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Mobile phones, income diversification, and poverty reduction in rural Bangladesh

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Abstract

The widespread adoption of mobile phones (MPs) presents the possibility of creating employment and self-employment opportunities. Although several studies have documented the impact of MPs on income, the link between MP ownership and poverty reduction channeled by income diversification 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 MP 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 deprived areas. In addition, owning a MP is also found to decrease poverty via income diversification. Therefore, policies aimed at enhancing access to mobile technologies could create a resilient income portfolio by decreasing transaction costs and improving market efficiency, ultimately mitigating poverty in rural regions.

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KEYWORDS
Bangladesh, ICT, income diversification, mobile phones, poverty reduction

JEL CLASSIFICATION
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 has witnessed a substantial increase in MP subscriptions. According to Figure 1 from the World Bank (2023), the MP subscription rate reached nearly 100% in 2019, a notable leap from the less than 50% recorded in 2010. Mobile technologies are expected to spearhead economic growth by enhancing productivity and efficiency across various sectors of the economy. For example, MP ownership is positively associated with the likelihood of participating in some types of off-farm work 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 farmers' access to critical information on weather, farming techniques, and market prices (GSM Association, 2021; Sekabira & Qaim, 2017a, 2017b; 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).

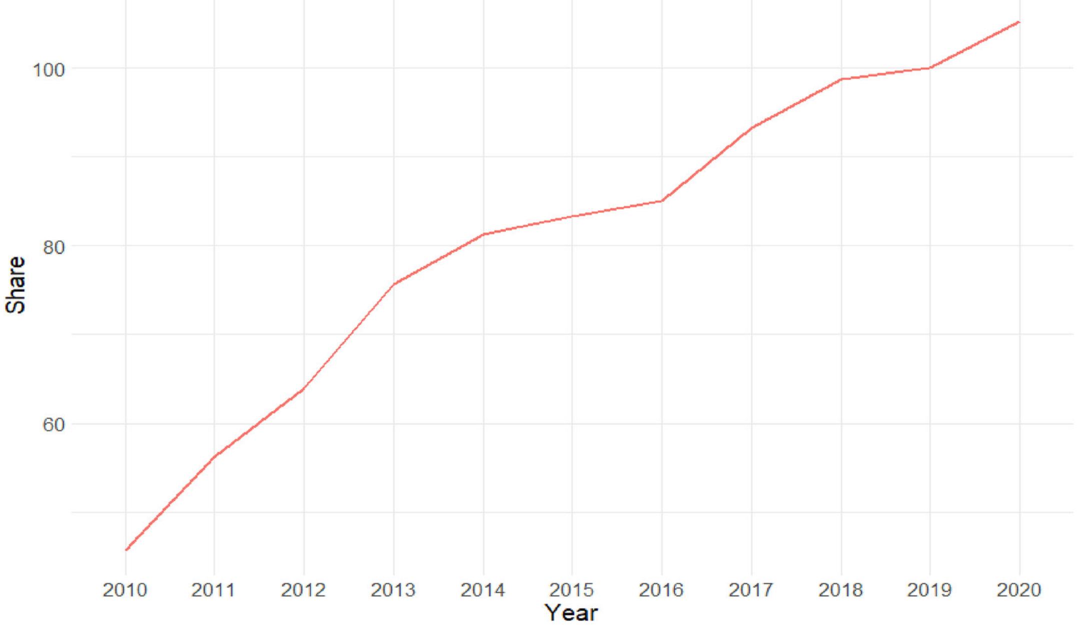

FIGURE 1 Expansion of mobile phone subscription in Bangladesh last 10 years. Mobile cellular subscriptions (per 100 people). *Source*: Calculated by authors from the World Bank (2023). [Colour figure can be viewed at wileyonlinelibrary.com]

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Little is known about whether MP 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. The pursuit of such opportunities can be hindered by high transaction costs. The growing ownership of MPs has the potential to alleviate these transaction costs. It is thus important to recognize the significance of mobile technology and investigate the relationship between MP ownership, income diversification, and poverty reduction to draw critical policy implications in developing countries.

In this paper, we examine how MP ownership influences income diversification and contributes to reducing poverty, considering both monetary and nonmonetary dimensions of poverty. Furthermore, in addition to examining the overall average effect of MP ownership, we explore the heterogeneity of associations to socioeconomic and geographical conditions. We employed a recent nationally representative panel dataset of rural households in Bangladesh spanning 7 years from 2012 to 2019.

