Abstract

In developing nations, the widespread adoption of mobile phones presents the possibility of creating employment and self-employment opportunities. Although several studies have documented the impact of mobile phones on income, the link between mobile phone ownership, income diversification, and poverty reduction has not been fully explored. This paper aims to examine this relationship using nationally representative panel data and fixed effect models to account for confounding factors and unobserved heterogeneity. Results indicate that mobile phone ownership is associated with increased income diversification, particularly through on-farm and off-farm self-employment, as well as non-earned income. This relationship is more pronounced in households with lower levels of education and in deprived areas. In addition, owning a mobile phone is also found to decrease poverty via income diversification. Therefore, policies aimed at enhancing access to mobile technologies could create resilient income portfolio by decreasing transaction costs and improving market efficiency, ultimately mitigating poverty in rural regions.

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

JEL code: C23, I32, Q12

1. Introduction

In developing nations, the widespread adoption of mobile phones (MPs) has played a significant role in fostering economic development. Bangladesh, in particular, has witnessed a substantial increase in mobile phone subscriptions. According to Figure A 1 from the World Bank (2023), the mobile phone subscription rate is projected to reach nearly 100% in 2019, a notable leap from the less than 50% recorded in 2010. The anticipation is that mobile technologies will spearhead economic growth by enhancing productivity and efficiency across various sectors of the economy. For example, mobile phone ownership is positively associated with the likelihood of participating in some types of off-farm work by reducing transaction costs (Rajkhowa & Qaim, 2022) and can generate income opportunities by supporting labor market participation, expanding social networks and reducing household exposure to risk (Aker & Mbiti, 2010). It also improves smallholder farmers' productivity by providing access to critical information on weather, farming techniques, and market prices (Sekabira & Qaim, 2017; GSM Association, 2021; Zheng & Ma, 2021). Furthermore, mobile platforms lead to human capital development by enabling remote delivery of academic lessons, reading materials and knowledge dissemination (Asongu & Nwachukwu, 2016; GSM Association, 2021).

Little is known about whether mobile phone ownership increases income diversification, which is a possible economic channel for alleviating poverty and vulnerability (Yang et al., 2023). Rural households in developing nations frequently rely on agriculture as their primary source of livelihood. However, the vulnerability of agricultural income to fluctuations in prices and weather conditions may prompt many to seek supplementary income through off-farm economic activities. Limited access to farmland can also drive participation in such activities. Off-farm employment in rural areas is typically informal and temporary. The pursuit of such opportunities can be hindered by high transaction costs, acting as a constraint for some households looking to engage in off-farm employment. The growing ownership of mobile phones has the potential to alleviate these transaction costs. It is thus important to recognize the significance of mobile technology and investigate the relationship between mobile phone ownership, income diversification, and poverty reduction to draw critical policy implications, particularly for developing nations.

In this paper, we examine how owning a mobile phone in rural Bangladesh influences income diversification and contributes to reducing poverty, considering both monetary and non-monetary dimensions of poverty. Furthermore, in addition to examining the overall average effect of mobile phone ownership, we explore heterogeneity of associations with respect to household head, educational level and geographical location. We employed a recently collected nationally representative panel dataset of rural households in Bangladesh spanning eight years from 2011 to 2019.

A substantial amount of literature exists on the relationship between household welfare and ownership of mobile phones. Numerous studies have identified a positive correlation between ownership and usage of mobile phones and household welfare including income and consumption i.e. mobile phone ownership increases household income (Asongu S., 2015; Ma et al., 2018; Miyajima, 2022; Munyegera & Matsumoto , 2016; Rajkhowa & Qaim, 2022; Sekabira & Qaim, 2017; Matsuura, et al., 2023A). However, less is known on the effect of mobile phone ownership on income diversification. To the best of our knowledge, only Leng et al. (2020), Ma et al. (2020), and Rajkhowa and Qaim (2022) have examined the effects of mobile phone usage or adoption of ICT on income diversification or off-farm employment. Moreover, the effects of mobile phone ownership on both monetary and non-monetary poverty have been documented, but the mechanism behind income diversification and the heterogeneous effect of mobile phone ownershps on poverty remains unclear.

The paper has three main contributions. One, it presents the first empirical micro-econometric evidence on how ownership of mobile phone affects both income diversification and poverty in the rural Bangladesh. It examines the implications of these findings for policymakers. Two, it uses a new nationally representative panel household dataset, which enables the control of time-invariant unobserved heterogeneity at a household level, to produce robust evidence in a South Asian context. Three, we examine the heterogeneous impact of mobile phone ownership, specifically related to human capital, geographic inequality, and gender. Interaction terms are utilized in the regression specifications to determine which groups benefit the most from owning mobile phones, yielding more appropriate policy recommendations.

The findings indicate that mobile phone ownership enhances income diversification as well as alleviates both monetary and non-monetary poverty. There is a positive association of mobile phone ownership with farm income, off-farm self-employment income, off-farm employment income and non-earned income. Increases in farm income, off-farm self-employment income, and non-earned income are found to play a role in reducing income poverty while off-farm self-employment income is observed to reduce non-monetary poverty. Furthermore, analyses of heterogeneity reveal that households with a less educated head and those situated in relatively impoverished regions derive particular benefits from mobile phones. The findings thus indicate that mobile phone ownership by rural households is a means of diversifying income and improve the overall welfare of the rural community.

