BACKGROUND PAPER

Mobile Phones, Off-Farm Income, and Employment of Rural Women: Evidence from Bangladesh

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ABSTRACT

Typically, women have lagged behind men in social and economic development. In South Asia, women labor force participation is still lower than that of men. Mobile technologies have the potential to enhance inclusiveness by lowering the transaction and communication costs in labor markets. Using an instrumental variable method and a nationally representative household panel survey in rural Bangladesh, we examine whether women's mobile phone ownership increases women's off-farm income via off-farm employment. The results show that women's mobile phone ownership increases women's off-farm income by increasing the likelihood of their off-farm employment. Further, our findings show that mobile phone adoption reduces gender disparity in off-farm income. Finally, results reveal that the benefits of mobile phone ownership are evenly distributed regardless of age, wealth, and remoteness. The results highlight the potential of digitalization in fostering inclusive development.

KEYWORDS

mobile phones, off-farm income, off-farm employment, female employment, rural, Bangladesh

I. INTRODUCTION

Women's empowerment has been centered in discussions about gender inequality. In developing economies, women have been behind men in various contexts, such as the labor market, social protection, education, gender-based violence, and household resource allocation (Duflo 2012, Heath 2014, Pesando 2022, Verma and Imelda 2023, Xu et al. 2022). For instance, attitudes regarding women in the labor market are less progressive in developing countries, resulting in low female labor force participation (Jayachandran 2015). Because an increase in labor supply leads to higher production according to the production function, improving female labor force participation would stimulate economic growth (Duflo 2012). Moreover, many households' livelihoods in developing countries rely on agriculture, which is vulnerable to climate change. Therefore, it is important to diversify livelihoods towards more resilient sources, such as those in the off-farm sector (Matsuura-Kannari et al. 2023, Van Den Broeck and Maertens 2017).

Information and communication technologies (ICTs) have contributed to many aspects of economic development, including poverty reduction, risk sharing, lower gender inequality, and lower mortality via promoting investment, increasing saving, and reducing transaction costs (Aker et al. 2016, Matsuura-Kannari et al. 2024, Riley 2024, Rotondi et al. 2020). The literature has shown that the introduction of mobile phones and smartphones affects societies and economies through increased remittance, migration, technology adoption, poverty reduction, income, food and nutritional security, political behaviors, and labor market (Bahia et al. 2024, Fluhrer and Kraehnert 2023, Jack and Suri 2014, Ma and Zheng 2022, Parlasca et al. 2020, Pesando 2022, Rajkhowa and Qaim 2022b, Varriale et al. 2022). Moreover, ICT also contributes to resilience to various economic shocks. It has been found that ICT mitigates the negative impacts of climate change-related shocks on rural livelihoods (Jack and Suri 2014, Matsuura et al. 2023, Riley 2018). Even with recent evidence from coronavirus disease (COVID-19), ICT adoption increases the resilience of firms and labor markets (Abidi et al. 2023, Oikonomou et al. 2023).

ICT has benefited females via increased accessibility to information and opportunities. ICT reduces transaction costs in communications and social networks, creating employment and enhancing safety for women who are often isolated from outside families and communities (Leng et al. 2020, Ma and Zheng 2022, Matsuura-Kannari et al. 2024, Pesando 2022, Rotondi et al. 2020, Zheng et al. 2023). Therefore, increased access to ICTs for women may be expected to improve their opportunities in labor markets and grow their off-farm income, thereby reducing the gender income gap. However, there is little evidence of the impact of ICT adoption on rural women's employment in developed and developing countries.[1] Further, extant literature has utilized household-level mobile phone ownership data to analyze women's off-farm employment (Amber and Chichaibelu 2023, Han et al. 2023). However, there is a lack of studies focusing on individual-level mobile phone ownership, which would directly attribute women's

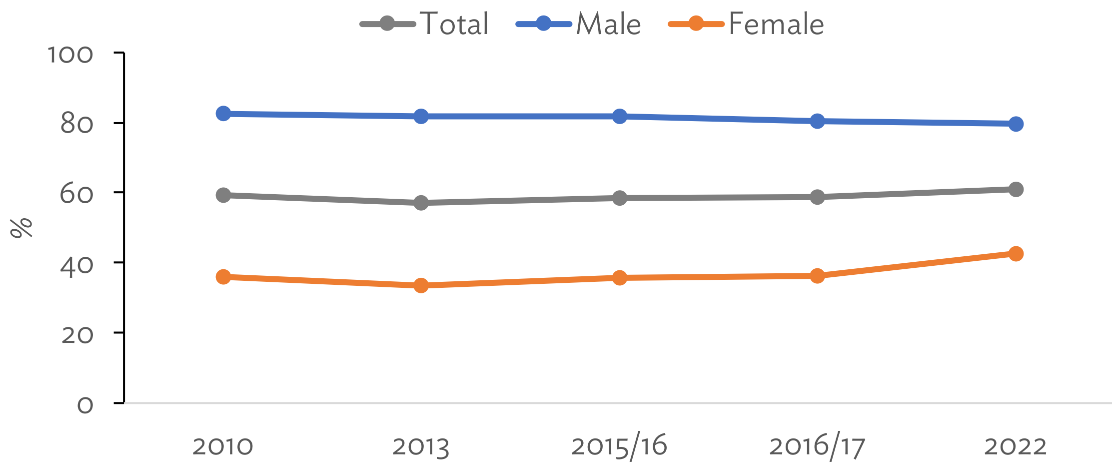
[1] There is little evidence from developing countries, such as Amber and Chichaibelu (2023), Han et al. (2023), Zheng et al. (2023), and developed countries (Albinowski and Lewandowski 2024).

mobile phones ownership (WMPO) to their involvement in off-farm employment.

This study analyzes the association between individual WMPO and their off-farm income using an instrumental variable and correlated random effect approach that controls for endogeneity and unobserved heterogeneity.[2] Further, we compare the results between the case of women and men to verify that mobile phone adoption reduces gender off-farm income gap. This study also explores possible working channels of why individual ownership of mobile phones increases off-farm income by examining women's off-farm employment. Empirically, we use information from nationally representative household panel surveys collected in Bangladesh from 2012 to 2019.