A substantial amount of literature exists on the relationship between household welfare and ownership of MPs. Numerous studies have identified a positive correlation between ownership and usage of MPs and household welfare (Asongu, 2015; Ma et al., 2018; Matsuura et al., 2024; Miyajima, 2022; Munyegera & Matsumoto, 2016; Rajkhowa & Qaim, 2022; Sekabira & Qaim, 2017a, 2017b). However, less is known about the effect of MP ownership on income diversification. To the best of our knowledge, only Leng et al. (2020), Ma, Grafton, and Renwick (2020), and Rajkhowa and Qaim (2022) have examined the effects of MP usage or adoption of information and communication technology (ICT) on income diversification or off-farm employment. Moreover, the effects of MP ownership on both monetary and nonmonetary poverty have been documented, but the mechanism behind poverty reduction and the heterogeneous effect of MP ownership on poverty remains unclear.

The paper has three main contributions. First, it presents the first empirical evidence on whether ownership of MPs reduces poverty channeled by income diversification in Bangladesh. It examines the implications of these findings for policymakers. Second, 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 MP ownership to determine which groups benefit the most from owning MPs, yielding more appropriate policy recommendations.

We find that MP ownership enhances income diversification as well as alleviates both monetary and nonmonetary poverty. MP ownership has a positive association 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 monetary poverty while off-farm self-employment income is observed to reduce nonmonetary poverty. Furthermore, heterogeneity analyses reveal that households with less educated heads and those situated in relatively impoverished regions derive benefits from MPs. The findings indicate that MP ownership is a means of diversifying income and improving 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 materials and methods. Section 4 presents the empirical results and discussion. In

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Section 5, the results of robustness checks are discussed while Section 6 concludes with policy implications and suggestions for future research.

2 | CONCEPTUAL FRAMEWORK

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. As a result, households have more options to diversify their income sourcesincluding on-farm and off-farm jobs, which reduce poverty and thus improve household welfare. The conceptual model is specified as follows:

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

where W is poverty status of households, D is decision of income diversification, MP is the mobile phone ownership, X is the vector of covariates, and Z is the vector of unobserved characteristics. The covariates include sex of a household head, age of the household head, household size, education level of the household head, size of farmland held by the household, livestock ownership, and access to the nearest town. Therefore, the impact of MP ownership and income diversification is described as follows:

$$\frac{\partial f(D(\mathrm{MP}, X), X; Z)}{\partial D} < 0. \tag{2}$$

MPs are hypothesized to influence income diversification decisions, denoted by $D(\mathrm{MP}, X)$, similar to Leng et al. (2020) who show that ICT adoption enhances income diversification. In our conceptual framework, income diversification plays a role in the "push" factors that reduce transaction costs at labor market as well as the risks and uncertainties of agricultural marketing. We, thus, hypothesize $\frac{\partial W}{\partial D} < 0$ in Equation (2). The conceptual framework is also depicted in Figure 2. The flow from MP to income diversification in Figure 2 presents $D(\mathrm{MP}, X)$ which suggests that MPs affect the decision of income diversification. Income diversification would be enhanced by the reduction of transaction cost along with the risks and uncertainties of the agricultural and labor market, and better access to information. The arrow from income

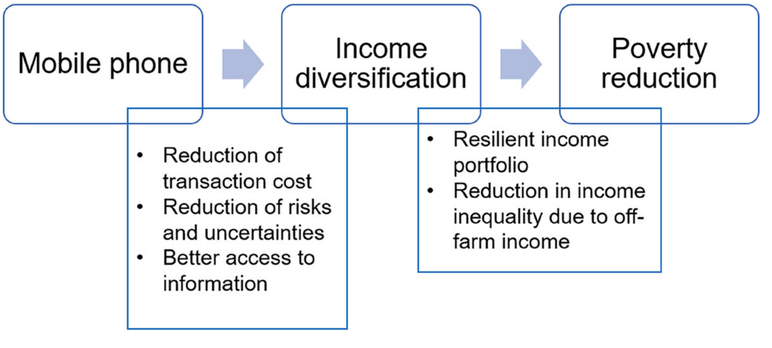

FIGURE 2 Conceptual framework. *Source*: Authors' design. [Colour figure can be viewed at wileyonlinelibrary.com]

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diversification to poverty reduction in Figure 1 describe that income diversification induces poverty reduction, meaning $\frac{\partial W}{\partial D} < 0$. Higher and more resilient income will likely result in a reduction in the incidence and depth of poverty, and non-monetary poverty thereby improving household welfare.

