Mobile phone ownership, income diversification, and household welfare in rural Bangladesh

Masanori Matsuura[*] Abu Hayat Md. Saiful Islam[†] Salauddin Tauseef[‡]

Abstract

Mobile phone has been widely adopted in developing countries with potential to enhance opportunities for finding off-farm work which builds resilience of rural livelihoods. Although the effect of mobile phones on income has been studied in the past, the potential to increase off-farm employment and reduce poverty has not been studied so much. To fill this gap, we investigate the linkage among mobile phone ownership, income diversification, and household welfare, using monetary and non-monetary aspects of poverty. Using instrumental variable approach, we find that mobile phone ownership increases income diversification then reduces the incidence and depth of poverty. It also has significant impact on non-monetary aspects of poverty. Our heterogeneity analysis shows the pro-poor impacts of mobile phone ownership as well as that female-headed households enjoy larger impact of mobile phone ownership on income diversification. Moreover, Gini decomposition of different income sources with propensity score matching indicates that the off-farm income results in an inequality-equalizing effect among the rural households owning mobile phones in Bangladesh, suggesting the income diversification through mobile phone ownership improves the overall welfare of the rural society.

Keywords: ICT, Mobile phone, Instrumental variable approach, Poverty reduction, Gini decomposition, Bangladesh

JEL code: C26, I32, Q12 Q55

---

[*]Institute of Developing Economies (IDE-JETRO), Masanori_Matsuura@ide.go.jp
[†]Bangladesh Agricultural University, saiful_bau_econ@yahoo.com. Corresponding author
[‡]International Food Policy Research Institute S.Tauseef@cgiar.org

We would like to acknowledge valuable comments from Kyoji Fukao, Takeshi Aida, Tatsuya Shimizu, Miki Hamada, Yuichi Watanabe, and Wataru Kodama.

1. Introduction

Mobile phone (MP) has been widely adopted in developing countries contributing to economic development. Mobile technologies are believed to lead economic growth by driving productivity and efficiency gains in other sectors of the economy. For example, mobile phone ownership is positively associated with the likelihood of participating in various types of off-farm work through reduction of transaction cost (Rajkhowa & Qaim, 2022). It also improves smallholder farmers' productivity by providing vital information on weather, cultivation techniques and market prices (Sekabira and Qaim, 2017; GSM Association, 2021). When it comes to human capital, mobile platforms enable the remote delivery of academic lessons, reading materials and diffusion of knowledgies (Asongu & Nwachukwu, 2016; GSM Association, 2021). Aker & Mbiti (2010) pointed out that mobile devices, including smartphones, may generate income gains by facilitating job market participation, expanding social networks, and reducing households' exposure to risks. Moreover, off-farm work opportunity is positively associated with mobile phone ownership (Rajkhowa & Qaim, 2022). Off-farm income improves food consumption expenditure, inequality, and nutritional condition as well as household income (Adams Jr., 2002; Mishra et al., 2015; Rajkhowa & Qaim, 2022; Debela et al., 2020). Therefore, investigating the linkage between income diversification and mobile phone ownership, and the inequality-equalizing effect of income diversification provides important policy implications, especially for poverty and inequality reduction in developing countries.

In this paper, first, we investigate whether mobile phone ownership increases income diversification, household total income and per capita income, and contributes to monetary and non-monetary poverty reduction in the context of rural Bangladesh. Second, in addition to the average effect of mobile phone ownership, we investigate the heterogeneous effect of mobile phone ownership for different types of households, differentiating by gender, farming scale, and wealth. Finally, to enrich our understanding of whether the income diversification through mobile phone ownership reduces income inequality, we use the Gini decomposition, separating our sample into households who own mobile phones and who do not. To investigate the above, we use a most recently collected longitudinal data set, spanning eight years and two data points from 2011 to 2019 of Bangladeshi rural households.

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

The contribution of this paper is fourfold. First, we provide the first empirical micro-econometrics evidence on the effect of mobile phone expansion on income diversification and household welfare in the context of rural Bangladesh. Second, unlike the previous study, we use high-quality household-level longitudinal data that allow controlling for time-invariant unobserved heterogeneity at the household level to generate robust evidence in Bangladesh. Estimating the effect of mobile phone ownership on multidimensional household welfare provides the robustness of our empirical results from the viewpoint of monetary and non-monetary poverty. Third, we investigate the heterogeneous impact of mobile phone ownership, in terms of gender, farmland size, and income. To this end, we use interaction terms in models and a quantile regression approach to find who benefits more from owning mobile phones, thus we can provide more appropriate policy implications. At last, to understand whether income diversification through mobile phone adoption reduces income inequality, we use Gini decomposition of different income sources combined with propensity score matching of households who own mobile phones and who do not.

We find that mobile phone ownership accelerates income diversifications as well as alleviates monetary and non-monetary poverty. Female headed households particularly benefit more from mobile phones, in terms of income diversification. Our quantile regression analysis reveals the pro-poor effect of mobile phone ownership. Furthermore, our result indicates that the off-farm income results in an inequality-equalizing effect among the rural households owning mobile phones in rural Bangladesh, suggesting the off-farm income of rural households owning mobile phones improves the overall welfare of the rural society

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

2. Materials and methods

2.1 Data

The household data for this study is drawn from a recently collected three-round panel survey, the Bangladesh Integrated Household Survey (BIHS), which was designed and supervised by

International Food Policy Research Institute (IFPRI) in 2011/2012, and 2019[4]. The sample is representative of rural Bangladesh as well as of the seven administrative division of the country (Islam et al., 2018; Ahmed and Tauseef, 2022). The sample design of the BIHS followed a two staged stratified sampling method. Following the sampling framework developed from the community series of the 2001 Population and Housing Census of Bangladesh, primary sampling units (PSUs) were randomly selected in the first stage and random selection of households within each PSU constitute the second stage (Ahmed and Tauseef, 2022). The total sample size in the first wave is 6503 households in 318 PSUs which are allocated among seven divisions. In addition, the total sample size in the third wave is 4891 households as shown in Table 1[5]. 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 is random. Therefore, the estimates presented in this paper are not adjusted for attrition. Descriptive statistics of the whole sample are presented in Table A 1.