We chose Bangladesh to examine this relationship because the gender digital divide in South Asian countries is larger than in other low-income and middle-income countries (GSMA 2023). Social norms in Bangladesh prevent women from engaging in meaningful employment. The norms set that men would go to work outside the house, while women would take care of household tasks (Makino 2024). Figure 1 shows the labor force participation rate in Bangladesh. While the male labor force participation rate has been more than 80% in the last decade, the female labor force participation rate in Bangladesh is just above 40% in 2022. Thus, a reduction in the gender gap in the labor market is urgently needed in Bangladesh for sustainable development. Such social norms are common among other South Asian countries too. Expanding access to mobile phones for women offers an opportunity to close the gender digital divide. This access can lead to an increase in off-farm employment opportunities for women by lowering transaction costs in labor markets. Moreover, promoting WMPO could increase the probability of off-farm income which, in turn, improves household welfare and the gender income gap (Rajkhowa and Qaim 2022a, Van Den Broeck and Maertens 2017).

Figure 1: Labor Force Participation Rate by Sex in Bangladesh



Source: Authors' design based on Bangladesh by Bangladesh Bureau of Statistics. 2023. *Labour Force Survey 2022*.

[2] The data limitations prevent us from differentiating between basic cellular phones and internet-enabled smartphones. Our dataset includes all mobile devices, regardless of their internet connectivity capabilities.

This study makes threefold contributions to literature. First, we are the first to examine the mechanism by which WMPO increases off-farm income through women's off-farm employment in South Asia using nationally representative panel data. While existing empirical literature often examines household-level mobile phone ownership, there is limited understanding of whether individual mobile phone ownership directly increases women's off-farm income and employment. Second, this paper is the first comprehensive study examining whether mobile phone adoption reduces the gender off-farm income gap in South Asia where gender disparities in the labor market remain deep-rooted. Third, our heterogeneity analysis provides deeper insights into the potential effects of ICT expansion in developing countries by identifying which groups benefit most from mobile phone ownership, which would enable policymakers and other stakeholders to implement more targeted and effective interventions.

The remainder of this paper is organized as follows. Section II presents the data, definition of key variables, and some summary statistics. In section III, the empirical framework is presented, first by discussing the estimation strategy. Section IV presents and discusses empirical results, and a discussion of the limitations of the results. Section V concludes with policy recommendations and suggestions for future research.

II. MATERIALS AND METHODS

A. Data

We use the Bangladesh Integrated Household Survey (BIHS) 2011–2012 (hereafter 2012), 2015, and 2018–-2019 (hereafter 2019), collected by the International Food Policy Research Institute. The BIHS is a nationally representative panel survey in rural Bangladesh, which enables us to conduct a comprehensive study in a South Asian country. Following the research question, we have chosen to retain information on individuals who are married and have a spouse, following Han et al. (2023), because we consider a typical gender norm in South Asia, in which married women are less likely to participate in the labor force than unmarried women (Afridi et al. 2018, Barhate et al. 2021). To take advantage of panel surveys, we dropped households which were observed only once throughout the surveys. Therefore, we use 4,136 households of BIHS 2012; 3,849 households of BIHS 2015; and 3,113 households of BIHS 2019 as samples in this study.
Given that our analysis uses panel data, our estimates would be subject to bias if attrition is associated with certain household characteristics. However, Ahmed and Tauseef (2021) demonstrate that attrition between BIHS 2012 and BIHS 2019 is random. Consequently, the estimates presented in this paper are not adjusted for attrition.

Moreover, one advantage of the BIHS is that it contains information on individual mobile phone ownership rather than households' mobile phone ownership. Although some empirical studies use WMPO to investigate the relationship between WMPO and women's health behavior (Pesando 2022, Rajkhowa and Qaim 2022b), a few studies using nationally representative data, namely the Demographic and Health Survey, rely on household mobile phone ownership (Pesando 2022, Rajkhowa and Qaim 2022a).[3] Therefore, we take advantage of the BIHS to

[3] Some econometric papers use other household surveys on the topic of mobile phone ownership and off-farm

investigate the individual effects of mobile phone ownership on off-farm income and employment.

B. Regression Models

This analysis aims to examine the relationship between WMPO and off-farm income channeled by off-farm employment, and whether mobile phone adoption reduces the gender income gap. To this end, first, we investigate whether WMPO increases women's off-farm income and compare the result to a result from the association between men's mobile phone ownership (MMPO) and off-farm income. Second, we investigate whether there are heterogeneous relationships. Finally, we test whether WMPO increases off-farm employment with heterogeneity analysis to reveal what employment is a path of the relationship between mobile phones and income. Our primary variable, WMPO (and MMPO), is a self-selection variable. To address these identification concerns, the analysis uses an instrumental variable (IV) strategy, also known as the control function approach, to reduce the self-selection bias of WMPO.[4] We employ the control function approach in the Tobit and Probit models as outcome equations. We build a household-level instrument that measures the share of households within the same union, which is the smallest administrative unit in Bangladesh—excluding the respondent's household—in which a woman has a mobile phone. Thus, we estimate the following two-stage equations:

$$WMP_{it} = \alpha_0 + \alpha_1 Z_{it} + \alpha_2 X_{it} + a_i + Division_d + Year_t + \mu_{it} \tag{1}$$
$$Y_{it} = \beta_0 + \beta_1 WMP_{it} + \beta_2 X_{it} + \beta_3 res^1_{it} + Division_d + Year_t + \epsilon_{it} \tag{2}$$

The first stage estimation is given by equation (1), where WMP_{it} is women's mobile phone ownership of household *i* in year *t* which is instrumented by Z_{it}. Z_{it} is an instrumental variable measured by the share of households adopting mobile phones in a union as mentioned above. In addition, a_i, $Division_d$, and $Year_t$ are household fixed effect (FE), division dummy and year dummy, respectively. μ_{it} is a random error term. Equation (1) is estimated by ordinary least square-fixed effect (OLS-FE) to obtain a residual. In the outcome equation, depicted in equation (2), Y_{it} is the outcome variable of interest. When the outcome variable is off-farm income, equation (2) is estimated by Tobit model because a significant proportion of the sample does not make money from off-farm employment. When the outcome variable is off-farm employment, equation (2) is estimated by Probit model since the variable represents a binary choice. X_{it} is a set of covariates to account for an omitted variable bias (e.g., age, education, wealth, and farm size). res^1_{it} is the residual calculated from equation (1) which captures the endogeneity of WMP_{it}. Therefore, when β_3 is statistically significant, it indicates that WMPO is endogenous. ϵ_{it} is a random error term. In each of our nonlinear models, we also employ the Mundlak-Chamberlain (also known as the correlated random effects, or CRE) device to address

employment, but they do not use individual-level mobile phone and smartphone ownership (Amber and Chichaibelu (2023); Sekabira and Qaim (2017b, 2017a); Zheng et al. (2023)).

