farm employment, respectively. Because the income diversification index measures evenness of each income source, mobile phones ownership improves not evenness of income sources but portfolio of income sources for resilient livelihood. Overall, it underlines the robustness of our main results.

5. Conclusion and policy implication

Mobile phones have spread rapidly in the developing world and a similar trend is also observed in rural Bangladesh. While previous studies have analyzed effects of mobile phone ownership on economic indicators – such as input and output prices, profits, and income – research on implications for broader social development is scarce. Better understanding social welfare effects is of particular importance against the backdrop of the United Nations' Sustainable Development Goals (SDGs). This study is the first we use nationally representative panel data, spanning eight years of rural households in Bangladesh to analyze average and heterogeneous effects of mobile phone ownership on income diversification, poverty headcount, depth of poverty, and MPI.

Our results indicate that mobile phone ownership has a positive and statistically significant effect on income diversification. At the same time, it reduces the incidence and depth of poverty as well as non-monetary poverty as measured by MPI. The channel analysis confirms that mobile phones are significantly associated with poverty reduction through income diversification, decomposing the diversification into on-farm self-employment, off-farm self-employment, and non-earned income. Furthermore, our findings show that less educated households and households living in impoverished areas benefit over-proportionally from mobile phones, which are encouraging findings from development policy perspectives.

This study thus sheds new light on the importance of access to mobile technologies for the masses. We find that that mobile phones can increase opportunities generating income sources for less educated households and households in Rangpur in Bangladesh. Therefore, access to mobile technologies and networks for all households, even those in rural areas, can lower transaction costs and boost the effectiveness of the labor market. It would make up for the disadvantage of low human capital accumulation and geographical inequality. As a result, income diversification

The results from this study should not be widely generalized and need more rigorous estimation methods such as randomized controlled trials, but the rural households surveyed in rural Bangladesh are quite typical for the South Asian rural settings. Despite the setting of this study, some valuable lessons can be held for rural development in the digital age. Follow-up studies in other settings and with longer panel data and methodologies will surely be needed to corroborate our findings on rural development in digital age.

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Appendix tables

Table A 1 Test on the validity of the instruments

	(1) MP ownership	(2) Income diversification	(3) Poverty Headcount	(4) Depth of poverty	(5) MPI score
Share of households adopting mobile phone in the village	0.471***	-0.057	-9.104	-2.974*	-10.726***
	(0.042)	(0.051)	(7.496)	(1.710)	(3.008)
Year × Division FE	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	9,879	1,346	1,365	1,365	1,348

∗Significant at the 10% level; ∗∗Significant at the 5% level; ∗∗∗Significant at the 1% level. Parameters for all the other variables are not reported. The full table is available upon requests.

Table A 2 Dimensions, indicators, deprivation cut-offs and weights of the MPI

Dimensions of poverty	MPI indicator	Deprived if…	Weight
Health	Nutrition	Any person below the age of 70 is undernourished+	1/6
	Dietary diversity	Dietary diversity score++ is less than 42	1/6
Education	Years of schooling	No household member aged ten years or older has completed six years of schooling	1/6
	School attendance	Any school-aged child is not attending school up to the age at which he/she would complete class 8	1/6
Living standards	Cooking fuel	The household cooks with dung, wood, or charcoal	1/18
	Sanitation	The household's sanitation facility is not improved (according to SDG guidelines) or it is improved but shared with other households*	1/18
	Drinking water	The household does not have access to improved drinking water (according to SDG guidelines) **	1/18
	Electricity	The household has no electricity	1/18
	Housing condition	The household has inadequate housing: the floor is of natural materials, or the roof or wall are of rudimentary materials***	1/18
	Assets	The household does not own more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck	1/18

Source: Adopted by Tauseef (2022).