In addition, we have used weather data which is taken from Bangladesh Meteorology Department. This data includes monthly precipitation and temperature from March, 1992 to February 2019 on 0.5-degree latitude by 0.5-degree longitude global grid. we use specifications that separate flood and drought shocks in two cropping seasons Kharif (March to October) and Rabi (November and February) since South Asian countries are drought and flood prone ((Auffhammer & Carleton, 2018)). Flood and drought shocks are defined as 20-year average ± 1 standard deviation (Carrillo, 2020).. An overview of the climate variables used in this paper are presented in Table A 1. The weather data is aggregated into district-level data, which

---

[4] BIHS consist of three rounds, but a variation of mobile phone ownership in the second round and third round is little. Therefore, we only use the first and third round of BIHS for the analysis.

[5] Although the original 3rd wave sample size is higher than 4891, it includes households who are split into several households due to marriage, etc. We follow the original household head to create a panel dataset.

consists of 64 districts in this study[6].

Table 1 shows the number of households owning and not owning mobile phone in our sample. In 2012, about 27% households in our sample did not own a mobile phone which dropped to 2% in 2019. Table 1 depicts that mobile phones were widely adopted in rural Bangaldesh from 2012 to 2019.

[6] For detailed explanation of climate variables used in this study, see Matsuura et al. (2022).

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

	2012	2019
Non-ownership	1775 (27%)	77 (2%)
Ownership	4728 (73%)	4814 (98%)
Total	6503	4891

Source: Bangladesh Integrated Household Survey 2011/12, 2019

2.2 Measurement of key variables

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

In terms of outcome variables, we are particularly interested in off-farm work, measures of monetary and non-monetary poverty, total household income (log), and per capita income (log). Moreover, we introduce an income diversification index that is transformed from the Simpson index usually used to indicate the degree of diversity (Asfaw et al., 2019)

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

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

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

where α is a parameter. When $\alpha = 0$, we get the incidence or headcount measure of poverty, since the normalized deprivation is equal to 1 for all of the poor. When $\alpha = 1$, normalized deprivation reflects the poverty gap or depth of poverty, with a higher value of d_i being assigned to poorer households. For the further explanation of calculation of poverty line using BIHS data, please see Tauseef (2021).

Poverty headcount and depth of poverty can capture the aspects of finance. However, the view of non-monetary should be observed to evaluate the poverty of households holistically. To capture the non-monetary aspects of poverty, we used 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 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[7]. For further explanation of the MPI score calculation using the same dataset, please see Tauseef (2022). Moreover, household income is measured from all income sources such as farm income, farm wage, off-farm wage and salary, off-farm self-employment, and non-earned income over a period of 12 months (Khandker, 2012; Matsuura et al., 2022).

2.3 Empirical strategy

[7]The dataset is available at https://www.ifpri.org/blog/ifpris-bangladesh-integrated-household-survey-bihs-second-round-dataset-now-available.

2.3.1 Identification strategy

Identifying the effect of mobile phone ownership on household welfare may be convoluted by possible endogeneity bias because mobile phone ownership may be related to the household's unobserved characteristics.

The main variable of interest, mobile phone adoption, is itself a decision variable. Hence, it may be correlated with the error term in the outcome equations. There are three possible sources of endogeneity. First, there may be reverse causality. Our hypothesis is that mobile phone ownership improves household welfare. However, a household may own mobile phone because they are already rich. Second, there may be self-selection into mobile phone ownership. Farmers can decide adoption of mobile phones on their own, thus unobserved factors and attributes would affect their decision making. In this case, systematic differences among households might affect their decision, such as socioeconomic and demographic factors. Third, there may be omitted variable bias caused by time-varying and unobservable variables (Maggio et al., 2021). However, the use of panel data and two-stage residual inclusion (2SRI) model, developed by Terza et al. (2008), can deal with those possible endogeneity problems, irrespective of functional form specification (Terza et al., 2008).

To perform 2SRI, we need valid instruments (exclusive restriction) which affect mobile phone ownership but do not affect household welfare (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 this study is the share of household owning mobile phones within a village which is the smallest administrative unit in Bangladesh. The variable is calculated by the percentage of households in the village owning mobile phones, excluding the household considered. Past studies such as Muto & Yamano(2009), and Miyajima (2022), also used peer effect variables as an instrument in studying the effects of mobile phone coverage and ownership. The logic behind is this that the neighbor's decisions would affect households' decision of mobile phone ownership (Murendo et al., 2018) but does not directly affect off-farm employment decision, poverty, and income.

2.3.2 Determinants of mobile phone ownership

We estimate the determinants of mobile phone ownership at the household level. The decision to own mobile phone depends on observed characteristics of the household in the form

$$M_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 X_{it} + \beta_3 V_{vt} + t_t + u_{it} \tag{1}$$

where M_{it} is a binary variable whether a household *i* owns mobile phones or not in year *t*, Z_{it} is the instrumental variable indicating the share of households owning a mobile phone in a village, X_{it} is a vector of control variables that may also influence mobile phone ownership, V_{vt} is a village-level average household characteristic variable, t_t is year dummy, and u_{it} is a random error term. The probit regression is employed with a random effects (RE) panel estimator. However, as households self-selected into using mobile phones, this assumption may be violated, which could lead to biased estimates (Sekabira & Qaim, 2017). Therefore, in addition to the RE estimates, we also use a pseudo fixed-effects estimator, as proposed by Mundlak (1978). The Mundlak (MK) estimator includes covariate mean values as additional explanatory variables and thus controls for bias that may arise from time-invariant unobserved heterogeneity (Cameron & Trivedi, 2005). Moreover, using MK estimator, we calculate the residual from Equation (1) to incorporate it in the outcome Equation (2) for controlling the endogeneity of mobile phone ownership. At last, we include village-level average household characteristic variables to mitigate the concerns about unobserved heterogeneity at the village level that is correlated with both mobile phone ownership and outcomes such as household income. As we shall show in the results section, the change of estimation method does not qualitatively change our results.