[4] In the linear and nonlinear cases including Probit model, a control function approach and two-stage residual inclusion (2SRI) is identical to the popular two-stage least squares (2SLS) (or linear instrumental variables [IVs]) method and, therefore, is consistent (Terza et al. 2008).

time-invariant unobserved effects that may be related to household decision-making. The correlated random effects model offers an advantage over fixed effects model in that time-invariant observed variables, which are dropped when applying fixed effects models, can be retained in the regression (Debela et al. 2021).

We are particularly interested in the coefficient estimate β_1. If β_1 is positive and statistically significant, it would provide evidence supporting the hypothesis that owning a mobile phone increases the off-farm income and the probability of off-farm employment.

In addition, we analyze MMPO and men's off-farm income using the same empirical framework of equations (1) and (2). After obtaining an estimation result for both women and men, we compare the results and check whether the impact of mobile phone ownership is relatively larger for women to confirm that mobile phone adoption reduces gender parity in off-farm income.

C. Heterogeneous Associations

In addition to the average associations estimated with equation (2), we also analyze heterogenous associations based on various individual and household characteristics, such as primary female decision-maker's age, primary female decision-maker's education, household wealth, or distance to the nearest town. To estimate the heterogeneous associations for several household characteristics, we use the 2SRI of the following type:

$$WMP_{it} = \gamma_0 + \gamma_1 Z_{it} + \gamma_2 X_{it} + a_i + Division_d + Year_t + \eta_{it} \tag{3}$$

$$WMP_{it} \times H_{it} = \theta_0 + \theta_1 Z_{it} \times H_{it} + \theta_2 X_{it} + a_i + Division_d + Year_t + \omega_{it} \tag{4}$$

$$\begin{aligned} Y_{it} = \phi_0 + \phi_1 WMP_{it} + \phi_2 WMP_{it} \times H_{it} + \phi_3 X_{it} + \phi_4 res_{it}^2 + \phi_5 res_{it}^3 \\ + a_i + Division_d + Year_t + \delta_{it} \end{aligned} \tag{5}$$

where H_{it} is one of the mentioned household characteristics that is interacted with WMP_{it} (note that H_{it} is also included in X_{it}). From equations (3) and (4), residuals res_{it}^2 and res_{it}^3 are calculated, respectively. The estimated residuals are then included in the outcome regression, which is equation (5), to control for the endogeneity. Other variables included in the regression are defined as before. We estimate separate models for each household characteristics of interest with a particular focus on the interaction term estimates ϕ_2. If ϕ_2 is significant, the household characteristics are associated with the relationship between mobile phone ownership and off-farm income and employment.

D. Validity of Instruments

Our instrument, the union-level variables as IVs for mobile phone access and use, has been tested in relevant studies on the topic (Ma and Wang 2020, Ma and Zheng 2022, Manacorda and Tesei 2020, Matsuura et al. 2023, Pesando 2022, Rotondi et al. 2020, Varriale et al. 2022) and originates from the findings of peer effects and social network literature (Conley and Christopher 2001, Munshi 2004). The validity of the instrumental variable depends on two conditions. First, the instrumental variable is a strong predictor of the potentially endogenous variable, that is, our instrument is not a "weak" instrument. As a statistical test for the strength of the instrumental variable, we report the diagnostic test for weak instruments called the Cragg–Donald Wald F test proposed by Staiger and Stock (1997). We reject the null hypothesis of weak instruments based on the Cragg–Donald Wald F statistic of 16.38, which is above 10 based on the rule of thumb, eliminating concerns about weak instruments. Second, the instrument meets the exclusion restriction. We assume that union-level variables, which consist of neighborhood decisions, do not directly affect the household's decision. Moreover, we conducted a falsification test for the exclusion restriction proposed by Di Falco et al. (2011). [5] Table A1 shows that the union-level IV, also known as the peer effect IV, is not significantly correlated to women's off-farm income. Therefore, we consider that the instrumental variable meets exclusion restriction criteria. Nevertheless, it is not possible to rule out with certainty that union-level mobile phone use does not correlate with the outcome variables channeled by other indirect mechanisms. We report the IV results, but we shy away from causation.

E. Key Variables

Our primary explanatory variable is WMPO (and MMPO). It is measured as a dummy variable whether the primary female (male) decision-maker owns a mobile phone or not. Figure 2 shows the share of WMPO and MMPO in rural Bangladesh over the decade. From 2012 to 2019, the share of WMPO increased from 26% to 39%, while the share of MMPO increased from 69% to 84%. Mobile phone adoption is becoming common among women as well as men, but the gender digital divide remains. Therefore, it is important to investigate whether the increase in WMPO improves women's welfare for future policy decisions in the field of digitalization.

Outcome variables that we are interested in are monthly off-farm income earned by the primary female and male decision-maker within a household, and several dummy variables of the primary female decision-maker's working status, such as off-farm employment, casual wage employment in non-agriculture, salaried employment, off-farm self-employment, and trade/production business. We use dummy variables of whether the primary female decision-maker has a job in a specific category of work. Figure 3 presents the likelihood of a primary female decision-maker working outside the home. It shows that the change in the likelihood of off-farm employment between 2012 and 2019 is small, from 8% to 10% in our sample. From Figure 3, we are not able to identify that WMPO increases off-farm employment. To do so, we need to conduct rigorous econometric analysis.

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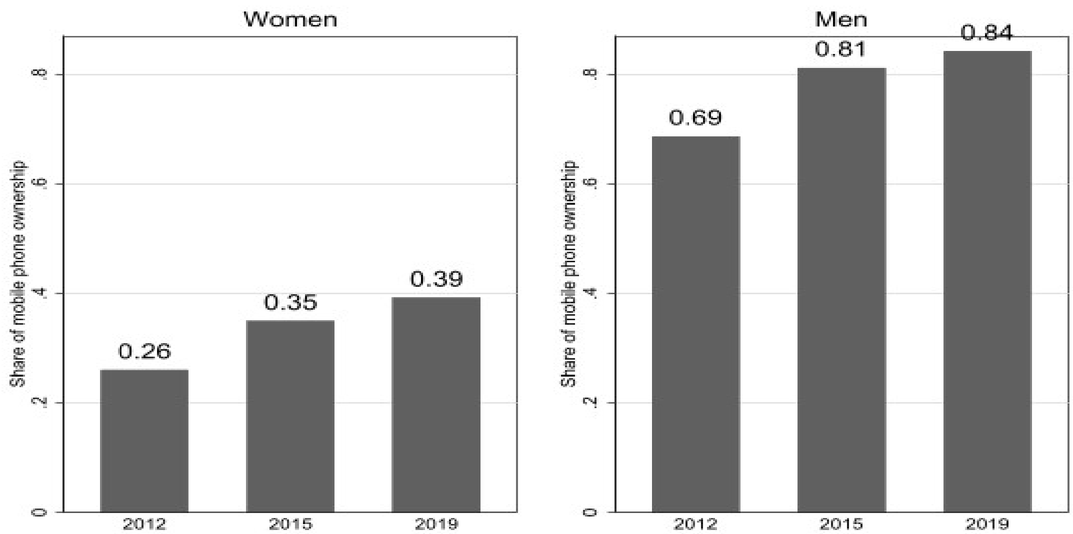
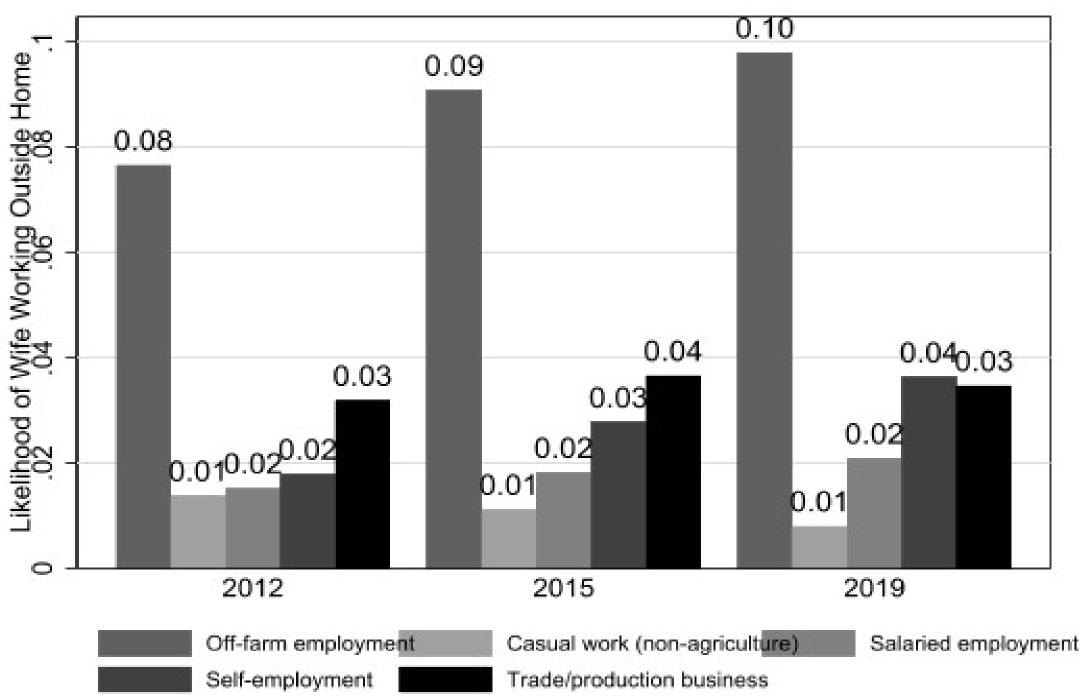
[5] If a variable is a valid selection instrument, it will not affect women's off-farm income among women who do not own mobile phones.

Figure 2: Share of Mobile Phone Ownership of Women and Men from 2012 to 2019



Source: Authors' calculation from Bangladesh Integrated Household Surveys 2012, 2015, and 2019.

Figure 3: Off-Farm Employment Status of Women



Source: Authors' calculation from Bangladesh Integrated Household Surveys 2012, 2015, and 2019.

F. Summary Statistics

Table 1 shows the definitions and descriptive statistics of the selected variables. It also presents whether there are any systematic differences between mobile phone owners and nonowners. The average age of female owners of mobile phones is 38.9, while the average age of the nonowner is 38.8. The difference is statistically insignificant. This is an interesting result because some studies present that younger age is positively correlated to ICT adoption (Leng et al. 2020, Zheng et al. 2023). A primary female decision-makers' secondary school completion rate is 8% for the owners and 3% for nonowners, and the difference is statistically significant. However, there is no statistically significant difference in assets brought to marriage between owners and nonowners. The difference in the number of children is considerably large between owners (1.92) and nonowners (1.94). Moreover, the difference in a dummy variable of the poor asset holding, which is lower than the bottom 10% between owners (0.05) and nonowners (0.10), is significant. We do not observe significant differences in access to the nearest town, indicating that geographical and infrastructure conditions between owners and nonowners are not so different.

Table 1: Descriptive Statistics

Variable		Owner		Nonowner		t-test
		Mean	Std. Dev.	Mean	Std. Dev.	Difference
Observation	Definition	3644		7454		
Off-farm income (women)	Off-farm income earned by a primary female decision-maker (wife)	309.92	1,654.94	129.72	755.14	180.20***
Off-farm income (men)	Off-farm income earned by a primary male decision-maker (husband)	6,152.08	9,101.12	4,224.65	7,664.17	1,927.43***
Men's mobile phone ownership	1 if a primary male decision-maker owns a mobile phone, 0 otherwise	0.87	0.34	0.73	0.44	0.14***
Age of primary female decision-maker	Age of primary female decision-maker	38.94	10.81	38.80	11.37	0.14
Secondary school certificate of primary female decision-maker	1 if a primary female decision-maker completes secondary school, 0 otherwise	0.08	0.27	0.03	0.17	0.05***
Asset brought to marriage	1 if a primary female decision-maker brought to an asset when marriage, 0 otherwise	0.82	0.38	0.81	0.40	0.02**
Women's access to credit	1 if a primary female decision-maker is a member of a credit or microfinance group in a community, 0 otherwise	0.29	0.46	0.27	0.45	0.02**
Number of children	Number of children	1.92	1.19	1.94	1.25	-0.02
Age of husband	Age of husband	47.30	12.34	46.95	13.00	0.35
Secondary school certificate of husband	1 if a husband completes secondary school, 0 otherwise	0.15	0.36	0.07	0.25	0.08***
Working status of husband	1 if a husband works, 0 otherwise	0.95	0.23	0.96	0.19	-0.02***
Farm size	decimal of cultivated farmland	85.99	121.97	81.54	118.67	4.45*
Poor asset holding	1 if the asset index based on ownership of various assets (refer to the notes below) is lower than the bottom 10%, otherwise zero	0.05	0.22	0.10	0.30	-0.05***
Distance to the nearest town	Minutes to go to the nearest town from the homestead	25.43	14.91	25.54	15.28	-0.11
Share of women's mobile ownership in a village	Share of women's mobile ownership in a village (except for sampled households)	0.41	0.21	0.26	0.19	0.14***
Share of men's mobile ownership in a village	Share of men's mobile ownership in a village (except for sampled households)	0.81	0.16	0.77	0.18	0.04***

Std. Dev. = standard deviation.

Notes: Authors build the table using Bangladesh Integrated Household Surveys 2012, 2015, and 2019. * p < 0.1; ** p < 0.05; *** p < 0.01 in mean differences between households with and without women's mobile phone ownership. 100 decimals are 0.4 hectares. We create a wealth index of assets using principal component analysis because the value of assets owned was not collected in the datasets. sum components of wealth, such as ownership of radios, televisions, computers, animal carts, bikes, motorbikes or fridges, and cars or trucks, are used for the calculation.

Source: Authors' calculations.

III. RESULTS AND DISCUSSION

A. Women's Mobile Phone Ownership and Off-Farm Income

Since many households do not have income from off-farm activities, we estimate equations (1) and (2) by IV-Tobit models since the Tobit model can address zero values in the income variable. Table 2 shows the estimation result of equation (2). The coefficient of WMPO in column (1) is positive and significant. It indicates that WMPO increases off-farm income by Tk123.847, which is a 95% increase in off-farm income of nonowners. The result is consistent with past studies (Rajkhowa and Qaim 2022a, Sekabira and Qaim 2017b). Column (6) shows the positive coefficient of MMPO and the outcome variable is men's off-farm income. It implies that MMPO increases off-farm income by Tk2,763.706, which is a 65% increase of the off-farm income of nonowners. The results from columns (1) and (6) imply that mobile phone adoption increases women's off-farm income more than men's off-farm income and reduces the gender off-farm income gap. This is the first and encouraging evidence because no studies show mobile phones reduce the gender off-farm income gap in South Asia using nationally representative panel surveys, and a previous study showed that off-farm income improves rural women's overall welfare (Van Den Broeck and Maertens 2017). The result implies that mobile network expansion for women would ultimately improve women's welfare and status in developing economies through an increase in off-farm income.

Next, we examine whether the size of the associations between WMPO and off-farm income varies across socioeconomic characteristics of women or the household. Columns (2)–(5) present the heterogeneous analyses to identify which women benefit more from mobile phone ownership. In column (2), we explore whether there is any differential effect of different ages of women. We find a negative but insignificant relationship implying that both younger and older women fairly benefit from mobile phones. Kaila and Tarp (2019) and Nguyen et al. (2023) show that internet usage is more beneficial to younger generations, and our findings are in line with them because our primary interest variable is mobile phone ownership, not the internet with which older generations, compared to the young, are relatively not familiar with in relation to ICT. Next, we explore heterogeneity in association with years of education of women. We find a positive and statistically significant coefficient of the interaction term of WMPO and secondary school completion, which implies that the benefits of mobile phones accrue more to women who have completed secondary school. This is indicative of more educated women being able to take advantage of mobile phones compared to the less educated.

For household wealth, column (4) of Table 2 suggests that women belonging to households with poor assets benefit more from mobile phone ownership. This highlights that women in poorer households face relative scarcities of productive assets and resources to generate income. Mobile phones could assist these women in increasing their off-farm income. The finding is consistent with Leng et al. (2020) and Matsuura-Kannari et al. (2024). Finally, in column (5), we explore whether remoteness for the distance of the household to the nearest town has any differential effect with a longer distance to the nearest town implying poorer access to information. Access to infrastructure may be an alternative to mobile phones for accessing information on off-farm employment and income. However, we do not find any statistically significant effect on the interaction term. Thus, the result suggests that infrastructure access measured in terms of the distance to the nearest town does not seem to have any differential effect on income because of mobile phone association. This is a welcome result because it indicates that geographically disadvantaged women can benefit just as much as geographically advantaged women.

Table 2: Association Between Women's Mobile Phone Ownership and Off-Farm Income: Instrumental Variable-Tobit Correlated Random Effects Model

	(1) Off-Farm Income	(2) Off-Farm Income	(3) Off-Farm Income	(4) Off-Farm Income	(5) Off-Farm Income		(6) Off-Farm Income (Men)
WMPO	123.847***	195.910*	52.147**	127.557**	123.437***	MMPO	2,763.706***
	(33.416)	(101.640)	(22.593)	(64.600)	(31.957)		(359.538)
WMPO # Primary female decision-maker's age		-1.848					
		(2.158)					
WMPO # Secondary school certificate of primary female decision-maker			1,448.906***				
			(402.293)				
WMPO # Poor asset				5.446			
				(107.575)			
WMPO # Distance to the nearest town					-0.125		
					(2.165)		
Residual of WMPO	-50.923	-154.216	-2.304	-40.955	-111.359	Residual of MMPO	-2.6e+03***
	(39.796)	(114.698)	(33.885)	(38.326)	(82.382)		(583.998)
Residual of interaction term		2.648	-990.732**	-143.826	2.334		
		(2.445)	(467.391)	(150.000)	(2.793)		
Control mean	129.72						4,224.65
Division dummy	Y	Y	Y	Y	Y		Y
Year dummy	Y	Y	Y	Y	Y		Y
Observations	11,098	11,098	11,098	11,098	11,098		11,098

MMPO = men's mobile phone ownership, WMPO = women's mobile phone ownership

Notes: Bootstrapped standard errors are in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. The full table is available upon request. We reject the null hypothesis of weak instruments based on the Cragg–Donald Wald F statistic 16.38. Control variables include the age of a primary female decision-maker, secondary school completion of a primary female decision-maker, asset brought to marriage, women's access to credit, age of husband, schooling year of husband, low wealth dummy, household size, and cultivated farm size. Means of time-varying household variables not reported.

Source: Authors' calculation using Bangladesh Integrated Household Surveys 2012, 2015, and 2019.

B. Heterogeneity and Mechanism Behind Between Women's Mobile Phone Ownership and Off-Farm Employment

In section III.A, we discussed whether WMPO is associated with women's off-farm income and the heterogeneity in association across some socioeconomic characteristics. In this section, we explore the types of off-farm employment that are increased by WMPO and the mechanisms behind the association between mobile phones and off-farm income.

Column (1) in Table 3 shows that the negative and significant coefficients of the interaction terms for age suggest that the positive association of WMPO with off-farm employment diminishes for older women. It indicates that younger women benefit more from mobile phone ownership in terms of off-farm employment opportunities. However, the other coefficients of the interaction terms in columns (2)–(5) are insignificant, while the coefficients of WMPO are significant for salaried employment and self-employment. Given that both younger and older women with mobile phones equally gain off-farm income in Table 2, the results indicate that women with mobile phones earn more off-farm income channeled by an increase in the likelihood of salaried employment and self-employment.

Next, we test the heterogeneity in employment because of differences in the levels of education of women. Table 4 shows that more educated women derive greater benefits from mobile phone ownership, particularly for general off-farm employment and salaried employment. The positive and significant interaction terms indicate that the completion of secondary school increases the positive associations of WMPO with women's employment prospects. This suggests that mobile technology allows more educated women to better leverage phones for job-seeking and professional networking because of readiness and other literacy (Rahman et al. 2022). This is consistent with the study investigating the relationship between WMPO and women's physical mobility (Rajkhowa and Qaim 2022b). Therefore, our findings suggest that educated women with mobile phones have more off-farm income through salaried employment.

For household wealth levels, results presented in Table 5 show that all the coefficients of the interaction term are insignificant and significant, while the coefficients of WMPO are positive and significant for off-farm employment, salaried employment, and trader/production business. Thus, the results indicate that women in poorer households can benefit to the same extent as women in richer households from mobile phone ownership, which is consistent with findings in Rajkhowa and Qaim (2022a). Poorer women would have fewer resources to launch their businesses, but our findings suggest that mobile phones play an important role, especially in connecting economically disadvantaged women to job opportunities they may otherwise lack access to.

ICT could overcome geographical disadvantages by allowing people to connect with others without the need for physical mobility. In Table 6, we investigate whether women who live far from a central area of a town benefit more from mobile phone ownership. We expect that the interaction term between WMPO and distance to the nearest town should be positive. The result shows that the coefficient of the interaction term is significant for trader/production business. Moreover, the coefficients of WMPO are significant for off-farm employment, salaried employment, and self-employment. These estimation results are in line with a similar study in India by Rajkhowa and Qaim (2022a). The results indicate that mobile phones provide more benefits for remote women's trade and production business, and women with mobile phones can have salaried and self-employment regardless of geographic remoteness. The technology appears to overcome distance-related barriers to accessing job information and opportunities.

Table 3: Heterogeneity by Age of Women: Instrumental Variable-Probit Correlated Random Effects Model

	(1)	(2)	(3)	(4)	(5)
	Off-Farm Employment	Casual Wage Employment (Non-agriculture)	Salaried Employment	Self-Employment	Trader/Production Business
WMPO	0.717***	0.371	0.756***	0.535*	0.080
	(0.193)	(0.360)	(0.286)	(0.305)	(0.233)
WMPO # Primary female decision-maker's age	-0.012**	-0.012	-0.013	-0.003	0.001
	(0.005)	(0.009)	(0.008)	(0.008)	(0.006)
Division dummy	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y
Observations	11,098	11,098	11,098	11,098	11,098

WMPO = women's mobile phone ownership.

Notes: Bootstrapped robust standard errors in parenthesis. * p < 0.1; ** p < 0.05; *** p < 0.01. From column (1) to column (5), the outcome variables are dummy. Control variables include the age of a primary female decision-maker, secondary school completion of a primary female decision-maker, asset brought to marriage, women's access to credit, age of husband, secondary school completion of husband, low wealth dummy, household size, and cultivated farm size. Means of time-varying household variables not reported. The full table is available upon request.

Source: Authors' calculation using Bangladesh Integrated Household Surveys 2012, 2015, and 2019.

Table 4: Heterogeneity by Women's Education: Instrumental Variable-Probit Correlated Random Effects Model

	(1)	(2)	(3)	(4)	(5)
	Off-Farm Employment	Casual Wage Employment (Non-agriculture)	Salaried Employment	Self-Employment	Trader/Production Business
WMPO	0.234***	-0.097	0.168	0.402***	0.105
	(0.055)	(0.109)	(0.103)	(0.078)	(0.072)
WMPO # Secondary school certificate of a primary female decision-maker	0.597***	0.327	0.573**	0.229	0.268
	(0.201)	(1.809)	(0.269)	(0.247)	(1.530)
Division dummy	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y
Observations	11,098	11,098	11,098	11,098	11,098

WMPO = women's mobile phone ownership.

Notes: Bootstrapped robust standard errors in parenthesis. * p < 0.1; ** p < 0.05; *** p < 0.01. From column (1) to column (5), the outcome variables are dummy. Control variables include the age of a primary female decision-maker, secondary school completion of a primary female decision-maker, asset brought to marriage, women's access to credit, age of husband, secondary school completion of husband, low wealth dummy, household size, and cultivated farm size. Means of time-varying household variables are not reported. The full table is available upon request.

Source: Authors' calculation using Bangladesh Integrated Household Surveys 2012, 2015, and 2019.

Table 5: Heterogeneity by Household Wealth: Instrumental Variable-Probit Correlated Random Effects Modell

	(1)	(2)	(3)	(4)	(5)
	Off-Farm Employment	Casual Wage Employment (Non-agriculture)	Salaried Employment	Self-Employment	Trader/Production Business
WMPO	0.274***	-0.116	0.277***	0.400***	0.124*
	(0.053)	(0.086)	(0.100)	(0.082)	(0.070)
WMPO # Poor asset	0.043	0.179	-0.115	0.350	-0.239
	(0.223)	(0.310)	(0.441)	(0.440)	(0.293)
Division dummy	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y
Observations	11,098	11,098	11,098	11,098	11,098

WMPO = women's mobile phone ownership.
Notes: Bootstrapped robust standard errors in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. From column (1) to column (5), the outcome variables are dummy. Control variables include the age of a primary female decision-maker, secondary school completion of a primary female decision-maker, asset brought to marriage, women's access to credit, age of husband, secondary school completion of husband, low wealth dummy, household size, and cultivated farm size. Means of time-varying household variables not reported. The full table is available upon request.
Source: Authors' calculation using Bangladesh Integrated Household Surveys 2012, 2015, and 2019.

Table 6: Heterogeneity by Distance from Home to Town: Instrumental Variable-Probit Correlated Random Effects Model

	(1)	(2)	(3)	(4)	(5)
	Off-Farm Employment	Casual Wage Employment (Non-agriculture)	Salaried Employment	Self-Employment	Trader/Production Business
WMPO	0.267***	0.135	0.425**	0.427**	-0.075
	(0.092)	(0.279)	(0.194)	(0.187)	(0.129)
WMPO # Distance to town	0.000	-0.011	-0.006	-0.001	0.007*
	(0.003)	(0.009)	(0.006)	(0.006)	(0.004)
District dummy	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y
Observations	11,098	11,098	11,098	11,098	11,098

WMPO = women's mobile phone ownership.
Note: Bootstrapped robust standard errors in parenthesis. * p < 0.1; ** p < 0.05; *** p < 0.01. From column (1) to column (5), the outcome variables are dummy. Control variables include the age of a primary female decision-maker, secondary school completion of a primary female decision-maker, asset brought to marriage, women's access to credit, age of husband, secondary school completion of husband, wealth index household size, and cultivated farm size. Means of time-varying household variables not reported. The full table is available upon request.
Source: Authors' calculation using Bangladesh Integrated Household Surveys 2012, 2015, and 2019.

IV. ROBUSTNESS CHECK

In this section, we conduct a robustness check to confirm the assumption of our analysis. There is a concern about reverse causality between WMPO and women's off-farm income. To verify that there is no concern about reverse causality, we introduce the lagged women's mobile phone ownership as an independent variable. We treat the value before one period as a lag variable.

Therefore, the estimation equation can be written as follows:

$$WMP_{it-1} = \omega_0 + \omega_1 Z_{jt} + \omega_2 X_{it-1} + a_i + Division_d + Year_t + v_{it} \quad (6)$$
$$Y_{it} = \tau_0 + \tau_1 WMP_{it-1} + \tau_2 X_{it} + \tau_3 res_{it}^4 + Division_d + Year_t + \kappa_{it} \quad (7)$$

where WMP_{it-1} is a lagged variable of WMPO, res_{it}^4 is a residual calculated from equation (6). v_{it} and κ_{it} are error terms. We are interested in the coefficient τ_1. If it is positive and significant, the result indicates that the past mobile phone ownership increases off-farm income.

Table 7 shows the estimated result of equation (7). The coefficient of WMPO is positive and statistically significant at a 1% level. The result confirms that there is no reverse causality between WMPO and women's off-farm income.

Moreover, we conduct an individual-level analysis. Using the individual male and female information on mobile phones, off-farm income, and demographic characteristics, we estimate the following equations based on equation (2).

$$Y_{ijt} = \sigma_0 + \sigma_1 MP_{ijt} + \sigma_2 X_{ijt} + Household_i + Division_d + Year_t + \omega_{ijt} \quad (8)$$

where Y_{ijt} is an outcome variable measured off-farm income of individual *j* of household *i* at year *t*. MP_{ijt} is an individual-level mobile phone ownership. X_{ijt} is an individual-level covariates. We also include various fixed effects such as household, division, and year fixed effects to account for unobserved and time-invariant heterogeneity which would affect mobile phone ownership and off-farm income. We estimate equation (8) by ordinary least squares with fixed effects. [6]

Table 8 shows the estimation result of equation (8). The coefficients of mobile phone ownership are positive and statistically significant at a 1% level in columns (1) and (2). The results indicate that mobile phone adoption increases off-farm income of women by 93%, while it increases off-farm income of men by 19%. The results confirm that mobile phones increase off-farm income and reduce the gender off-farm income gap as shown in previous sections.

[6] In an individual-level analysis, we are not able to find a suitable instrumental variable to account for the self-selection bias of mobile phone ownership, but we employ fixed effects as many as possible to do so.

Table 7: Lagged Women's Mobile Phone Ownership and Off-Farm Income: Instrumental Variable-Tobit Correlated Random Effects Model

	(1) Off-Farm Income
Lagged women's mobile phone ownership	150.547***
	(42.252)
Residuals	-168.305*
	(85.997)
Division dummy	Y
Year dummy	Y
Observations	5,356

Notes: Bootstrapped robust standard errors in parenthesis. * p < 0.1; ** p < 0.05; *** p < 0.01. In column (1), the outcome variable is continuous. Control variables include the age of a primary female decision-maker, secondary school completion of a primary female decision-maker, asset brought to marriage, women's access to credit, age of husband, secondary school completion of husband, wealth index household size, and cultivated farm size. Means of time-varying household variables not reported. The full table is available upon request.
Source: Authors' calculation using Bangladesh Integrated Household Surveys 2012, 2015, and 2019.

Table 8: Mobile Phones and Off-Farm Income: Individual-Level Analysis Fixed Effect Model

	(1) Off-Farm Income (Women)	(2) Off-Farm Income (Men)
Mobile phone ownership	164.160***	751.872***
	(44.465)	(188.905)
Control mean	176.605	3921.055
Individual fixed effects	Y	Y
Household fixed effects	Y	Y
Division fixed effects	Y	Y
Year fixed effects	Y	Y
Observations	16,517	15,184

Notes: Robust standard errors are in parenthesis. * p < 0.1; ** p < 0.05; *** p < 0.01. The full table is available upon request. Column (1) uses a subsample of women aged 18–64 and column (2) uses a subsample of men aged 18–64. They are not necessarily primary decision-makers within a household. Outcome variable is individual off-farm income. Control variables include the age, secondary school completion.
Source: Authors' calculation using Bangladesh Integrated Household Surveys 2012, 2015, and 2019.

V. CONCLUSIONS AND POLICY IMPLICATIONS

This study contributes to the growing literature on the role of ICT in social and economic development by examining the relationship between WMPO and off-farm income and employment in rural Bangladesh. The analysis yields several key findings.

First, we find a positive and significant association between WMPO and women's off-farm income. The result also implies that mobile phone ownership reduces the gender off-farm income gap. Our findings demonstrate the potential of mobile technologies in reducing information asymmetries and transaction costs in rural economies, consistent with previous studies such as Jack and Suri 2014, Sekabira and Qaim 2017b.

Second, our heterogeneity analysis shows that the benefits of mobile phone ownership are evenly distributed regardless of age, wealth, and remoteness. Older women, women from poorer households, and geographically disadvantaged women are found to benefit to the same extent as younger, richer, and geographically advantaged women in terms of off-farm income and employment opportunities. This finding underscores the importance of considering socioeconomic factors in the design and implementation of ICT-based development initiatives.

Third, we find that WMPO is associated with an increased likelihood of women's participation in off-farm employment, particularly in salaried employment and self-employment. This result suggests that mobile phones would facilitate job search and reduce information barriers in rural labor markets, consistent with the findings of Rajkhowa and Qaim (2022a) in the Indian context.

Fourth, our analysis shows that women in geographically disadvantaged areas benefit over-proportionally from mobile phones. This finding suggests that mobile technology could overcome spatial barriers to information and job access, potentially contributing to more inclusive rural development.

These results have several important policy implications. First, they suggest that policies aimed at increasing mobile phone access and ownership among rural women could be an effective strategy for improving their economic opportunities and gender income gaps. There are some examples of expanding mobile phone access and ownership. Feed the Future (2021) suggests some strategies, such as asset financing models, bulk purchasing, and installment payment plans, to lower the cost of phones and divide up payments. For example, Juhudi Kilimo Ltd. in Kenya launched a mobile phone loan product which gives incentives for farmers using phones, [7] Second, the expansion of WMPO overcome the gender digital divide and the gender off-farm income gap in rural areas.

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[7] In Malawi during the COVID-19 era, TNM, which is the oldest telecommunications company, sold mobile phones to the smallholder farmers on an installment plan that spread the payments for the phones over three equal monthly payments. Payments were collected by lead farmers who deposited the funds with the farmer-based organization for repayment to TNM (Feed the Future 2021). Finally, it increases the mobile penetration rate by 25%.

While our study provides valuable insights, it is not without limitations. The instrumental variable approach, while addressing some endogeneity concerns, does not eliminate the possibility of omitted variable bias. Future research could benefit from experimental or quasi-experimental designs to establish more robust causation. In addition, examining the quality of jobs accessed through mobile phones and the long-term impact on women's empowerment would be a valuable extension of this work.

In conclusion, our findings contribute to the understanding of how digital technologies could promote women's economic participation in rural areas. As digital transformation continues to reshape the economic landscape, policymakers should consider using these tools to address gender disparities in economic opportunities and contribute to more inclusive rural development.

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Table A 1 Falsification test of instrumental variable: IV-Tobit CRE

	(1)
	Off-farm employment
Share of households adopting mobile money in the union	-61.720
	(50.386)
Age of women	-9.790
	(8.370)
Secondary school certificate of women	57.417
	(247.774)
Asset brought to marriage	-9.194
	(34.884)
Women's access to credit	53.179*
	(28.109)
Household size	-5.292
	(15.431)
Age of HH	7.732
	(7.039)
Secondary school certificate of HH	-427.199**
	(166.728)
Current working status of husband	-18.388
	(74.870)
Poor asset	-3.943
	(46.021)
Farm Size	-0.195
	(0.180)
Distance to near town	-0.383
	(0.740)
Mean variable of covariates	
Age of women	6.718
	(8.661)
Secondary school certificate of women	183.600
	(256.495)
Asset brought to marriage	-85.882*
	(46.866)
Women's access to credit	34.348
	(42.829)
Household size	3.120
	(16.415)
Age of HH	-6.855
	(7.337)
Secondary school certificate of HH	559.158***
	(170.733)
Current working status of husband	28.502
	(95.937)
Poor asset	54.762
	(59.910)
Farm Size	-0.174
	(0.202)
Distance to near town	-0.841
	(1.158)
District dummy	Y
Year dummy	Y
Observations	7454

Note: Bootstrapped standard errors are in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: Authors' calculation using BIHS 2012, 2015, and 2019.