Notes: + Adults 20 to 70 years are considered malnourished if their Body Mass Index (BMI) is below 18.5 m/kg2. Those aged five to 20 are identified as malnourished if their age-specific BMI cut-off is below minus two standard deviations. Children under five years are considered malnourished if their z-score of either height-for-age (stunting) or weight-for-age (underweight) is below minus two standard deviations from the median of the World Health Organization 2006 reference population. ++ Measured using the food consumption score (FCS). The FCS is calculated as a weighted summation (out of 112) of the number of days a household has consumed a food group (staples, pulses, vegetables, fruits, meat/fish, milk, sugar, and oil) in the past seven days, where the weights reflect the differential nutritional benefit of each food group. * A household is considered to have access to improved sanitation if it has some type of flush toilet or latrine, or ventilated improved pit or composting toilet, provided that this is not shared. ** A household has access to clean drinking water if the water source is any of the following types: piped water, public tap, borehole, or pump, protected well, protected spring or rainwater purified before consumption. *** Deprived if the floor is made of mud/clay/earth, sand or dung; or if the dwelling has no roof or walls or if either the roof or walls are constructed using natural materials such as cane, palm/trunks, sod/mud, dirt, grass/reeds, thatch, bamboo, sticks, or rudimentary materials such as carton, plastic/ polythene sheeting, bamboo with mud/stone with mud, loosely packed stones, uncovered adobe, raw/reused wood, plywood, cardboard, unburnt brick or canvas/tent.

Table A 3 Description of variables used in this study.

Variables	Description of variables
Outcome Variables	
Income diversification	Measured by income diversification index from 0 to 1
Poverty headcount	100 if household is poor, 0 otherwise
Poverty gap	Measures depth of poverty and takes 0 to 100
MPI score	Measures multidimensional poverty and takes 0 to 100
Socioeconomic variables	
Female household head	1 if households is female, 0 otherwise
Age of HH	Age of household head
Household size	Number of household member
Schooling year of HH	Years that household head attend a school
Farm Size	Farm size that household owns, and the unit is decimal
Livestock ownership	1 if household owns livestock, 0 otherwise
Distance to the nearest town	Distance to the nearest town from homestead (km)

Note: 100 decimal is equivalent to 0.4 ha

Table A 4 Possible mechanisms underlying the effects of MP ownership and income diversification on poverty (FE-models)

	(1) Poverty Headcount	(2) Depth of poverty	(3) MPI score
Income diversification index	-4.066**	-0.531	-0.593
	(2.025)	(0.423)	(0.908)
MP ownership	-8.238***	-1.942***	-5.771***
	(1.776)	(0.368)	(0.640)
Female household head	3.068*	0.687*	0.416
	(1.861)	(0.417)	(0.839)
Age of HH	-0.002	-0.001	0.056*
	(0.065)	(0.016)	(0.032)
Household size	3.475***	0.497***	1.081***
	(0.443)	(0.088)	(0.204)
Schooling year of HH	-0.449*	-0.058	-0.350**
	(0.260)	(0.062)	(0.149)
Farm Size (decimal)	-0.011**	-0.002**	-0.004
	(0.005)	(0.001)	(0.003)
Livestock ownership (=1)	-0.146	-0.089	-1.436***
	(1.214)	(0.225)	(0.542)
Distance to the nearest town (km)	12.964	3.540	37.317***
	(15.027)	(2.823)	(7.222)
Household FE	Yes	Yes	Yes
Year×Division FE	Yes	Yes	Yes
Observations	7,582	7,582	6,918

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. Robust standard errors clustered by households in parenthesis.

Table A 5 Possible mechanisms underlying the effects of MP ownership and income sources on poverty (FE-models)

	(1) Poverty Headcount	(2) Depth of poverty	(3) MPI score
Farm self	-0.202*	-0.038*	-0.038
	(0.110)	(0.022)	(0.052)
Farm wage	0.480***	0.082**	0.084
	(0.169)	(0.034)	(0.066)
Off-farm self	-0.431**	-0.029	-0.217***
	(0.167)	(0.037)	(0.073)
Off-farm wage and salary	-0.067	-0.004	-0.069
	(0.124)	(0.025)	(0.055)
Non-earned	-0.269***	-0.047***	-0.035
	(0.093)	(0.018)	(0.048)
MP ownership	-7.638***	-1.870***	-5.640***
	(1.765)	(0.367)	(0.641)
Female household head	3.853**	0.911**	-0.109
	(1.912)	(0.421)	(0.864)
Age of HH	0.021	0.004	0.064**
	(0.065)	(0.016)	(0.032)
Household size	3.424***	0.485***	1.098***
	(0.439)	(0.087)	(0.204)
Schooling year of HH	-0.362	-0.040	-0.343**
	(0.264)	(0.062)	(0.149)
Farm Size(decimal)	-0.006	-0.002*	-0.002
	(0.005)	(0.001)	(0.003)
Livestock ownership (=1)	0.451	-0.003	-1.209**
	(1.206)	(0.226)	(0.542)
Distance to nearest town (km)	19.912	4.551	38.692***
	(14.577)	(2.799)	(7.302)
Household FE	Yes	Yes	Yes
Year×Division FE	Yes	Yes	Yes
Observations	7,636	7,636	6,972