2.3.3 Effect of mobile phone ownership on off-farm work, poverty, and income

We aim to estimate the effect of mobile phone ownership on off-farm work and household welfare, we estimate the following panel data model:

$$Y_{it} = \gamma_o + \gamma_1 M_{it} + \gamma_2 X_{it} + rR_{it} + a_i + t_t + \varepsilon_{it} \quad (2)$$

where Y_{it} is the outcome variable of interest referring to household i in year t, R_{it} is a residual which comes from Equation (1) estimated by Mundlak Probit regression. The coefficient of residual R_{it} tests whether M_{it} is an endogenous variable or not. ε_{it} is a random error term, and the other variables are as defined above. As mentioned above, we use six outcome variables, namely income diversification, poverty headcount (binary), poverty gap (censored to zero), MPI score, total household income (log), and per capita income (log), and estimate a separate regression for each of them. Equation (2) is estimated by MK Probit regression for binary outcomes. Furthermore, for a censored outcome, Equation (2) is estimated by MK Tobit while Fixed Effect OLS is employed for the continuous outcome equations. We are particularly interested in the estimates for γ_1. In the regression analysis, we do not differentiate between farm households and non-farm households, but we control for the farmland size, as this may influence the likelihood of off-farm employment (Rajkhowa & Qaim, 2022). For income diversification, total household income (log), and per capita income (log), positive and significant estimates would imply that mobile phone ownership significantly increase the income diversification, total household income, per capita income after controlling for other factors that are included in the vector X_{it} while negative estimates for poverty headcount (binary), poverty gap, and MPI score, would imply that mobile phone ownership significantly reduces the monetary and non-monetary poverty.

2.3.4 Income inequality of rural households

In the Gini decomposition method, the Gini coefficient (G) is presented as follows:

$$G = \sum_{\{k=1\}}^{K} S_k G_k R_k$$

where S_k is the share of income source k in total household income, G_k represents the Gini coefficients of income source *k*, R_k refers to is the Gini correlation of income source *k* with the distribution of total income (Lerman & Yitzhaki, 1985). The partial derivative of *G* with respect to a one percent change (*e*) in income source *k* is equal to:

$$\frac{\partial G}{\partial e} = S_k(G_k R_k - G) \tag{3}$$

Dividing Equation (3) by *G,* yields the source's marginal effect relative to the overall Gini, which can be written as the source's inequality contribution as a percentage of the overall Gini minus the source's share of total income (Lerman & Yitzhaki, 1985)*:*

$$\frac{\frac{\partial G}{\partial e_k}}{G} = \frac{S_k G_k R_k}{G} - S_k$$

The sum of relative marginal effects is zero. Multiplying all sources by *e* leaves the overall Gini unchanged. This Gini decomposition method is applied to the whole sample and to a subsample depending on mobile phone ownership. The evaluation of this sub-sample allows us to compare the effect of off-farm work on income inequality reduction due to mobile phone ownership.

3. Results and discussion

3.1 Descriptive statistics

Table 2 shows the comparison of outcome variables between households who own a mobile phone and who do not[8]. We find that mobile phone owners are more likely to diversity income sources, have higher total household income as well as higher per capita income than non-owners. These observed differences are consistent with Sekabira & Qaim (2017); Rajkhowa & Qaim (2022) Furthermore, the incidence of poverty of household owning mobile phones is lower than households not owning mobile phones. Even poverty gap and MPI score of

[8] Full table of descriptive statistics is at Appendix Table A 1

households not owning mobile phones are worse than mobile phone owners. The results are reasonable that non-poverty households can afford to own mobile phones and utilize them.

Moreover, Table 2 presents descriptive statistics for the socioeconomic characteristics that we use as explanatory variables in the econometric models, differentiating between mobile phone users and non-users. In most of the variables, we observe significant differences. Mobile phone owners are likely to be male, younger, have more family members, with better educated household head. Moreover, households who own mobile phones have larger farmland than household not owning mobile phones.

Table 2 Summary statistics by mobile phone ownership

	2011/12			2019		
Outcome Variable	**Ownership**	**Non-ownership**		**Ownership**	**Non-ownership**	
Income diversification	0.419	0.361	***	0.390	0.263	***
	(0.004)	(0.007)		(0.004)	(0.030)	
Poverty headcount	0.096	0.308	***	0.072	0.078	
	(0.004)	(0.011)		(0.258)	(0.270)	
Poverty gap	0.015	0.059	***	0.010	0.007	
	(0.001)	(0.003)		(0.456)	(0.041)	
MPI score	0.386	0.568	***	0.279	0.405	***
	(0.177)	(0.163)		(0.156)	(0.126)	
Total household income	150729.4	75161.01	***	248420.7	95903.27	***
	(204225.2)	(73194.83)		(411281.7)	(97486.54)	
Per capita income (log)	36409.440	21335.580	***	46650.87	22434.57	***
	(49155.010)	(21938.310)		(76182.71)	(25756.34)	
Socioeconomic variable						
Female household head	0.166	0.207	***	0.198	0.494	***
	(0.372)	(0.406		(0.398)	(0.503)	
Age of HH	43.822	45.103	***	47.147	56.142	***
	(13.544)	(15.047)		(12.936)	(15.631)	
Household size	4.381	3.701	***	5.582	4.792	***
	(1.634)	(1.506)		(2.135)	(2.086)	
Schooling year of HH	3.993	1.565	***	3.752	1.299	***
	(4.105)	(2.764)		(4.049)	(2.417)	

Farm Size(decimal)	105.317	54.005	***	94.840	64.840	*
	(158.663)	(92.290)		(136.446)	(110.680)	
Periodic bazaar access (minute)	17.214	18.066	***	13.218	12.213	
	(10.462)	(11.374)		(8.443)	(7.700)	
Road access (minute)	14.403	15.340	***	12.127	10.481	
	(11.131)	(12.390)		(11.228)	(9.609)	

Source: Bangladesh Integrated Household Survey 2011/12, 2019.