3 | MATERIALS AND METHODS

3.1 | Data

We use nationally representative household panel surveys conducted in 2011–2012 (hereafter 2012) and 2018-2019 (hereafter 2019) titled the Bangladesh Integrated Household Survey (BIHS) designed and supervised by the International Food Policy Research Institute. The sample is representative of rural Bangladesh as well as of the seven divisions of the country (Ahmed & Tauseef, 2022; Islam et al., 2018). 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 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 2012 round was 6503 households in 325 PSUs allocated among seven divisions while the sample size in the 2019 round was 5604 households. For this study, we use the balanced subsample of rural households which were interviewed in both survey rounds, resulting in 7636 observations from 3818 households as shown in Table 2.[1] Since our analysis uses panel data, our estimates would be biased if the attrition is associated with some household characteristics. However, Ahmed and Tauseef (2022) shows that the attrition between 2012 and 2019 was 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 is MP ownership.[2] We consider a household to be a MP owner if at least one household member owns a MP during a survey year. We construct a dummy variable of MP ownership at the household level which is equal to 1 if the household owns a MP and 0 otherwise.

For outcome variables, we are particularly interested in income diversification and measures of monetary and nonmonetary poverty. 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., 2023), as shown below:

$$\text{Simpson} = 1 - \sum\nolimits_{k=1}^{n} \left[\frac{s_k}{S}\right]^2 \tag{3}$$

where s_k is income for income k, and S is total income. The index ranges 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, nonfarm wage, nonfarm self-employment, and non-earned income which includes remittance and social network program transfer, and so forth, following Khandker (2012). Table 1 shows

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TABLE 1 Breakdown of household income.

	2012					2019				
	MP ownership		Nonownership			MP ownership		Nonownership		
Income sources	**Mean**	***SD***	**Mean**	***SD***	**Diff**	**Mean**	***SD***	**Mean**	***SD***	**Diff**
Farm self-income (taka)	23,955	89,814	12,730	34,032	***	44,765	368,607	13,252	35,186	
Farm wage (taka)	7049	22,072	14,323	24,506	***	10,835	44,919	7003	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	9332	29,345	***	29,741	71,833	11,079	34,585	**
Non-earned (taka)	7620	120,845	2278	16,690		4441	22,669	2277	7911	
Total household income (taka)	162,925	228,462	87,483	78,000	***	260,705	452,964	103,738	103,025	***

Note: Calculation by authors based on a balanced panel. BDT is an abbreviation of Bangladesh Taka which 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 nonownership.

*$p < .1$; **$p < .05$; ***$p < .01$.

Source: Authors' calculations from BIHS 2012 and 2019.

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the breakdown of the household income sources by MP ownership. Results indicate that the share of nonfarm income including nonfarm wage, and nonfarm self-employment is more than 50% of the total income of households.

Our second outcome of interest, namely the monetary indicators of poverty, constitutes of two indicators derived from the FGT class of poverty measures (Foster et al., 1984), that is, the poverty headcount and poverty gap measure. The measures are defined in the following manner: Let $s=(s_1,s_2,...,s_n)$ 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.[3] The normalized deprivation score for the rich, that is, those whose income weakly exceeds z, is set equal to 0 (Tauseef, 2022).

To obtain a more comprehensive understanding of household well-being, 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 and adopted by the United Nations Development Program (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 SA2 shows the dimensions of the MPI as well as the detailed definition of the indicators included in each dimension.

Table 2 shows the number of households owning and not owning MPs in our sample. In 2012, about 23% of households in our sample did not own a MP which dropped to 2% in 2019, indicating wide adoption of MPs in rural Bangladesh over this period. Over the same period, the prevalence of poverty in our sample, calculated using the FGT measure and $1.90 per

TABLE 2 Number of households by mobile phone ownership.

	2012	2019
Nonownership	877 (23%)	58 (2%)
Ownership	2941 (77%)	3.760 (98%)
Total	3818	3818

Note: Authors' calculations from BIHS 2012 and 2019.

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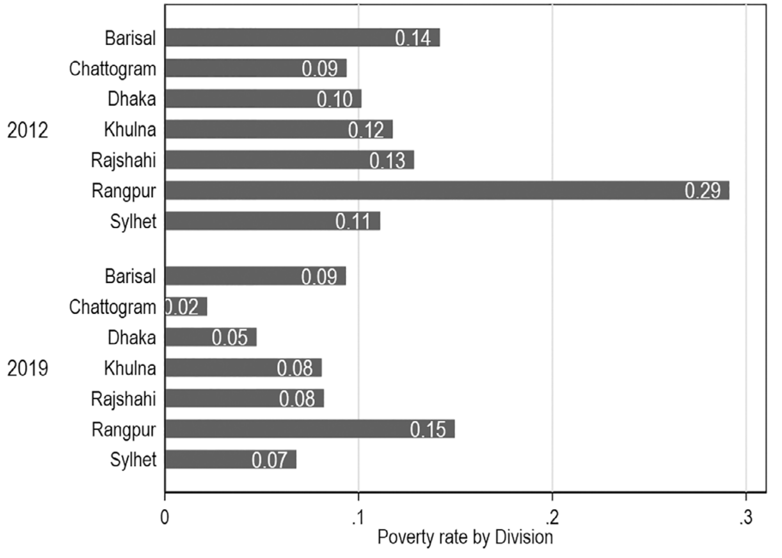

FIGURE 3 Poverty rate of division by year. Authors' calculations from BIHS 2012 and 2019. The poverty rate is estimated as stated in Section 3.2.

person per day poverty line, decreased from 13% in 2012 to about 7% in 2019, as shown in Figure 3. Considerable regional heterogeneity 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 statistics (see, e.g., Bangladesh Bureau of Statistics, 2023). In subsection 3.4, we examine the geographical heterogeneity of the effect of MP ownership on economic resilience through income diversification, especially in the poorest division, Rangpur. Further descriptive statistics of the whole sample are presented in Table 3.

3.3 | Empirical strategy

3.3.1 | Association among MP ownership, income diversification, and poverty

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

$$D_{it} = \beta_o + \beta_1 \mathrm{MP}_{it} + \beta_2 X_{it} + a_i + t_t + \varepsilon_{it}, \tag{4}$$

$$Y_{it} = \gamma_o + \gamma_1 \mathrm{MP}_{it} + \gamma_2 X_{it} + a_i + t_t + \varepsilon_{it}, \tag{5}$$

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 Equations (4) and (5) are estimated by ordinary least

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TABLE 3 Summary statistics by MP ownership.

	2012					2019				
	MP ownership		Nonownership			MP ownership		Nonownership		
	Mean	*SD*	Mean	*SD*	Diff	Mean	*SD*	Mean	*SD*	Diff
Outcome variables										
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 2012 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 nonownership. One hundred decimals are equal to 0.4 ha. Table SA3 describes the variables.
$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

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squares methodology with FE. We are particularly interested in the coefficients for MP ownership, that is, the estimates for β_1 and γ_1. For β_1, a positive and statistically significant coefficient would imply that MP ownership significantly accelerates income diversification, while negative γ_1 would imply that MP ownership significantly reduces 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 nonfarm households, but we include a control farmland size, as this may influence the likelihood of employment opportunities.

Moreover, MP ownership can be negatively associated with poverty through various mechanisms, of which income diversification is a path. MP 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:

$$Y_{it} = \theta_o + \theta_1 \mathrm{MP}_{it} + \theta_2 D_{it} + \theta_3 X_{it} + a_i + t_t + \varepsilon_{it}. \tag{6}$$

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 MPs are negatively associated with monetary and non-monetary poverty at least partly through the income diversification mechanism.

The main variable of interest, MP 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 MP ownership. Rural households can decide on the adoption of MPs 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 FEs 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 MPs are nowadays used widely even among the very poor households in rural Bangladesh, including households with and without income diversification and poverty status. However, there is another concern about dynamic causal relationships between past treatment and current outcomes. There are two important identification assumptions of the FEs model—past treatments do not directly affect current outcomes, and past outcomes do not influence current treatment. Imai and Kim (2019) suggest 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 MPs. One potential source of endogeneity that neither the FE estimator, the DR, nor the PSM-DID can control is reverse causality.[6]

3.3.2 | Heterogeneous associations

The association between MP ownership and income diversification may vary depending on household characteristics. Aside from the average association evaluated with Equation (4), we

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also analyze heterogeneous associations for 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:

$$D_{it} = \eta_0 + \eta_1 \mathrm{MP}_{it} + \eta_2 X_{it} + \eta_3 \mathrm{MP}_{it} \times H_{it} + a_i + t_t + \varepsilon_{it}, \tag{7}$$

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 3 shows the mean comparison of the outcome variables between households by MP ownership as well as a test of the statistical significance of the difference in mean between MP owners and non-owners. These descriptive statistics suggest that MP owners are more likely to diversify income sources and have higher total household income as well as higher per capita income than non-owners. These observed differences are consistent with findings from Sekabira and Qaim (2017a, 2017b) and Rajkhowa and Qaim (2022). Furthermore, the incidence of poverty in households owning MPs is lower than in households not owning MPs. At the same time, the poverty gap and MPI score of households not owning MPs are worse than MP owners. It is thus reasonable to conclude that households not in poverty can afford to own and make use of MPs.

Moreover, Table 3 presents descriptive statistics for the socioeconomic characteristics that are used as control variables in the econometric models, differentiating between MP owners and non-owners. In most of the variables, we observe significant differences in MP ownership. MP owners are likely to be younger, male, have more family members, with better educated household heads. Furthermore, households who own MPs have larger farmland than households not owning MPs. A detailed description of the variables is provided in Table SA3. The covariates are chosen based on relevant literature such as Leng et al. (2020), Rajkhowa and Qaim (2022), Fowowe (2023), Ma et al. (2023), and Amber and Chichaibelu (2023).

4.2 | Association between MP ownership and income diversification

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

Given that we find MP ownership to increase income diversification, we further decompose the relationship between MP ownership and income diversification by different income sources. Column 2 shows that MP ownership increases the income of those in farm self-employment, that is, income from agricultural production, while it decreases income from on-farm

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

	(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** (0.013)	0.343* (0.204)	−0.505** (0.199)	0.433*** (0.159)	0.729*** (0.207)	0.628*** (0.210)
Female household head	−0.152*** (0.016)	−1.165*** (0.258)	−1.572*** (0.199)	−2.832*** (0.227)	−1.645*** (0.267)	3.969*** (0.270)
Age of HH	0.001 (0.001)	0.025*** (0.009)	−0.018** (0.008)	0.014* (0.008)	−0.003 (0.010)	0.039*** (0.011)
Household size	0.007** (0.004)	−0.107* (0.062)	0.013 (0.049)	0.103** (0.049)	0.107 (0.071)	−0.133* (0.070)
Schooling year of HH	0.001 (0.003)	0.024 (0.048)	−0.087** (0.035)	−0.011 (0.039)	−0.010 (0.047)	0.051 (0.047)
Farm size	0.000*** (0.000)	0.010*** (0.001)	−0.003*** (0.001)	0.005*** (0.001)	−0.001 (0.001)	0.002** (0.001)
Livestock ownership	0.035*** (0.010)	0.750*** (0.181)	−0.333** (0.148)	0.785*** (0.119)	0.090 (0.178)	0.193 (0.194)
Access to nearest town	−0.000 (0.000)	0.005 (0.004)	0.012*** (0.004)	−0.002 (0.003)	−0.000 (0.004)	−0.001 (0.005)
Household FE	No	No	No	No	No	No
Year × Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7582	7636	7636	7636	7636	7636

Note: The models are estimated by OLS with FE. Outcome variables in Columns 2–6 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 2–6 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.
*$p < .1$; **$p < .05$; ***$p < .01$.

employment in Column 3. The result is consistent with findings from Jensen (2007). In general, the nonfarm 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 using MPs. Furthermore, Columns 4 and 5 show that MP ownership increases off-farm income by both employment and self-employment which is consistent with the findings from Rajkhowa and Qaim (2022). Non-earned income also shows a positive and statistically significant association with MP ownership, that is, MP ownership increases non-earned income which may be a consequence of lower transaction costs and easy accessibility of non-earned income through MP technologies.

In summary, MP ownership typically boosts income diversification, notably increasing earnings from on-farm self-employment, off-farm self-employment, off-farm employment, and

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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.

4.3 | Association between MP ownership and household poverty

Table 5 presents the association between MP ownership and poverty, estimated using a panel FEs model to account for the endogeneity of MP ownership. We find that MP ownership decreases the prevalence of poverty as depicted by the statistically significant negative coefficient observed in Column 1. The probability of being poor decreased by 8.3% as a result of MP ownership which is consistent with the poverty reduction effect of MP adoption found by Asongu (2015). Furthermore, MP 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 MP adoption (see Column 2). The magnitude of the coefficient is similar to that of Beuermann et al. (2012) for Peru. On the other hand, MP 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 MPs not only contributes to a decrease in monetary poverty but also has a holistic impact on welfare through a reduction in the non-monetary dimensions of poverty.

These significant associations may be guided by an increased resilience of household income resulting from the diversification of income sources. Table 6 shows the results of the possible mechanisms by additionally controlling for the income diversification index in Panel A and the different categories of income sources in Panel B. The first key result is that income diversification itself has a negative association with poverty headcount, as seen in Column 1, while coefficients of income diversification in Columns 2 and 3 are not statistically significant. This indicates that income diversification reduces the probability of being poor. Moreover, an

TABLE 5 Association between MP ownership and poverty (FE model).

	(1) Poverty headcount	(2) Depth of poverty	(3) MPI score
MP ownership	−8.325*** (1.773)	−1.962*** (0.365)	−5.782*** (0.639)
Female household head	3.595** (1.808)	0.727* (0.404)	0.394 (0.813)
Age of HH	−0.009 (0.065)	−0.000 (0.016)	0.059* (0.032)
Household size	3.424*** (0.441)	0.490*** (0.087)	1.061*** (0.204)
Schooling year of HH	−0.416 (0.260)	−0.050 (0.062)	−0.350** (0.149)
Farm size	−0.012*** (0.004)	−0.002*** (0.001)	−0.004 (0.003)
Livestock ownership	−0.211 (1.208)	−0.081 (0.225)	−1.421*** (0.539)
Access to the nearest town	0.025 (0.029)	0.004 (0.006)	−0.024* (0.014)
Household FE	Yes	Yes	Yes
Year × Division FE	Yes	Yes	Yes
Observations	7636	7636	6972

Note: Robust standard errors clustered by households in parenthesis. The models are estimated by OLS with FE.
*$p < .1$; **$p < .05$; ***$p < .01$.

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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** (2.024)	−0.535 (0.422)	−0.689 (0.908)
MP ownership	−8.219*** (1.775)	−1.936*** (0.367)	−5.708*** (0.642)
Household l FE	Yes	Yes	Yes
Year × Division FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	7582	7582	6918
	(4)	**(5)**	**(6)**
Panel B	**Poverty headcount**	**Depth of poverty**	**MPI score**
Farm self	−0.204* (0.110)	−0.038* (0.022)	−0.037 (0.052)
Farm wage	0.472*** (0.169)	0.080** (0.034)	0.084 (0.066)
Off-farm self	−0.431** (0.167)	−0.029 (0.037)	−0.217*** (0.073)
Off-farm wage	−0.068 (0.124)	−0.004 (0.025)	−0.071 (0.055)
Non-earned	−0.266*** (0.093)	−0.047*** (0.018)	−0.030 (0.047)
MP ownership	−7.613*** (1.763)	−1.864*** (0.367)	−5.578*** (0.642)
Household FE	Yes	Yes	Yes
Year × Division FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	7636	7636	6972

Note: 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 Tables SA4 and SA5.

*$p < .1$; **$p < .05$; ***$p < .01$.

absolute value of the coefficient of MP ownership in Column 1, which is $|\theta_1|$ in Equation (4), is smaller than the one in Column 1 of Table 5, which is $|\gamma_1|$ in Equation (5). The results confirm that MP 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 MPs by Munyegera and Matsumoto (2016), Sekabira and Qaim (2017a, 2017b), Ma et al. (2018), Rajkhowa and 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 is 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 is beneficial to households for poverty alleviation.

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4.4 | Who benefits more from MPs?

In this section, we disentangle the relationship between MP ownership and income diversification based on certain household characteristics to explore whether there are any heterogeneous effects with respect to these characteristics. Using the regression specifications detailed in Equation (7) above, we interact MP ownership with the education of the household head, place of residence, gender of household head, and access to the nearest town.

Table 7 shows the estimated coefficients on the interaction between household characteristics and MP ownership. In Column 1, the coefficient of the interaction term between years of schooling and MP ownership is negative and statistically significant implying that less educated households are more likely to engage in income diversification when the households own MPs. This is an insightful result that MP 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 MPs than households in other Divisions as seen from the interaction term in Column 2. This highlights the potential of MPs to reduce geographical inequality and have a pro-poor effect. It is, therefore, an important finding from a social development perspective.

The coefficient for the interaction term between MP ownership and female household heads in Column 3 is not statistically significant. Finally, in Column 4, we look at the access to the nearest town measured using the time (min) it takes to travel to the nearest town center, as it may be an alternative to MPs 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

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*** (0.014)	0.017 (0.014)	0.033** (0.014)	0.042* (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	7582	7582	7582	7582

Note: Robust standard errors clustered by household in parenthesis. The models are estimated by OLS with FE. Control variables used in regression models are a gender of household head, age of household head, household size, schooling year of household head, farm size, livestock ownership, and access to the nearest town. The full regression table is in Table SA6.
$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

expectation, the coefficient of the interaction term between the distance and MP ownership is also not statistically significant.

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 DR estimator and the PSM-DID method to estimate the robustness of the association between MP 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 eliminated if there are significant unobservable variables in the model.