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

2. Conceptual framework

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Mobile phones have the potential to reduce transaction costs and improve communication with potential employers and business partners as well as provide better access to helpful market information (Leng, et al., 2020; Rajkhowa & Qaim, 2022; Nie, et al., 2020; Zheng & Ma, 2021). As a result, households have more options to diversify their income sources including on-farm and off-farm jobs, which reduces poverty and thus improves household welfare. The conceptual model is specified as follows:

$$W = f(D(MP, \boldsymbol{X}), \boldsymbol{X}; \boldsymbol{Z})$$

where W is poverty status of households, D is decision of income diversification, MP is the mobile phone ownership, $\boldsymbol{X}$ is the vector of covariates, and $\boldsymbol{Z}$ is the vector of unobserved characteristics. The covariates include sex of a household head, age of the household head, a household size, education level of the household head, size of farmland held by the household, livestock ownership, and an access to the nearest town (Ma, et al., 2021; Rajkhowa & Qaim, 2022; Zhuo, et al., 2023; Matsuura, et al., 2023A). Therefore, the impact of mobile phone ownership and income diversification is described as follows:

$$\frac{\partial f(D(MP, \boldsymbol{X}), \boldsymbol{X}; \boldsymbol{Z})}{\partial D} < 0 \ (1)$$

Mobile phones are hypothesized to influence income diversification decisions, denoted by $D(MP, \boldsymbol{X})$, similar to Leng, et al., (2020) who 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, risks and uncertainties of agricultural marketing (Leng, et al., 2020; Barrett, et al., 2001). We thus hypothesize $\frac{\partial W}{\partial D} < 0$ in Equation (1). The conceptual framework is also depicted in Figure 1. The flow from mobile phone to income diversification in Figure 1 presents $D(MP, \boldsymbol{X})$ which suggests that mobile phone affect decision of income diversification. Income diversification would be enhanced by reduction of transaction cost and risks and uncertainties on agricultural and labor market, and better access to information (Barrett, et al., 2001; Aker & Mbiti, 2010; Leng, et al., 2020). The arrow from income diversification to poverty reduction in Figure 1 describe that income diversification induce poverty reduction, meaning $\frac{\partial W}{\partial D} < 0$. Higher and more resilient income will likely result in reduce incidence of poverty, depth of poverty, and non-monetary poverty (Asfaw, et al., 2019; Asongu, 2015). Thus, it will improve household welfare (Matsuura, et al., 2023B; Mishra, et al., 2015).

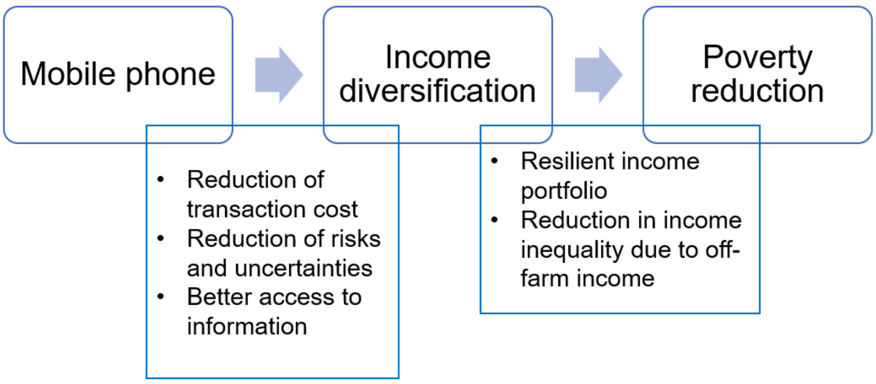

Figure 1 Conceptual framework
Source: Authors' design

3. Materials and methods

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3.1. Data

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We use data from a nationally representative household panel survey conducted in 2011/12 and 2019 titled the Bangladesh Integrated Household Survey (BIHS) designed and supervised by the International Food Policy Research Institute (IFPRI). The sample is representative of rural Bangladesh as well as of the seven division of the country (Islam et al., 2018; Ahmed & Tauseef, 2022). The sample design of the BIHS follows a two-stage stratified sampling procedure. Following the community series of the 2001 Population and Housing Census of Bangladesh, 325 villages were randomly selected in the first stage and constituted as the primary sampling units (PSUs). Then, from each PSU, 20 households were selected at random for the second stage (Ahmed & Tauseef, 2022). The original sample size in the 2011/12 wave was 6503 households in 325 PSUs allocated among seven divisions while the sample size in the 2019 wave was 5604 households. For this study, we use the balanced subsample of rural households which were interviewed in both survey rounds, resulting in 7,636 observations from 3,818 households as shown in Table and 2[1]. Since our analysis uses panel data, our estimates would be biased if the attrition is related to some household characteristics. However, Ahmed & Tauseef (2022) shows that the attrition between 2011/12 and 2019 were random. Therefore, the estimates presented in this paper are not adjusted for attrition.