Note: Mean values are shown with standard deviations in parentheses Asterisks (*, **, and ***) denote significance at 10, 5, and 1 per cent levels of the results of t-test detecting the difference between ownership and non-ownership. 100 decimals are equal to 0.4 ha..

3.2 Determinants of mobile phone ownership

Table 3 shows the determinants of mobile phone ownership. The coefficient of the share of households adopting mobile phone in the village is positively significant both in Column (1) and (2). It indicates that higher share of households adopting mobile phone in the village increase a households' mobile phone ownership. This result is consistent with Miyajima (2022). Furthermore, the coefficient of the instrumental variable is significant for mobile phone ownership so that we can reject the null hypothesis of an weak instrumental variable[9].

Regarding socioeconomic characteristics, male headed households are more likely to own mobile phones. Moreover, a younger household head is more likely to own a mobile phone. In terms of schooling year of household head, the coefficient is positively significant in column (1). It indicates that better educated household heads are more likely to own a mobile phone. This result is consistent with Tadesse & Bahigwa (2015), and Munyegera & Matsumoto (2016). This could partly capture the literacy effect of educated household heads who could be more able to operate mobile handsets (Munyegera & Matsumoto , 2016). Moreover, a better access to periodic bazaars is associated with higher propensity of mobile phone ownership. It indicates that improving infrastructures disseminates ICT in rural areas. In addition, village-level average access to agricultural extension service is negatively correlated to households' mobile phone ownership.[10]

[9] We also reject the null hypothesis of weak instruments based on the Cragg–Donald Wald F statistic 113.470, which is used as a rule of thumb to test the hypothesis (Staiger & Stock, 1997)

[10] In Table 3, we use year-division interaction terms to control for possible unequal regional developments over time.

Table 3 Determinants of mobile phone ownership

	(1) RE Probit		(2) MK Probit	
Share of households adopting mobile phone in the village	1.314***	(0.189)	1.344***	(0.195)
Flood shock in Kharif	0.117	(0.073)	0.117	(0.075)
Drought shock in Kharif	0.204***	(0.063)	0.095	(0.090)
Female household head	-0.137**	(0.057)	-0.328***	(0.121)
Age of HH	-0.008***	(0.002)	-0.011**	(0.005)
Household size	0.152***	(0.016)	0.030	(0.034)
Schooling year of HH	0.101***	(0.007)	-0.020	(0.021)
Farmsize (log)	0.158***	(0.015)	0.135***	(0.036)
Periodic bazaar access (minute)	-0.003	(0.002)	0.000	(0.004)
Road access (minute)	-0.000	(0.002)	0.003	(0.003)
Village-level average household characteristics				
Age of HH	0.014**	(0.006)	0.014**	(0.006)
Household size	-0.007	(0.051)	-0.019	(0.053)
Periodic bazaar access (minute)	-0.001	(0.004)	-0.001	(0.004)
Female household head (=1 if yes)	-0.002***	(0.000)	-0.002***	(0.000)
Farm size (log)	-0.000	(0.004)	0.000	(0.004)
Road access (minute)	0.037*	(0.020)	0.029	(0.020)
Schooling year of HH	-0.044*	(0.025)	-0.055**	(0.025)
Covariate mean values	No		Yes	
Year dummy	Yes		Yes	
Division dummy	Yes		Yes	
Division*Year dummy	Yes		Yes	
Observations	11,087		11,087	

Note: Robust standard errors clustered by households in parentheses. Asterisks (*, **, and ***) denote significance at 10, 5, and 1 per cent levels. Instrumental variable is share of households adopting mobile phone in the village. Full regression table is available upon requests.
Source: Bangladesh Integrated Household Survey 2011/12, 2019.

3.3 Impact of mobile phone ownership on household welfare

Table 4 presents the impact of mobile phone ownership on income diversification and household welfare, by 2SRI to account for the endogeneity of mobile phone ownership[11]. First, we find a statistically significant coefficient of mobile phone ownership to income diversification as depicted in Columns (1) using OLS-FE model. This is consistent with the findings of Rajkhowa & Qaim (2022). It indicates that mobile phone ownership enriches an income portfolio of rural households for building resilience livelihood. Moreover, mobile phone ownership decreases the prevalence of poverty as depicted by the statistically significant negative impact presented in Columns (2). The probabilty of being poor decreased by 14.4% as a result of mobile phone ownership as seen in Column (2). The poverty reduction effect of mobile phone adoption is consistent with Asongu (2015). Moreover, Column (3) shows that mobile phone ownership also reduces the depth of poverty as seen by the statistically significant negative impact on the poverty gap measure, decreasing 23.4% of poverty depth as seen in Column (3). One plausible channel of poverty reduction through mobile phones is mobile remmitance. Lee et al. (2021) find that rural consumption increased by 7.5 percent, and extreme poverty fell as well as rural households borrowed less, saved more, sent additional migrants, and consumed more in the lean season by introducing mobile banking. Furthermore, mobile phone ownership has an impact on non-monetary aspects of poverty, reducing the multidimensional poverty score by 7.9% in Column (4). As Sekabira & Qaim (2017) find that mobile phone use is positively associated with women empowerment, food security, and dietary diversity. The results, thus, indicate that mobile phone adoption not only contributes to reduction in monetary poverty but has a holistic impact on other non-monetary dimensions of poverty as well.

---

[11] Full regression table is available upon request.

In contrast to the poverty reduction effect, Columns (5) and (6) present the positive but insignificant coefficient of mobile phone ownership for household total income and per capita income. It indicates that mobile phone ownership do not directly affect income, but there is a possibility that households indirectly benefit from mobile phone ownership. Therefore, we examine the mechanism how mobile phone and income diversification affect poverty and income based on Equation (2). Table 5 shows results of the channel analysis. Except for colum (4), the coefficients of income diversification are significant. They indicate that income diversification allevetates poverty headcount and depth of poverty as well as increase total household income and per capita income. The results suggest that income diversification through mobile phone ownership increases income, meaing an indirect effect of mobile phone ownerhsip. Our results are consistent with the findings about welfare enhancing effects of mobile phones by Munyegera and Matsumoto (2016); Sekabira and Qaim (2017); Ma et al., (2018); Rajkhowa and Qaim (2022); and Miyajima (2022). Moreover, our channel analysis corroborates the findings about positive impacts may be channelled through higher farm and/or off-farm incomes, online remittance availability (Lee et al., 2021; Rajkhowa and Qaim, 2022).

Table 4 Impact of mobile phone ownership on income diversification, poverty, and income (2SRI)

	(1)	(2)	(3)	(4)	(5)	(6)
	Income diversification	Poverty headcount	Depth of poverty	MPI score	Total household income (log)	Per capita income (log)
	FE OLS	MK Probit (dy/dx)	MK Tobit (dy/dx)	FE OLS	FE OLS	FE OLS
Mobile phone ownership	0.061**	-0.144***	-0.234***	-0.079***	0.128	0.125
	(0.025)	(0.043)	(0.035)	(0.016)	(0.157)	(0.121)
Residual-mobile	-0.030	0.049	0.083***	0.020	0.130	0.086
	(0.023)	(0.035)	(0.031)	(0.014)	(0.126)	(0.096)
Household FE	Yes	No	No	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Division dummy	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,006	11,087	11,087	10,701	11,087	11,087

Note: Asterisks (*, **, and ***) denote significance at 10, 5, and 1 per cent levels. Bootstrap robust standard errors clustered by household in parenthesis in column (1), (2), (4), (5) and (6) while standard errors in in parenthesis in Column (3). Full regression table is available upon requests.

Source: Bangladesh Integrated Household Survey 2011/12, 2018/19.

Table 5 Potential mechanism among mobile phone ownership, income diversifications and household welfare (2SRI)

	(2)	(3)	(4)	(5)	(6)
	Poverty Headcount	Depth of poverty	MPI score	Total household income (log)	Per capita income (log)
	MK Probit (dy/dx)	MK Tobit (dy/dx)	FE OLS	FE OLS	FE OLS
Income diversification	-0.046*	-0.073***	-0.004	0.923***	0.914***
	0.025	0.016	(0.009)	(0.056)	(0.072)
Mobile phone ownership	-0.185***	-0.301***	-0.070***	-0.129	-0.129
	(0.060)	(0.047)	(0.020)	(0.148)	(0.148)
Residual-mobile	0.092	0.154***	0.015	0.256	0.222
	(0.057)	(0.045)	(0.019)	(0.156)	(0.146)
Household FE	No	No	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes
Division dummy	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	11,006	11,006	10,701	11,006	11,006

Note: Asterisks (*, **, and ***) denote significance at 10, 5, and 1 per cent levels. Bootstrap robust standard errors clustered by household in parenthesis in column (1), (2), (4), (5) and (6) while standard errors in in parenthesis in Column (3). Full regression table is available upon requests.

Source: Bangladesh Integrated Household Survey 2011/12, 2019.

3.4 Who benefits more from mobile phone ownership

In this section, we disentangle the relationship between mobile phone ownership and characteristics of households to the outcome variables. Using the models explained in Equation (2) above, we interact mobile phone ownership with gender of household heads and farm size. We instrument the interaction between gender of household heads, farm size and mobile phone ownership with the interaction between the respective instruments on share of mobile phone owners in a village and gender of household heads and farm size which are exogenous in our model. Moreover, we estimate the IV-quantile regression to address the distributional effect of mobile phone ownership on per capita income conditioned on 10%, 25%, 50%, 75% and 90% quantiles.

The results summarized in Table 6 show the estimated coefficients on the interaction between the three household characteristics and mobile phone ownership. In panel A of Table 6, the coefficient of the interaction term for income diversification is positively significant. It indicates that female headed households are more likely to engage in income diversification when the households own a mobile phone. The result is consistent with Rajkhowa and Qaim (2022) studying about India. This is an welcome result that mobile phone ownership can enhance the income diversification which improves livelihood, especially for female headed household. However, we find insignificant coefficient for the interaction term between mobile phone ownership and female household head to poverty headcount, depth of poverty, and MPI. This implies that there is no significant difference in the impact of mobile phone ownership on poverty reduction over gender of household heads. Moreover, the coefficients for the interaction term between mobile phone ownership and female household head to both total household income and per capita income are insignificant. These results imply that female headed and male headed household fairly benefit from mobile phone ownership for poverty reduction and increase in income. As women in developing countries are often restricted in their movements and have fewer outside options to access information (Rajkhowa & Qaim, 2022), the results are encouraging to policy makers challenging gender inequality. Our results recommend that mobile phones could be used as devices that accelerate women empowerment and gender-inclusive adoption of technologies (Rola-Rubzen et al., 2020).

The results in panel B of Table 6 show that the coefficients of interaction term between mobile phone ownership and farm size are negatively significant for poverty headcount and depth of poverty. The results indicate that smallholder farmers benefit less from mobile phones than large scale farmers, in terms of monetary poverty reduction. This underlines that large scale farmers utilize mobile phones for information sharing and mobile banking such as remittance effectively rather than smallholder farmers do, supporting the findings of Munyegera & Matsumoto (2016). However, we have to be cautious about that the coefficient is almost zero indicating the magnitude of the heterogeneity is small. On the other hand, with regards to income diversification, MPI, total household income, and per capita total income, the coefficients of the interaction terms are insignificant. They indicate that both smallholder farmers and large-scale farmers equally enjoy the benefits of mobile phone ownership.

Table 7 reports the estimated coefficients associated with the mobile phone ownership at 0.10, 0.25, 0.50, 0.75, 0.90 quantile of the per capita income distribution. All the coefficients of mobile phone ownership are positively significant, indicating that mobile phone ownership increases per capita income among the poorest, middle and richest households. However, the impact of mobile phone ownership is higher at the lowest segments of the distribution. It indicates that especially the poorest households benefit more from mobile phone ownership. This is also welcome result, as we find that mobile phone ownership has pro-poor effect in the present study.

Table 6 Heterogeneous effect of mobile phone ownership (2SRI)

	(1) Income diversification	(2) Poverty Headcount	(3) Depth of poverty	(4) MPI score	(5) Total household income (log)	(6) Per capita total income (log)
Panel A	**FE OLS**	**MK Probit (dy/dx)**	**MK Tobit(dy/dx)**	**FE OLS**	**FE OLS**	**FE OLS**
Mobile phone (dummy)	0.090**	-0.174***	-0.283***	-0.283***	-0.073***	-0.170
	(0.041)	(0.068)	(0.049)	(0.049)	(0.022)	(0.196)
Mobile phone × Female hh head	0.509**	0.149	0.137	0.137	-0.142	1.210
	(0.217)	(0.459)	(0.298)	(0.298)	(0.119)	(1.590)
Individual FE	Yes	No	No	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Division dummy	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,006	11,087	11,087	10,701	11,088	11,088
Panel B						
Mobile phone (dummy)	0.066	-0.174***	-0.283***	-0.068***	-0.061	-0.063
	(0.044)	(0.062)	(0.049)	(0.021)	(0.224)	(0.194)
Mobile phone × Farm size	-0.000	-0.001***	-0.001***	-0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Household FE	Yes	No	No	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Division dummy	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,006	11,087	11,087	10,701	11,088	11,088

Note: Asterisks (*, **, and ***) denote significance at 10, 5, and 1 per cent levels. Bootstrap robust standard errors clustered by household in parenthesis. Full regression table is available upon requests.
Source: Bangladesh Integrated Household Survey 2011/12, 2019.

Table 7 Quantile effect of mobile phone ownership on per capita income

	(1) 0.10 quantile	(2) 0.25 quantile	(3) 0.50 quantile	(4) 0.75 quantile	(5) 0.90quantile
Mobile phone (dummy)	0.637***	0.528***	0.531***	0.563***	0.590***
	(0.129)	(0.055)	(0.046)	(0.045)	(0.061)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes
Division dummy	Yes	Yes	Yes	Yes	Yes
Division * year dummy	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	11,088	11,088	11,088	11,088	11,088

Note: Asterisks (*, **, and ***) denote significance at 10, 5, and 1 per cent levels. Bootstrapped robust standard errors clustered by household in parenthesis. Full regression table is available upon requests.
Source: Bangladesh Integrated Household Survey 2011/12, 2019.

3.5 Inequality and redistribution of income of rural households in Bangladesh

Another dimension of rural household welfare is income inequality. We applied a decomposition approach to determining the marginal impact of various income sources on overall income inequality (Lerman & Yitzhaki, 1985). The decomposition results reported in Table 8 are for the whole sample matched by a propensity score matching method, which matched the subsamples of households who own and do not own mobile phones to correct for endogeneity. For the propensity score matching (PSM), we used the nearest neighbor matching technique and keeping only those on common support to create a treated group (ownership) and an untreated group (non-ownership) (Cliendo & Kopeinig, 2008).

Figure 1 shows the common support assumption is implemented after matching the two groups using PSM. The results of Gini decomposition are shown in Table 8. The Gini coefficient of off-farm income is higher for households who do not own mobile phones in Column (2) of Table 8. Moreover, in Table 8, Column (5) presents percentage changes of off-farm income in the overall Gini coefficient. For households who own mobile phones, an increase of one percentage point in off-farm income decreases the Gini coefficient by 0.064% while an increase of one percentage point in off-farm income decreases the Gini coefficient by 0.049% for households not owning a mobile phone. Our findings indicate that the equalizing effect of income diversification especially off-farm income is more sizable considering mobile phones. This is consistent with Adams Jr. (1994; 2002). Miyajima (2022) found that the impact of mobile phone ownership on consumption remains significant, particularly among those in the lower part of the consumption distribution, indicating the reduction of inequality by mobile phone ownership. Although Miyajima (2022) used FE-IV to show the finding, our results using Gini decomposition analysis are consistent with Miyajima (2022). These results add empirical evidence regarding the impact of mobile phones on reducing income inequality. Reardon et al. (2000) stated that it is crucial for public investments and policy to favor an increase in the access of the poor to assets that allow them to overcome non-farm work entry barriers. Our results indicate that mobile phone penetration and adoption would reduce these barriers and thereby inequality due to increase in off-farm work opportunities.

Figure 1 Common support assumption of propensity score matching

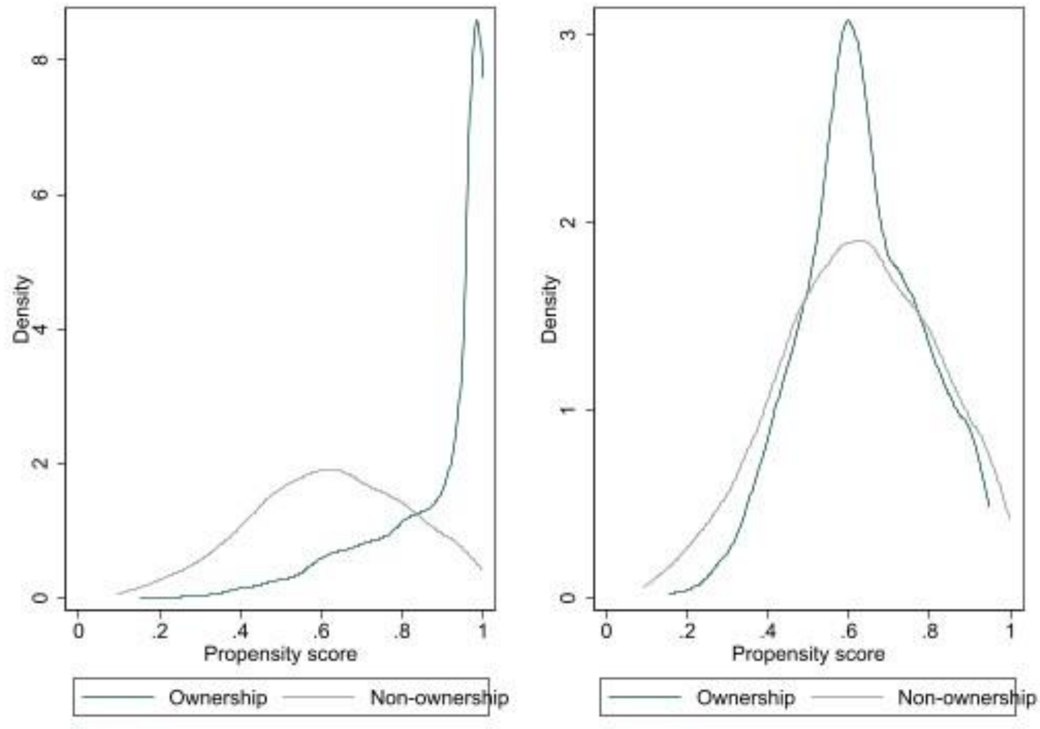

Table 8 Gini decomposition by income source

Source	(1) S_k	(2) G_k	(3) R_k	(4) Share	(5) % Change
Farm self	0.128	0.85	0.732	0.18	0.052
Farm wage	0.119	0.819	0.122	0.027	-0.093
Off-farm self	0.379	0.641	0.78	0.428	0.049
Off-farm income	0.107	0.865	0.258	0.054	-0.053
Non-earned	0.107	0.894	0.402	0.087	-0.02
Total income		0.443			
Ownership					
Farm self	0.133	0.847	0.722	0.19	0.056
Farm wage	0.083	0.855	0.038	0.006	-0.076
Off-farm self	0.384	0.621	0.77	0.427	0.043
Off-farm income	0.104	0.847	0.196	0.04	-0.064
Non-earned	0.128	0.877	0.412	0.108	-0.02
Total income		0.429			
Non-ownership					
Farm self	0.121	0.847	0.727	0.172	0.051
Farm wage	0.168	0.787	0.239	0.073	-0.095
Off-farm self	0.374	0.647	0.774	0.432	0.058
Off-farm income	0.112	0.88	0.278	0.063	-0.049
Non-earned	0.08	0.897	0.255	0.042	-0.038
Total income		0.433			

Note: S_k G_k R_k represent the share of income source *k* in total household income, the Gini coefficients of income source *k*, the Gini correlation of income source *k* with the distribution of total income, respectively. % Change is marginal percentage change of income source k in income inequality.
Source: Bangladesh Integrated Household Survey 2011/12, 2015, 2018/19.

4. Conclusion and policy implication

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

Our results indicate that mobile phone ownership has a positive, statistically significant effects on income diversification. At the same time, it reduces the incidence and depth of poverty as well as non-monetary poverty as measured by a multidimensional poverty index. The results are consistent with past theoretical and empirical studies (see Aker and Mbiti (2910); Sekabira and Qaim (2017); Pallavi and Qaim (2022); Miyajima (2022)). The channel analysis reveals that income diversification through mobile phone ownership increases income as well as reduce povety. Furthermore, our findings show that female-headed households benefit more from mobile phone ownership, which are encouraging findings from development policy perspectives. The quantile regression analysis presents the more sizable impact of mobile phone ownership on the poorest households. Lastly, our results also suggest that off-farm income reduces income inequality. Particularly, the inequality-equalizing effect of off-farm income for households owning a mobile phone is more sizable than the effect of households that do not own a mobile phone.

This study sheds new light on the importance of access to mobile phones and implies that mobile phone ownership can improve household income and poverty status for female-headed households in rural Bangladesh. Digital policies targeting rural areas should ensure that households have access to and ownership of mobile phones to reduce the transaction cost for finding employment and business opportunites and improving household welfare, and thus contributing to reduction in income inequality and poverty.

On the premise of the current expansion of mobile phone coverage, more specific polices about digitalization are needed such as financial inclusion. Looking ahead, it is important because rural households that are relatively vulnerable has to confront various risks such as climate change, pandemic, and geopolitics. Because number of studies showed that appropriate financial services have substantial benefits for consumers, especially women and poor adults (Asli & Drothe, 2017), promoting mobile banking will reduce the transaction cost at agricultural markets (Sekabira & Qaim, 2017) and improve rural financial conditions and reduce spatial inequality (Lee et al., 2021).

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

References

Adams Jr., R. (1994). Non-farm income and inequality in rural Pakistan:. *The Journal of Development Studies*, 110-133.

Adams Jr., R. (2002). Nonfarm Income, Inequality, and Land in Rural Egypt. *Economic Development and Cultural Change*, 339-363.

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., & Mbiti, I. (2010). Mobile Phones and Economic Development in Africa. *Journal of Economic Perspectives*, 207-232.

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

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

Asli, D.-K., & Drothe, S. (2017). Financial Inclusion and Inclusive Growth: A Review of Recent Empirical Evidence. *World Bank Policy Research Working Paper*, No. 8040.

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

Asongu, S., & Nwachukwu, J. (2016). The Mobile Phone in the Diffusion of Knowledge for Institutional Quality in Sub-Saharan Africa. *World Development*, 133-147.