Estimates from the DR estimator (shown in Table SA7) and the PSM-DID method (shown in Table SA8) show similar results to those in Tables 4–6, but the association between MP ownership and income diversification index is statistically insignificant in Table SA8. It indicates that MP ownership would enhance off-farm income, farm self-employment income, and non-earned income but reduce on-farm wage income. Because the Simpson diversification index measures the evenness of each income source, the result implies that MP ownership improves not the evenness of income sources, but the portfolio of income sources for resilient livelihood. Overall, it underlines the robustness of our main results.

6 | CONCLUSION AND POLICY IMPLICATIONS

MPs 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 MP 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. This study uses a nationally representative, 8-year panel dataset of rural households in Bangladesh to examine the average and varied impacts of MP ownership on income diversification, prevalence of poverty, depth of poverty, and a MPI.

Our findings demonstrate that MP 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 MP ownership significantly aids in poverty reduction through income diversification, particularly 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 MPs. These encouraging findings suggest opportunities to expedite income diversification for poverty reduction in such contexts.

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This research underscores the significance of widespread access to mobile technology. The study reveals that MPs 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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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in "Harvard Dataverse" at https://doi.org/10.7910/DVN/OR6MHT and at https://doi.org/10.7910/DVN/NXKLZJ.

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ENDNOTES

[1] Due to the attrition of the households and split households because of marriage, and so forth 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 limited data availability, we cannot distinguish mobile phones with or without internet access. They include cellular phones and smartphones.

[3] Bangladesh was a low-income country in 2011–2012, 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).

[5] To address the omitted variable bias, the instrumental variable (IV) approach can be used. However, the use of IV requires that IV affects an endogenous variable but does 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 phones, the IV used in some studies is the share of households owning mobile phones within a local community (Ma, Nie, et al., 2020; Zheng et al., 2023). However, our falsification test cannot reject the null hypothesis of the exclusion restriction in Table SA1. Hence, we do not use IV approach in this paper.

[6] We conduct the PSM-DiD as follows. First, we match the observations from subsamples of the two groups "obtained phones between the two waves" and "never own phones." We assume common support, in 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 address unobserved time-invariant characteristics and observed characteristics.

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

REFERENCES

Ahmed, A., & Tauseef, S. (2022). Climbing up the ladder and watching out for the fall: Poverty dynamics in rural Bangladesh. *Social Indicators Research*, *160*, 309–340.

Aker, J. C., & Ksoll, C. (2016). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *Food Policy*, *60*, 44–51.

Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *Journal of Economic Perspectives*, *24*, 207–232.

Alkire, S., Kanagaratnam, U., & Suppa, N. (2018). *The global multidimensional poverty index (MPI): 2018 revision OPHI MPI* (Methodological Notes 46). Oxford Poverty and Human Development Initiative.

Amber, H., & Chichaibelu, B. B. (2023). Narrowing the gender digital divide in Pakistan: Mobile phone ownership and female labor force participation. *Review of Development Economics*, *27*, 1354–1382.

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. *Journal of the American statistical Association*, *91*(434), 444–455.

Asfaw, S., Scognamillo, A., Caprera, G. D., Sitko, N., & Ignaciuk, A. (2019). Heterogeneous impact of livelihood diversification on household welfare: Cross-country evidence from sub-Saharan Africa. *World Development*, *117*, 278–295.

Asongu, S. A. (2015). The impact of mobile phone penetration on African inequality. *International Journal of Social Economics*, *42*, 706–716.

Asongu, S. A., & Nwachukwu, J. C. (2016). The mobile phone in the diffusion of knowledge for institutional quality in sub-Saharan Africa. *World Development*, *86*, 133–147.

Bangladesh Bureau of Statistics. (2023). *Report on the household income and expenditure survey 2022*. Bangladesh Bureau of Statistics.

Beuermann, D. W., Mckelvey, C., & Vakis, R. (2012). Mobile phones and economic development in rural Peru. *The Journal of Development Studies*, *48*(11), 1617–1628.

Cameron, A., & Trivedi, P. (2005). *Microeconometrics: Methods and applications*. Cambridge University Press.

Foster, J., Green, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica*, *52*(3), 761–766.

Fowowe, B. (2023). Financial inclusion, gender gaps and agricultural productivity in Mali. *Review of Development Economics*, 1–40. https://doi.org/10.1111/rode.13034

Fu, X., & Akter, S. (2016). The impact of Mobile phone technology on agricultural extension services delivery: Evidence from India. *The Journal of Development Studies*, *52*(11), 1561–1576.