3.2. Measurement of key variables

The main explanatory variable of interest in our analyses is mobile phone ownership[2]. We consider a household to be a mobile phone owner if at least one household member owns a mobile phone during a survey year. We construct a dummy variable of mobile phone ownership at the household level which is equal to 1 if household owns a mobile phone and 0 otherwise.

With respect to outcome variables, we are particularly interested in income diversification and measures of monetary and non-monetary poverty. Moreover, we introduce an income diversification index that is derived from the Simpson index, usually used to indicate the degree of diversity (Asfaw et al., 2019; Matsuura, et al., 2023B), as shown below:

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

[1] 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.

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

where s_k is income for income k, and S is total income. The index range from [0,1] with higher values indicating a more diversified household, while a fully specialized household would have a value of 0. We divide 12-monthly income sources into categories of farm income, farm wage, non-farm wage, non-farm self-employment, and non-earned income which includes remittance and social network program transfer, etc., following Khandker (2012). エラー! 参照元が見つかりません。 shows the breakdown of the household income sources by mobile phone ownership. Results indicate 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.

Our second outcome of interest, namely monetary indicators of poverty, constitutes of two indicators derived from the FGT class of poverty measures (Foster et al., 1984), i.e. the poverty headcount and poverty gap measure. The measures are defined in the following manner: Let $s = (s_1, s_2, \ldots, s_n)$ be the income distribution among n households, where $s_i \geq 0$ is the income of the household i. The poverty line is denoted by z ($1.90 per person per day). The household i is poor if $s_i < z$. The normalized deprivation of household i who is poor with respect to z is given by the relative shortfall from the poverty line:

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

where α is a parameter. When $\alpha = 0$, we get the incidence or headcount rate of poverty since the normalized deprivation is always set equal to 1 for all the poor. When $\alpha = 1$, the 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, converted to local currency (Bangladesh *Taka*) using the 2011 Purchasing Power Parity (PPP) exchange rates

(World Bank, 2020)[3]. The normalized deprivation score for the rich, i.e., those whose income weakly exceeds z, is set equal to 0 (Tauseef, 2022).

To obtain a more comprehensive understanding of household wellbeing, we additionally consider non-monetary dimensions of deprivation, such as education, health, and living standards. We use the Alkire and Foster (AF) counting approach to construct a multidimensional poverty index (MPI) 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[4]. Table A 2 shows the dimensions of the MPI as well as the detailed definition of the indicators included in each dimension.

[3] Bangladesh was a low-income country in 2011/12, when the first round of survey was conducted.
[4] The dataset is available at https://www.ifpri.org/blog/ifpris-bangladesh-integrated-household-survey-bihs-second-round-dataset-now-available. For more details on index construction see Alkire et al. (2018) or Tauseef (2022).

Table 1 Breakdown of household income

	2011/12					2019				
	MP ownership		Non-ownership		Diff	MP ownership		Non-ownership		Diff
Income sources	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	
Total household income (taka)	162,925	228,462	87,483	78,000	***	260,705	452,964	103,738	103,025	***

Source: BIHS 2011/12 and 2019.

Note: Calculation by authors based on a balanced panel. Taka is a nominal value and the currency of Bangladesh. Mean values are shown along with standard deviations (SD). Diff is the results of t-tests on the equality of means of mobile phone ownership and non-ownership. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

Table 2 shows the number of households owning and not owning mobile phones in our sample. In 2011/12, about 23% of households in our sample did not own a mobile phone which dropped to 2% in 2019, indicating wide adoption of mobile phone in rural Bangladesh over this period. Over the same period, prevalence of poverty in our sample, calculated using the FGT measure and $1.90 per person per day poverty line, decreased from 13% in 2011/12 to about 7% in 2019, as shown in Figure 12. Considerable regional hetergeniety exists in the rate of poverty with Rangpur Division having the highest poverty rate compared to the other six divisions, which is consistent with trends seen in national statistices (see for e.g. BBS (2023)). In the subsection 3.4, we examine the geographical hetergeniety of the effect of mobile phone ownership on economic resilience through income diversification, especially in the poorest division, Rangpur. Further descriptive statistics of the whole sample are presented in Table 1.

コメントの追加 [ST4]: BBS (Bangladesh Bureau of Statistics) (2023). "*Report on the Household Income and Expenditure Survey 2022*". Bangladesh Bureau of Statistics, Statistics Division, Ministry of Planning, Government of the People's Republic of Bangladesh, Dhaka.

Table 2 Number of households by mobile phone ownership

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

Note: Authors' calculations from BIHS 2011/12 and 2019.

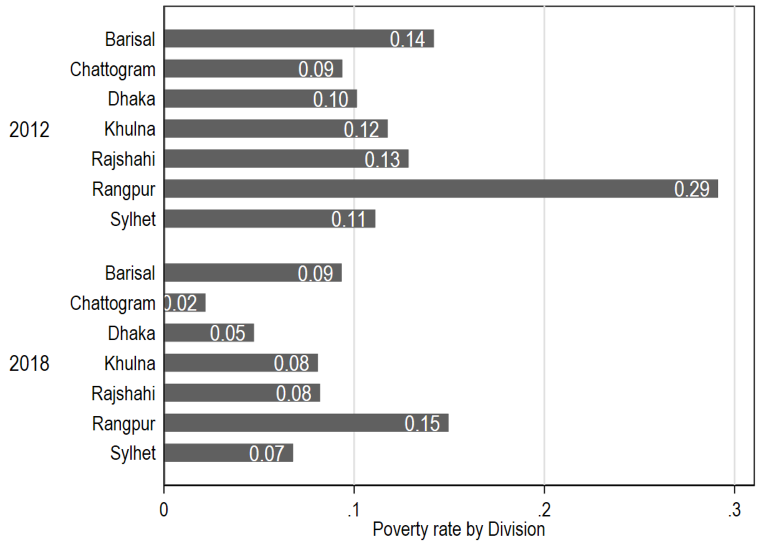

Figure 1 Poverty rate of Division by year

Note: Authors' calculations from BIHS 2011/12 and 2019. The poverty rate is estimated as stated in sub-section 2.2.

3.3. Empirical strategy

3.3.1. 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:

$$D_{it} = \beta_o + \beta_1 MP_{it} + \beta_2 X_{it} + a_i + t_t + \varepsilon_{it} \ (2)$$

$$Y_{it} = \gamma_o + \gamma_1 MP_{it} + \gamma_2 X_{it} + a_i + t_t + \varepsilon_{it} \ (3)$$

where D_{it} is the income diversification index (Simpson index) derived from each income source shown in Table 1; Y_{it} denotes is the outcome variables, namely poverty headcount, depth of poverty, and MPI score which are estimated in separate specifications; X_{it} a vector of controls which includes household characteristics; a_i and t_t are household and year fixed effects (FE), respectively; and ε_{it} is an error term. Both Equation (2) and (3) are estimated by ordinary least squares (OLS) methodology with FE. We are particularly interested in the coefficients for mobile phone ownership i.e. the estimates for β_1 and γ_1. For β_1, a positive and statistically significant coefficient would imply that mobile phone ownership significantly accelerates income diversification, while negative γ_1 would imply that mobile phone ownership significantly reduces the monetary and non-monetary poverty, after controlling for other factors included in the vector X_{it}. In the regression analysis, we do not differentiate between farm households and non-farm households, but we include a control farmland size, as this may influence the likelihood of employment opportunities (Rajkhowa & Qaim, 2022).

Moreover, mobile phones ownership 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:

$$Y_{it} = \theta_o + \theta_1 MP_{it} + \theta_2 D_{it} + \theta_3 X_{it} + a_i + t_t + \varepsilon_{it} \quad (4)$$

In this regression, θ_2 should be negative and statistically significant when D_{it} is the income diversification index, which would imply that income diversification reduces monetary and non-monetary poverty. Comparing the estimates in Equation (3) and (4), $|\theta_1| < |\gamma_1|$ would support our hypothesis, which 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 ownership, 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 due to socioeconomic and demographic factors may affect their decision. Given these conditions, the fixed effects estimator is a better choice because it controls time-invariant unobserved heterogeneity (Cameron & Trivedi, 2005)[5].

We do not consider 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 affect current outcome, and past outcomes do not influence current treatment (Imai & Kim, 2019). Imai & Kim (2019) 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 rounds of data, we cannot follow the reasonable test. We emphasize that our interpretation of the empirical results are associations rather than causality.

In robustness checks, we employ a doubly robust (DR) method and Propensity Score Matching combined with 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, nor the PSM-DID can control is reverse causality[6].

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[5] 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 et al., 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.

[6] 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”. In this matching, we assume common support, which there is enough similarity between the traits of treated and untreated units to establish suitable matches. After matching, we estimate an ordinary difference in differences so that we can account for unobserved time-invariant characteristics and observed characteristics.

3.3.2. Heterogeneous associations

The association between mobile phone ownership and income diversification may vary depending on household characteristics. Aside from the average association evaluated with Equation (2), we also analyze heterogeneous associations with respect to some household characteristics, namely, education of household head, location of residence, gender of household head, and distance to the nearest town. We estimate heterogeneous associations using a FE model as follows:

$$D_{it} = \eta_o + \eta_1 MP_{it} + \eta_2 X_{it} + \eta_3 MP_{it} \times H_{it} + a_i + t_t + \varepsilon_{it} \quad (5)$$

where H_{it} is one of the household characteristics mentioned which is interacted with M_{it} (note that H_{it} is also included in X_{it}). The other variables are defined as before. We estimate separate models for each household characteristic of interest with a particular focus on the interaction term estimate η_3.

4. Results and discussion

4.1. Descriptive statistics

Table 1 shows the mean comparison of the outcome variables between households by mobile phone ownership as well as a test of the statistical significance of the difference in mean between mobile phone owners and non-owners. These descriptive statistics suggest 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 findings from Sekabira & Qaim (2017) and 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. It is thus reasonable to conclude that households not in poverty can afford to own and make use of mobile phones.

Moreover, Table 1 presents descriptive statistics for the socioeconomic characteristics that are used as control variables in the econometric models, differentiating between mobile phone owners and non-owners. In most of the variables, we observe significant differences by mobile phone ownership. Mobile phone owners are likely to be younger, male, 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 detailed description of the variables is provided in Table A 3. The covariates are chosen based on relevant literature such as Leng, et al., (2020); Rajkhowa & Qaim (2022); Fowowe (2023); Amber & Chichaibelu (2023).

Table 1 Summary statistics by MP ownership

	2011/12					2019				
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	
Depth of poverty	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	
Access to the nearest town	25.624	15.105	25.407	14.713		26.167	14.748	25.483	14.571	

Note: Authors' calculations from BIHS 2011/12 and 2019. Mean values are shown along with standard deviations (SD). Diff is the results of t-tests on the equality of means of mobile phone ownership and non-ownership. *Significant at the 10% level; **Significant at the 5% level; *** Significant at the 1% level. 100 decimals are equal to 0.4 ha. Table A 3 provides the description of the variables.

4.2. Association between mobile phone ownership and income diversification

Table 4 presents the regression results of Equation (2) from Section 3.3.1. We find that mobile phone ownership has a positive and statistically significant association with income diversification (see Column (1)). Ownership of mobile phones are associated with a 3.1% higher likelihood of having income diversification as measured by the Simpson index[7]. This suggests that owning a mobile phone enhances the income diversity of rural households and contributes to building resilience in livelihoods. .

Given that we find mobile phone ownership to increase income diversification, we further decompose the relationship between mobile phone ownership and income diversification by different 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 from on-farms employment in Column (3). The result is consistent with findings from Jensen (2007). In general, the non-farm sector offers relatively more stable wages than on-farm employment does which is highly susceptible to changes in price and weather conditions. A plausible explanation is that rural individuals are more inclined to engage in off-farm employment rather than on-farm employment, owing to improved access to labor market information facilitated by the use of mobile phones. Furthermore, Columns (4) and (5) show that mobile phone ownership increases off-farm income by both employment and self-employment which is consistent with the findings from Rajkhowa & Qaim (2022). Non-earned income also shows a positive and statistically significant association with mobile phone ownership i.e. mobile phone ownership increases non-earned income which may be consequent of lower transaction costs and easy accessibility of non-earned income through mobile phone technologies (Lee, et al., 2021).

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

In summary, mobile phone ownership typically boosts income diversification, notably increasing earnings from on-farm self-employment, off-farm self-employment, off-farm employment, and non-earned sources. We posit that the rise in these income streams could lead to a reduction in poverty and proceed to test this hypothesis in the subsequent section.

Table 4 Association between MP ownership and income diversification (FE model)

	(1)	(2)	(3)	(4)	(5)	(6)
	Income diversification	*Income source*				
		Farm self	Farm wage	Off-farm self	Off-farm wage	Non-earned
MP ownership	0.031**	0.343*	-0.505**	0.433***	0.729***	0.628***
	(0.013)	(0.204)	(0.199)	(0.159)	(0.207)	(0.210)
Female household head	-0.152***	-1.165***	-1.572***	-2.832***	-1.645***	3.969***
	(0.016)	(0.258)	(0.199)	(0.227)	(0.267)	(0.270)
Age of HH	0.001	0.025***	-0.018**	0.014*	-0.003	0.039***
	(0.001)	(0.009)	(0.008)	(0.008)	(0.010)	(0.011)
Household size	0.007**	-0.107*	0.013	0.103**	0.107	-0.133*
	(0.004)	(0.062)	(0.049)	(0.049)	(0.071)	(0.070)
Schooling year of HH	0.001	0.024	-0.087**	-0.011	-0.010	0.051
	(0.003)	(0.048)	(0.035)	(0.039)	(0.047)	(0.047)
Farm size	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	0.035***	0.750***	-0.333**	0.785***	0.090	0.193
	(0.010)	(0.181)	(0.148)	(0.119)	(0.178)	(0.194)
Access to nearest town	-0.000	0.005	0.012***	-0.002	-0.000	-0.001
	(0.000)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)
Household FE	No	No	No	No	No	No
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. The models are estimated by OLS with FE. Outcome variables in Columns (2) to (6) are logarithm of income. Standard errors are clustered by households in parenthesis. The number of observations in Column (1) is less than the one in Columns (2) to (6) because, if all the income sources are 0, the index cannot be calculated resulting in missing values of the income diversification index in Column (1).

4.3. Association between mobile phone ownership and household poverty

Table presents the association between mobile phone ownership and poverty, estimated using a panel fixed effects model to account for the endogeneity of mobile phone ownership. We find that mobile phone ownership decreases the prevalence of poverty as depicted by the statistically significant negative coefficient observed in Column (1). The probabilty of being poor decreased by 8.3% as a result of mobile phone ownership which is consistent with the poverty reduction effect of mobile phone adoption found by Asongu (2015). Furthermore, mobile phone ownership is also found to reduce the depth of poverty by about 2% meaning the poor are moving closer to the poverty line as a result of mobile phone adoption (see Column 2). The magnitude of the coefficient is similar to that of Beuermann et al., (2012) for Peru. On the other hand, mobile phone ownership has a statistically significant negative impact on non-monetary aspects of poverty, reducing the multidimensional poverty score by 5.8% as seen in Column (3). The findings thus suggest that the adoption of mobile phones not only contributes to a decrease in monetary poverty but also has a holistic impact on welfare through reduction in the non-monetary dimensions of poverty.

These significant associations may be guided through an increased resilience of household income resulting from the diversification of income sources. . Table shows the results of the possible mechanisms by additionally controlling for the income diversification index in Panel A and the different categories of income source in Panel B. The first key result is that income diversification itself has a negative association with povery headcount, as seen in Column (1), while coefficients of income diversification in Column (2) and (3) are not statistically significant. This 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 (4), is smaller than the one in Column (1) of Table , which is $|\gamma_1|$ in Equation (3). 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 on welfare enhancing effects of mobile phones by Munyegera & Matsumoto (2016); Sekabira & Qaim (2017); Ma, et al., (2018); Rajkhowa & Qaim (2022); and Miyajima (2022).

Furthermore, we investigate which income sources contribute to poverty reduction in addition to diversifying income. In Column (4), income from on-farm self employment, off-farm self employment, and non-earned income are negatively associated with poverty headcount, indicating that such sources of income reduce the incidence of poverty. In Column (5), income from on-farm self employment and non-earned income are negatively associated with depth of poverty while off-farm self employment is significantly associated with MPI. The results confirm that a more diversified income source for households such as those from on-farm self employment, off-farm self employment,and non-earned income are beneficial to households with respect to poverty alleviation.

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

	(1) Poverty Headcount	(2) Depth of poverty	(3) MPI score
MP ownership	-8.325***	-1.962***	-5.782***
	(1.773)	(0.365)	(0.639)
Female household head	3.595**	0.727*	0.394
	(1.808)	(0.404)	(0.813)
Age of HH	-0.009	-0.000	0.059*
	(0.065)	(0.016)	(0.032)
Household size	3.424***	0.490***	1.061***
	(0.441)	(0.087)	(0.204)
Schooling year of HH	-0.416	-0.050	-0.350**
	(0.260)	(0.062)	(0.149)
Farm size	-0.012***	-0.002***	-0.004
	(0.004)	(0.001)	(0.003)
Livestock ownership	-0.211	-0.081	-1.421***
	(1.208)	(0.225)	(0.539)
Access to the nearest town	0.025	0.004	-0.024*
	(0.029)	(0.006)	(0.014)
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. The models are estimated by OLS with FE.

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	-4.077**	-0.535	-0.689
	(2.024)	(0.422)	(0.908)
MP ownership	-8.219***	-1.936***	-5.708***
	(1.775)	(0.367)	(0.642)
Household l FE	*Yes*	*Yes*	*Yes*
Year × Division FE	*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	-0.204*	-0.038*	-0.037
	(0.110)	(0.022)	(0.052)
Farm wage	0.472***	0.080**	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	-0.068	-0.004	-0.071
	(0.124)	(0.025)	(0.055)
Non-earned	-0.266***	-0.047***	-0.030
	(0.093)	(0.018)	(0.047)
MP ownership	-7.613***	-1.864***	-5.578***
	(1.763)	(0.367)	(0.642)
Household FE	*Yes*	*Yes*	*Yes*
Year × Division FE	*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. The models are estimated by OLS with FE. 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, access to the nearest town. A full regression table is available in Table A 4 and Table A 5.

4.4. Who benefits more from mobile phones?

In this section, we disentangle the relationship between mobile phone ownership and income diversification on the basis of certain household characteristics to explore whether there are any heterogenous effects with respect to these characteristics. Using the regression specifications detailed in Equation (4) above, we interact mobile phone ownership with education of household head, place of residence, gender of household head, and access 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 between years of schooling and mobile phone ownership is negative and statistically significant implying that less educated households are more likely to engage in income diversification when the households own mobile phones. This is an insightful result that mobile phone ownership can enhance income diversification which improves livelihood, especially for less educated households.

Furthermore, 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 seen from the interaction term in Column (2). This highlights the potential of mobile phones in reducing geographical inequality and having a pro-poor effect. It is, therefore, an important finding from a social development perspective.

The coefficient for the interaction term between mobile phone ownership and female household head in Column (3) is not statistically significant. Finally, in Column (4), we look at the access to the nearest town measured using the time (minutes) it takes to travel to the nearest town center, as it may be an alternative to mobile phones for accessing information on job and market opportunities. Note that a longer time to a town indicates worse access to information. however, contrary to our expectation, the coefficient of the interaction term between the distance and mobile phone ownership is also not statistically significant.

Table 7 Heterogeneous associations based on various household characteristics (FE model)

	(1) Income diversification	(2) Income diversification	(3) Income diversification	(4) Income diversification
MP ownership	0.052***	0.017	0.033**	0.042*
	(0.014)	(0.014)	(0.014)	(0.023)
Years of schooling of HH × MP ownership	-0.013***			
	(0.004)			
Rangpur Division × MP ownership		0.109***		
		(0.037)		
Female-headed HH × MP ownership			-0.015	
			(0.032)	
Access to the nearest town × MP ownership				-0.000
				(0.001)
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. The models are estimated by OLS with FE. 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, access to the nearest town. The full regression table is in Table A 6.

5. Robustness check

In this section, we carry out robustness checks to examine whether our findings vary when we use different estimation methods. Specifically, instead of the household FE model used in our main specifications, we employ the doubly robust (DR) estimator and the Propensity Score Matching combined with Difference in Difference (PSM-DID) method to estimate the robustness of the association between mobile phone ownership, income diversification, and poverty. The DR method, or more precisely, an inverse-probability weighted regression with adjustment of covariates, combines the regression and propensity score weights and is more robust than the PSM estimator and the inverse-probability-weighting estimator (Mano et al., 2022). Furthermore, PSM-DID can address potential limitations that arise when using a PSM estimator in the model. This is because bias cannot be entirely eliminated if there are significant unobservable variables in the model (Imai & Azam, 2012).

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Estimates from the DR estimator (shown in Table A 7) and the PSM-DID method (shown in Table A 8) show similar results to those in Table 4 and Table 5, but the association between mobile phone ownership and income diversification index is statistically insignificant in Table A 8. It indicates that mobile phone ownership enhances off-farm income, farm self-employment income, and non-earned income but reduces on-farm wage income. Because the Simpson diversification index measures evenness of each income source, the result implies that 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.

6. Conclusion and policy implications

Mobile phones have rapidly spread in developing countries, including in rural Bangladesh, and have the potential to play a significant role in fostering economic development. Previous studies have focused on the economic impacts of mobile phone ownership, such as input and output prices, profits, and income. However, there is limited research on the broader social development implications. It is crucial to better understand the social welfare effects, especially in the context of the United Nations' Sustainable Development Goals (SDGs). This study uses a nationally representative, eight-year panel dataset of rural households in Bangladesh to examine the average and varied impacts of mobile phone ownership on income diversification, prevalence of poverty, depth of poverty, and a multidimensional poverty index (MPI).

Our findings demonstrate that mobile phone ownership has a positive and significant association with income diversification. It also leads to a reduction in both the prevalence and severity of monetary poverty as well as non-monetary poverty as measured by the MPI. Further analysis into possible mechanisms of effect reveals that mobile phone ownership significantly aid in poverty reduction through income diversification, particular diversifying income streams into on-farm and off-farm self-employment, as well as non-earned income. Additionally, our results indicate that households with less educated heads and those residing in impoverished areas experience disproportionately greater benefits from mobile phones. These encouraging findings suggest opportunities to expedite income diversification for poverty reduction in such contexts.

This research underscores the significance of widespread access to mobile technology. The study reveals that mobile phones contribute to expanded opportunities and income generation, particularly benefiting less educated households and those residing in economically disadvantaged areas. Ensuring access to mobile technology and networks for all households, even in rural areas, has the potential to reduce transaction costs and enhance labor market efficiency. This approach may help address challenges associated with limited human capital accumulation and geographical inequality.

The results from this study should not be broadly generalized and require more rigorous estimation methods such as randomized controlled trials or other causal inference strategies. However, the households surveyed for this study in rural Bangladesh are quite typical for the

South Asian rural settings which enables us to glean valuable insights for advancing rural development in the digital age. Follow-up studies in other settings, utilizing longer panel data and rigorous methodologies will undoubtedly be necessary to substantiate our conclusions.

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Appendix tables

Table A 1 Test on the validity of the instruments (FE model)

	(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	0.458***	-0.099*	-11.842	-3.866*	-10.918***
	(0.047)	(0.059)	(8.631)	(2.024)	(3.573)
Year × Division FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	7,636	926	935	935	920

Note: *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 models are estimated by OLS with FE. 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, access to the nearest town. The full table is available upon request.

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 from 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
Farm self-income	Income from running farm (Taka)
Farm wage	Income from on-farm employment (Taka)
Off-farm self-income	Income from off-farm self-employment (Taka)
Off-farm wage	Income from off-farm employment (Taka)
Non-earned income	Income by neither employment nor self-employment such as social protection, remittance, and pension (Taka)
Poverty headcount	100 if household is poor, 0 otherwise
Depth of poverty	Measures poverty gap and takes 0 to 100
Multidimensional poverty index (MPI) score	Measures multidimensional poverty and takes 0 to 100
Socioeconomic variables	
Female household head	1 if household head is female, 0 otherwise
Age of household head	Age of household head
Household size	Number of household member
Years of schooling of household head	Years that household head attend a school
Farm size	Farm size that household owns (in decimals)
Livestock ownership	1 if household owns livestock, 0 otherwise
Access to the nearest town	Time to the nearest town from homestead (minute)

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 model)

	(1) Poverty Headcount	(2) Depth of poverty	(3) MPI score
Income diversification index	-4.077**	-0.535	-0.689
	(2.024)	(0.422)	(0.908)
MP ownership	-8.219***	-1.936***	-5.708***
	(1.775)	(0.367)	(0.642)
Female household head	3.069*	0.686	0.385
	(1.860)	(0.417)	(0.838)
Age of HH	-0.002	-0.001	0.056*
	(0.066)	(0.016)	(0.032)
Household size	3.463***	0.495***	1.081***
	(0.443)	(0.088)	(0.204)
Schooling year of HH	-0.447*	-0.057	-0.349**
	(0.260)	(0.062)	(0.150)
Farm size	-0.011**	-0.002**	-0.004
	(0.005)	(0.001)	(0.003)
Livestock ownership	-0.108	-0.081	-1.394**
	(1.212)	(0.225)	(0.542)
Access to the nearest town	0.024	0.004	-0.025*
	(0.029)	(0.006)	(0.014)
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. The models are estimated by OLS with FE.

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

	(1) Poverty Headcount	(2) Depth of poverty	(3) MPI score
Farm self	-0.204*	-0.038*	-0.037
	(0.110)	(0.022)	(0.052)
Farm wage	0.472***	0.080**	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	-0.068	-0.004	-0.071
	(0.124)	(0.025)	(0.055)
Non-earned	-0.266***	-0.047***	-0.030
	(0.093)	(0.018)	(0.047)
MP ownership	-7.613***	-1.864***	-5.578***
	(1.763)	(0.367)	(0.642)
Female household head	3.822**	0.904**	-0.153
	(1.911)	(0.420)	(0.863)
Age of HH	0.021	0.004	0.064**
	(0.065)	(0.016)	(0.032)
Household size	3.413***	0.483***	1.096***
	(0.439)	(0.087)	(0.204)
Schooling year of HH	-0.362	-0.040	-0.343**
	(0.264)	(0.062)	(0.149)
Farm size	-0.006	-0.002*	-0.002
	(0.005)	(0.001)	(0.003)
Livestock ownership	0.494	0.007	-1.174**
	(1.205)	(0.226)	(0.543)
Access to the nearest town	0.019	0.004	-0.025*
	(0.029)	(0.006)	(0.014)
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. The models are estimated by OLS with FE.

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

	(1) Income diversification	(2) Income diversification	(3) Income diversification	(4) Income diversification
MP ownership	0.052***	0.017	0.033**	0.042*
	(0.014)	(0.014)	(0.014)	(0.023)
Schooling year of HH × MP ownership	-0.013***			
	(0.004)			
Rangpur Division × MP ownership		0.109***		
		(0.037)		
Female of HH × MP ownership			-0.015	
			(0.032)	
Access to the nearest town × MP ownership				-0.000
				(0.001)
Female household head (=1)	-0.152***	-0.152***	-0.139***	-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	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Livestock ownership	0.034***	0.036***	0.035***	0.035***
	(0.010)	(0.010)	(0.010)	(0.010)
Access to the nearest town	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)
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. The models are estimated by OLS with FE.

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

	(1) Income diversification	(2) Farm self	(3) Farm wage	(4) Off-farm self	(5) Off-farm wage	(6) Non-earned	(7) Poverty headcount	(8) Depth of poverty	(9) MPI
ATE MP ownership	0.054***	0.376	-0.645**	0.898***	0.702***	0.934***	-6.991***	-1.520***	-11.012***
	(0.018)	(0.254)	(0.253)	(0.247)	(0.200)	(0.275)	(1.558)	(0.384)	(0.862)
Controls	*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. The doubly robust estimator is used for the estimations. 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 Columns (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×2019)	-0.057	1.158*	-0.897	0.594	1.933***	3.288***	-21.798***	-5.314***	-25.449***
	(0.039)	(0.593)	(0.557)	(0.487)	(0.731)	(0.627)	(5.530)	(1.293)	(1.906)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Household FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year × Division FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1548	1562	1562	1562	1562	1562	1562	1562	1492

Note: *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. Robust standard errors clustered by households in parenthesis. The models are estimated by the combination of PSM and DID. 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 Columns (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.

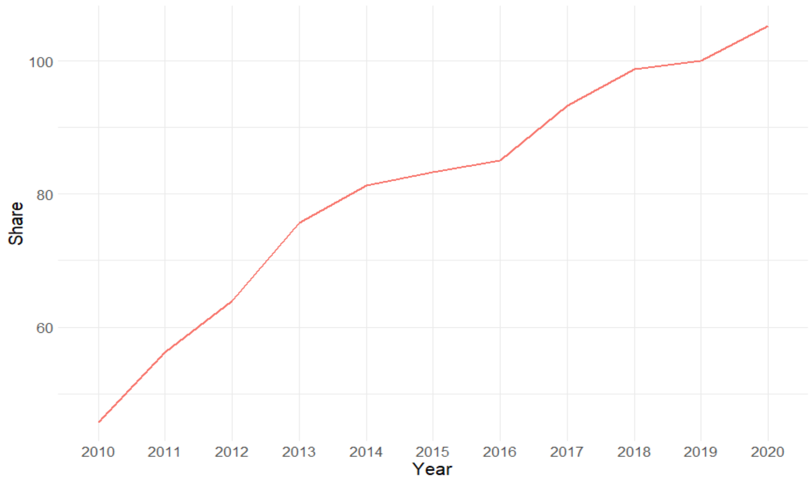

Figure A 1 Expansion of Mobile phone subscription in Bangladesh last 10 years
Source: World Bank (2023)
Note: Mobile cellular subscriptions (per 100 people)

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