Auffhammer, M., & Carleton, T. (2018). Regional Crop Diversity and Weather Shocks in India. *Asian Development Review*, 113-130.

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

Carrillo, B. (2020). Early Rainfall Shocks and Later-Life Outcomes: Evidence from Colombia. *The World Bank Economic Review*, 179-209.

Cliendo, M., & Kopeinig, S. (2008). SOME PRACTICAL GUIDANCE FOR THE IMPLEMENTATION OF PROPENSITY SCORE MATCHING. *Journal of Economic Surveys*, 31-72.

Debela, B., Gehrke, E., & Qaim, M. (2020). LINKS BETWEEN MATERNAL EMPLOYMENT AND CHILD NUTRITION IN RURAL TANZANIA. *American Journal of Agricultural Economics*, 812-830.

Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica*, 761-766.

GSM Association. (2021). *Achieving mobile-enabled digital inclusion in Bangladesh.* London, United Kingdom: GSMA Association.

Islam, A., & Pakrashi, D. (2020). Labour Market Participation of Women in RuralBangladesh: The Role of Microfinance. *The Journal of Development Studies*, 1927-1946.

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

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

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

Lee, J., Morduch, J., Ravindran, S., Shonchoy, A., & Zaman, H. (2021). Poverty and Migration in the Digital Age: Experimental Evidence on Mobile Banking in Bangladesh. *American Economic Journal: Applied Economics*, 38-71.

Lerman, R., & Yitzhaki, S. (1985). Income inequality effects by income source: A new approach and applications to the United States. *Review of Economics and Statistics*, 151-156.

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*, 80-94.

Matsuura, M., Luh, Y.-H., & Islam, A. (2021). Climate Variability, Livelihood Diversification, and Household Food Security in Bangladesh. *2021 ASAE 10th International Conference (Virtual), December 6-8*, 603-642.

Mishra, A., Mottaleb, K., & Mohanty, S. (2015). Impact of off-farm income on food expenditures in rural Bangladesh: an unconditional quantile regression approach. *Agricultural Economics*, 139-148.

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

Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica*, 69-85.

Munyegera, G., & Matsumoto , T. (2016). Mobile Money, Remittances, and Household Welfare: Panel Evidence from Rural Uganda. *World Development*, 127-137.

Murendo, C., Wollni, M., Brauw, A., & Mugabi, N. (2018). Social Network Effects on Mobile Money Adoption in Uganda. *The Journal of Development Studies*, 327-342.

Muto, M., & Yamano, T. (2009). The Impact of Mobile Phone Coverage Expansion on Market Participation: Panel Data Evidence. *World Development*, 1887-1896.

Rajkhowa, P., & Qaim, M. (2022). Mobile phones, off-farm employment and household income in rural India. *Journal of Agricultural Economics*, 1-17.

Reardon, T., Taylor, J., Stamoulis, K., Lanjouw, P., & Balisacan, A. (2000). Effects of Non-Farm Employment on Rural Income Inequality in Developing Countries: An Investment Perspective. *Journal of Agricultural Economics*, 266-288.

Rola-Rubzen, M., Paris, T., Hawkins, J., & Sapkota, B. (2020). Improving Gender Participation in Agricultural Technology Adoption in Asia: From Rhetoric to Practical Action. *Applied Economic Perspectives and Policy*, 113-125.

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

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

Staiger, D., & Stock, J. (1997). Instrumental Variables Regression with Weak Instruments. *Econometrica*, 557-586.

Tadesse, G., & Bahigwa, G. (2015). Mobile Phones and Farmers' Marketing Decisions in Ethiopia. *World Development*, 296-307.

Tauseef, S. (2021). Can Money Buy Happiness? Subjective Wellbeing and Its Relationship with Income, Relative Income, Monetary and Non-monetary Poverty in Bangladesh. *Journal of Happiness Studies*, 1073-1098.

Vysas, S., & Kumaranayake, L. (2006). Constructing socio-economic status indices: how to use principal components analysis . *Health Policy and Planning*, 459-468.

Wnaglin, M., Quentin Grafton, R., & Renwick, A. (2020). Smartphone use and income growth in rural China: empirical results and policy implications. *Electronic Commerce Research*, 713-736.

Appendix tables

Table A 1 Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
	2012			2019		
Income diversification	6,425	0.403	0.285	4,879	0.388	0.267
Headcount poverty (1/0)	6,503	0.154	0.361	4,890	0.072	0.258
Depth of poverty	6,503	0.027	0.081	4,890	0.010	0.046
MPI score	6,503	0.436	0.192	4,495	0.280	0.157
Total household income (taka)	6,503	130103.000	181430.800	4,891	246019.500	408653.100
Per capita income (taka)	6,503	32295.020	43966.110	4,891	46269.630	75708.750
Mobile phone ownership	6,503	0.727	0.446	4,891	0.984	0.124
Share of households adopting mobile phone in the village	6,503	0.727	0.000	4,891	0.829	0.097
Flood shock in Kharif	6,503	0.172	0.378	4,891	0.003	0.059
Drought shock in Kharif	6,503	0.345	0.475	4,891	0.595	0.491
Female of household head	6,503	0.177	0.382	4,891	0.202	0.402
Age of HH	6,503	44.171	13.980	4,891	47.289	13.030
Household size	6,503	4.196	1.628	4,891	5.570	2.136
Schooling year of HH	6,502	3.330	3.938	4,888	3.713	4.039
Farm Size (decimal)	6,503	3.452	1.684	4,891	0.056	0.260
Periodic bazaar access (minute)	6,411	17.446	10.724	4,870	13.203	8.433
Road access (minute)	6,355	14.655	11.491	4,834	12.102	11.205

Source: Bangladesh Integrated Household Survey 2011/12, 2015, 2018/19

Note: 100 decimals are equal to 0.4 ha