GSM Association. (2021). *Achieving mobile-enabled digital inclusion in Bangladesh*. GSMA Association.

Imai, K., & Kim, I. S. (2019). When should we use unit fixed effects regression models for causal inference with longitudinal data? *American Journal of Political Science*, *63*(2), 467–490.

Islam, A. H. M. S., Braun, J. V., Thorne-Lyman, A. L., & Ahmed, A. U. (2018). Farm diversification and food and nutrition security in Bangladesh: Empirical evidence from nationally representative household panel data. *Food Security*, *10*, 701–720.

Jensen, R. (2007). The digital provide: Information (technology), market performance, and welfare in the south Indian fisheries sector. *Quarterly Journal of Economics*, *122*(3), 879–924.

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Khandker, S. (2012). Seasonality of income and poverty in Bangladesh. *Journal of Development Economics*, *97*, 244–256.

Leng, C., Ma, W., Tang, J., & Zhu, Z. (2020). ICT adoption and income diversification among rural households in China. *Applied Economics*, *52*, 3614–3628.

Ma, W., Grafton, R. Q., & Renwick, A. (2020). Smartphone use and income growth in rural China: Empirical results and policy implications. *Electronic Commerce Research*, *20*, 713–736.

Ma, W., Nie, P., Zhang, P., & Renwick, A. (2020). Impact of internet use on economic well-being of rural households: Evidence from China. *Review of Development Economics*, *24*, 503–523.

Ma, W., Renwick, A., Nie, P., Tang, J., & Cai, R. (2018). Off-farm work, smartphone use and household income: Evidence from rural China. *China Economic Review*, *52*, 80–94.

Ma, W., Owusu-Sekyere, E., Zheng, H., & Owusu, V. (2023). Factors influencing smartphone usage of rural farmers: Empirical analysis of five selected provinces in China. *Information Development*. https://doi.org/10.1177/02666669231201828

Mano, Y., Njagi, T., & Otsuka, K. (2022). An inquiry into the process of upgrading rice milling services: The case of the Mwea irrigation scheme in Kenya. *Food Policy*, *106*, 102195.

Matsuura, M., Islam, A. H. M. S., & Tauseef, S. (2024). Mobile money mitigates the negative effects of weather shocks: Implications for risk sharing and poverty reduction in Bangladesh. In S. Bera, Y. Yao, A. Palit, & D. B. Rahut (Eds.), *Digital transformation for inclusive and sustainable development in Asia* (pp. 121–144). Asian Development Bank Institute.

Matsuura, M., Luh, Y.-H., & Islam, A. H. M. S. (2023). Weather shocks, livelihood diversification, and household food security: Empirical evidence from rural Bangladesh. *Agricultural Economics*, *54*(4), 455–470.

Miyajima, K. (2022). Mobile phone ownership and household welfare: Evidence from South Africa's household survey. *World Development*, *154*, 105863.

Munyegera, G. K., & Matsumoto, T. (2016). Mobile money, remittances, and household welfare: Panel evidence from rural Uganda. *World Development*, *79*, 127–137.

Rajkhowa, P., & Qaim, M. (2022). Mobile phones, off-farm employment and household income in rural India. *Journal of Agricultural Economics*, *73*, 789–805.

Sekabira, H., & Qaim, M. (2017a). Can mobile phones improve gender equality and nutrition? Panel data evidence from farm households in Uganda. *Food Policy*, *73*, 95–103.

Sekabira, H., & Qaim, M. (2017b). Mobile money, agricultural marketing, and off-farm income in Uganda. *Agricultural Economics*, *48*, 597–611.

Tauseef, S. (2022). Can money buy happiness? Subjective wellbeing and its relationship with income, relative income, monetary and non-monetary poverty in Bangladesh. *Journal of Happiness Studies*, *23*, 1073–1098.

World Bank. (2023). Mobile cellular subscriptions (per 100 people)—Bangladesh.

Yang, B., Wang, X., Wu, T., & Deng, W. (2023). Reducing farmers' poverty vulnerability in China: The role of digital financial inclusion. *Review of Development Economics*, *27*(3), 1445–1480.

Zheng, H., & Ma, W. (2021). Smartphone-based information acquisition and wheat farm performance: Insights from a doubly robust IPWRA estimator. *Electronic Commerce Research*, *23*, 633–658.

Zheng, H., Zhou, Y., & Rahut, D. B. (2023). Smartphone use, off-farm employment, and women's decision-making power: Evidence from rural China. *Review of Development Economics*, *27*, 1327–1353.

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