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. Robust standard errors clustered by households in parenthesis.

Table A 6 Heterogeneous associations based on various household characteristics (FE-models)

	(1)	(2)	(3)	(4)
	Income diversification	Income diversification	Income diversification	Income diversification
MP ownership	0.052***	0.017	0.034**	0.031*
	(0.014)	(0.014)	(0.014)	(0.017)
Schooling year of HH×MP ownership	-0.012***			
	(0.004)			
Rangpur Division×MP ownership		0.113***		
		(0.037)		
Female of HH ×MP ownership			-0.016	
			(0.032)	
Distance to the nearest town ×MP ownership				0.025
				(1.171)
Female household head	-0.152***	-0.153***	-0.138***	-0.152***
	(0.016)	(0.016)	(0.032)	(0.016)
Age of HH	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Household size	0.007*	0.007*	0.007*	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Schooling year of HH	0.013***	0.001	0.001	0.001
	(0.004)	(0.003)	(0.003)	(0.003)
Farm Size(decimal)	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)

Livestock ownership (=1)	0.035***	0.037***	0.036***	0.036***
	(0.010)	(0.010)	(0.010)	(0.010)
Distance to nearest town (km)	-0.367**	-0.488***	-0.440***	-0.461
	(0.153)	(0.163)	(0.157)	(1.158)
Household FE	Yes	Yes	Yes	Yes
Year×Division FE	Yes	Yes	Yes	Yes
Observations	7,582	7,582	7,582	7,582

Note: ∗Significant at the 10% level; ∗∗Significant at the 5% level; ∗∗∗Significant at the 1% level. Robust standard errors clustered by households in parenthesis.

Table A 7 Mobile phone ownership, income diversification, and poverty (Doubly robust estimator)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Income diversification	Farm self	Farm wage	Off-farm self	Off-farm wage	Non-earned	Poverty headcount	Depth of poverty	MPI
ATE									
MP ownership	0.057***	0.376	-0.645**	0.898***	0.702***	0.934***	-5.425***	-1.258***	-10.569***
	(0.022)	(0.254)	(0.253)	(0.247)	(0.200)	(0.275)	(1.743)	(0.454)	(1.010)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,608	6,795	6,795	6,795	6,795	6,795	7,635	7,635	7,302

Note: ∗Significant at the 10% level; ∗∗Significant at the 5% level; ∗∗∗Significant at the 1% level. Robust standard errors clustered by households in parenthesis. Control variables used in regression models are gender of household head, age of household head, household size, schooling year of household head, farm size, livestock ownership, distance to the nearest town. Outcome variables in from Column (2) to (6) are logarithm of income.

Table A 8 Mobile phone ownership, income diversification, and poverty (PSM-DID)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Income diversification	Farm self	Farm wage	Off-farm self	Off-farm wage	Non-earned	Poverty Headcount	Depth of poverty	MPI score
DID (MP ownership×2018)	0.016	0.884***	-0.987***	1.333***	0.948***	3.740***	-14.887***	-3.569***	-20.101***
	(0.011)	(0.170)	(0.174)	(0.150)	(0.175)	(0.169)	(1.621)	(0.363)	(0.535)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,084	2,122	2,122	2,122	2,122	2,122	2,122	2,122	2,022

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. Robust standard errors clustered by households in parenthesis. Control variables used in regression models are gender of household head, age of household head, household size, schooling year of household head, farm size, livestock ownership, distance to the nearest town. Outcome variables in from Column (2) to (6) are logarithm of income. A common support condition is imposed by dropping treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls.