Bangladesh Development Studies
Vol. XLIV, March-June 2021, Nos. 1&2

Agricultural Information through Mobile Phone: Evidence on Farm Household Welfare in Bangladesh

TAZNOORE SAMINA KHANAM*

This paper assesses the determinants of access to agricultural information through mobile phones and examines its impact on welfare using two rounds of household panel data. A control function approach with correlated random effects has been used in this analysis to control possible endogeneity of access to agricultural information. The empirical results show that access to agricultural information through mobile phones is positively correlated with yield, asset holdings, and own rice consumption. We disaggregate results by climate-risk vulnerable groups to explore whether the impact of access to information has heterogeneous effects. The results reveal that access to agricultural information through mobile phones strongly impacts climate-risk vulnerable households. Overall, increasing access to agricultural information through mobile phones is critical for food security, especially for smallholder farmers who live in climatically stress-prone areas.

Keywords: Agricultural Information, Climate Risks, Mobile Phones, Food Security, Bangladesh

JEL Classification: C23, D83, O33, Q12, Q15

I. INTRODUCTION

Hundreds of millions of the world's poorest households rely on smallholder agricultural systems for their livelihoods and food (Cohn et al., 2017). In Bangladesh, rice contributes one-half of the agricultural GDP, one-sixth of the national income, and 48 per cent of rural employment (BBS, 2018). About 77 per cent of marginal and small farmers depend on rice for food security and their livelihoods (IFPRI, 2016). Climate stress-prone areas are typically significant rice-producing areas in Bangladesh, where farmers rely on rice production for income, employment, and livelihood. Climate risk is posing a growing threat to the rice output of poor and vulnerable farmers in those areas. Smallholder farmers are, in

---

*Bangladesh Institute of Development Studies, Dhaka, Bangladesh. The author would like to thank Takashi Yamano and International Rice Research Institute (IRRI) for providing data.

particular, facing more extreme weather shocks, resulting in devastating crop losses and lower agricultural productivity (OCHA, 2014). Ultimately, these farmers have to make decisions in extremely unstable and insecure circumstances. Raising the productivity and stability of rice production in this region is crucial for reducing poverty.

Aside from crop failure due to unpredictable weather, farmers face a variety of challenges, including limited access to quality inputs and a lack of knowledge of modern technologies, which have contributed to a shift in farmers' need for new technology and know-how (Mittal, Mehar, & Hariharan, 2019). Agricultural, market, and weather information are essential for agricultural productivity, especially in minimising the uncertainty and risk associated with extreme weather (Baumüller, 2013). Farmers require significant information to assess new technologies and make better management decisions regarding the agricultural inputs and practices to use, ultimately giving them more bargaining power when dealing with buyers (Jack & Tobias, 2017).

Access to agricultural information is critical for new technology adoption, market circumstances, better agricultural practices for rice, as well as for increasing smallholder farmers' output, income, and well-being. In most developing nations, agricultural extension services are expected to play a role in facilitating technology transfer and productivity among small, resource-poor farmers. However, traditional methods of disseminating information to farmers, such as agricultural extension services in Bangladesh, are ineffective, and many farmers in Bangladesh have received little or no agricultural extension services (Afrad, Wadud, & Babu, 2019). In addition, correct information may not always reach farmers at the right time. The inadequate or ineffective sharing of information can limit a farmer's ability to assess new technology, ultimately lowering yields and earnings (J-PAL, 2018). Adopting information and communications technology (ICT) to contact farmers directly can improve agricultural information and extension services, which help increase the productivity of agriculture and market participation, including innovative solutions (Jack & Tobias, 2017). ICTs, specifically mobile phones, have the potential to meet farmers' information and communication needs more rapidly and accurately than ever before (Daum, 2018). The role of mobile phones in extension services can be supplemented, and thus they can serve to improve the penetration of extension services to a great extent (Mittal et al., 2019). Mobile phones significantly improve farmers' decision-making capacity by accessing information and addressing information asymmetries and help overcome the information gap, especially for rural farmers who live in remote areas. Mobile phones significantly impact the entire farming life-cycle, resulting in considerable changes in livelihood structures, more opportunities, and reduced risks for rural farmers (Furuholt & Matotay, 2011).

Several studies show the effects of mobile phone usage on agricultural production, market access, and household income. Access to information via mobile phone reduces price dispersion and transaction costs and improves market efficiencies (Jensen, 2007; Duncombe & Boateng, 2009; Aker & Mbiti, 2010; Aker, 2011; Aker & Ksoll, 2016; Nakasone & Torero, 2016). Mobile phones also increase farm productivity and farmers' income (Jensen, 2007; Aker & Mbiti, 2010; Aker, 2010; Aker, 2011; Mittal & Mehar, 2012; Kikulwe, Fischer, & Qaim, 2014; Ogunniyi & Ojebuyi, 2016; Aker & Ksoll, 2016; Nakasone & Torero, 2016). Investment in agricultural extensions or market information services for farm households in order to address information asymmetries has mixed results, probably due to the irrelevancy or untimeliness of information delivery (Aker, 2010). Over the last decade, the widespread expansion of mobile phone coverage has created new opportunities to reduce search and transaction costs and increase the potential to improve welfare (Aker & Ksoll, 2016).

Studies that have looked into the impact of ICT-based extension systems have resulted in minimised crop loss, enhanced adoption of effective pesticides, and increased yield in rural areas (Camacho & Conover, 2010; Cole & Fernando, 2012; Casaburi, Kremer, Mullainathan & Ramrattan, 2014). Studies that assessed the link between access to agricultural information and mobile phones or extension services have observed that the wide use of mobile phones in rural regions of Bangladesh has provided farmers with the chance to access agricultural information. But the potential for utilising ICT based agricultural extension services remains untapped (Rahman, Ara, & Khan, 2020; Rahman, Haque, & Afrad, 2020). However, the magnitude of the effects is not yet estimated. In addition, there may be a digital divide in rural areas; small farmers are likely to be disproportionately affected by climate risk exposure with systematic variations in access and use of services. Although several studies have been conducted focusing on mobile phone use alone, studies assessing the impact of agricultural information on household welfare are few; past studies relied on cross-sectional data, which limited their ability to identify causal impacts. Therefore, this study attempts to assess agricultural information received through mobile phones and its impact on household welfare in rural Bangladesh by using large sample panel data. This research may contribute to the growing literature on the impact of access to agricultural information on smallholders' welfare. It also presents new insights into how access to information through mobile phones has heterogeneous effects on climate stressed vulnerable groups of households. These findings can shed light on the importance of well-organised extension services that are capable of delivering information to farmers through ICT.

This paper is structured as follows. After the introduction in Section I, Section II explains the empirical approach. Section III provides a brief description of the data used. Section IV presents the results and discusses them, and Section V concludes the paper with policy implications.

II. EMPIRICAL APPROACH

This study aims to assess the access to agricultural information through mobile phones and its impact on household welfare using two round panel data from rural farm households in Bangladesh. When estimating the panel models for agricultural information access and welfare functions, there are some challenges in regard to dealing with unobserved heterogeneity and potential endogeneity of some of the variables. The estimation issues of the estimated models are discussed below.

2.1 Estimated Models

In developing countries such as Bangladesh, farmers operate with missing or imperfect markets, and they are not fully commercialised. Given the prevalence of market failures in rural areas, market prices do not reflect the entire opportunity cost of many items, especially inputs and services such as agricultural knowledge. Under this condition, farmers' actual prices are shadow prices but not market prices that reflect their farm, household, and community characteristics, along with market characteristics (Ragasa & Mazunda, 2018). Non-separability between production and consumption decisions is attributed to the absence and imperfection of factor and product markets (Sadoulet & De Janvry, 1995). Natural, human, financial, physical, and social capital endowments in households constitute the resource constraints which maximise well-being (Verkaart, Munyua, Mausch, & Michler, 2017).

To examine the factors explaining the access to agricultural information, we use the following model, which includes a vector of the farm, household, and village characteristics as determinants. The impact of access to information on household welfare is estimated, which gives a measure of how that information affects household welfare. Here, the household welfare is a utility framework such that

$$Y = f[K(X, Z, T), Z, T, V] \tag{1}$$

where, Y is household welfare or outcome variables, K represents access to agricultural information, X is farmers' ability to access information (which incorporates the proportion of people who received services in a village), T is household, farm, community, and market characteristics, Z is climate risk characteristics (or whether households experienced crop loss in any of their rice fields due to any climate stresses), and V is the regional level covariates.

The possible effects of access to agricultural information by using mobile phones on household welfare are fairly straightforward. We hypothesise that if the farmers can access information on mobile phones over several seasons, this information will increase knowledge and reduce transaction costs, which, in turn, improves technology, better agricultural practices and markets, and thus increases productivity and income. In general, farmers use agricultural production for home consumption or to generate income. Ultimately, agricultural and other sources of income lead to asset and wealth accumulation and then affect household food security and future investments on and off the farm.

Accordingly, starting from equation (1) in our conceptual model, we specify the following:

$$K_{it} = \alpha + \beta_1 X_{it}^{EA} + T_{it}\theta + Z_{it}\emptyset + D_t + V + \epsilon_{it} \tag{2}$$

where, K_{it} is the access to agricultural information by the household i in year t, and X_{it}^{EA} is the proportion of people who received extension advice. T_{it} is a vector of household characteristics, and Z_{it} is a vector of whether the household experienced crop loss in any of their rice plots. We also include D_t which is year dummy for 2017 and V is divisional dummies to control other common shocks and unobserved regional characteristics that affect the access to agricultural information. The term ϵ_{it} is a mean zero as well as an identically and independently distributed random error, assumed to be uncorrelated to all explanatory variables.

As we intend to analyse the impact of access to agricultural information on household welfare, we use the following equations:

$$Y_{it} = \alpha + \gamma_1 K_{it} + T_{it}\theta + Z_{it}\emptyset + D_t + V + \epsilon_{it} \tag{3}$$

where, Y_{it} is the welfare measurement (asset holdings, own rice consumption and rice yield), K_{it} is the access to agricultural information by the household i in year t. T_{it} is a vector of household characteristics, Z_{it} is a vector of whether the household experienced crop loss in any of their rice plots, D_t is a year dummy for 2017, and V is a divisional dummy to control other common shocks and unobserved regional characteristics that affect the welfare indicator. The term ϵ_{it} is the same as equation (2).

There are two potential causes of endogeneity in our household model. Unobserved heterogeneity is one potential source. It is because unobserved time-invariant household characteristics may be correlated with our welfare measurements. Another form of endogeneity issue may exist in the welfare outcome equation itself. The variable of interest, i.e., access to agricultural information, is itself an outcome variable and thus may be correlated with the error term in the dependent variable. We address these in turn.

2.2 Estimation Issues

2.2.1 Controlling for Endogenous Regressor

We use Smith and Blundell's (1986) control function (CF) approach to control for possible endogeneity. This approach offers more efficient outcomes for intricate models or those requiring nonlinear models for the endogenous variable (Imbens & Wooldridge, 2007).

For estimating CF, we follow two steps from Wooldridge (2015). First, we run a probit function to estimate the reduced form of the model for access to agricultural information and obtain the generalised residual. Then we include the generalised residual as a covariate in the structural welfare equation. The significance of the coefficient on the residual is tested and controlled for the endogeneity of agricultural information access.

For CF approaches, we need instrument variables (IVs) that must be correlated with household access to agricultural information but uncorrelated with the error term in the structural model or the outcome variables. It also satisfies the orthogonality conditions of IVs. We test two instrumental variables for accessing agricultural information: 1) the proportions of farmers in the village who received extension services, and 2) the distance to the location of the services. These two instruments represent the availability of knowledge about agriculture and crops in the village and also the information spillover within the community. In rural areas of Bangladesh, despite farmers accessing agricultural information from different sources, governmental extension services are the main provider and source where farmers receive information by direct contact if they meet the extension agents. Ragasa & Mazunda (2018) also found these variables as significant instruments. We use the first variable because it satisfies the statistical validity test. This variable is found to be significant in the first stage model but is not significant in the second stage outcome model and other controls. Besides, we estimate access to agricultural information as both endogenous and exogenous for checking robustness of our results.

We incorporate all exogenous variables, year and regional dummies, the means of time-varying variables, and the generalised residuals from the reduced form equation. As we include generalised residuals in the structural model, which are likely to be biased, in the second stage, we use bootstrapping to adjust standard errors for the two-step procedure.

2.2.2 Controlling for Unobserved Heterogeneity

Our study deals with the presence of household heterogeneity; it generates selection bias because some households have access to agricultural information and others do not, and the unobserved household effect in the error term may be correlated with access to agricultural information.

This study uses the Correlated Random Effect (CRE) model of Mundlak (1978) and Chamberlain (1984) to overcome the incidental variables problem that fixed effects introduce in non-linear panel models. If the unobserved effect is time-invariant, then this approach allows for correlation between the unobserved household omitted variable and variables of interest, i.e., access to agricultural information (Imbens & Wooldridge, 2007; Wooldridge, 2014). By allowing dependence between observed and unobserved variables, the CRE approach relaxes the strict exogeneity assumption in the random effects estimator and integrates both the fixed effect and random effect approaches.

By including the mean of time-variant variables in the household controls for time-invariant unobserved heterogeneity (Wooldridge, 2010), the reduced form of access to agricultural information and the structural welfare equation are estimated using the CRE estimator.

III. DATA AND DESCRIPTIVE STATISTICS

3.1 Data

This study used the Rice Monitoring Survey (RMS) data collected by International Rice Research Institute (IRRI) (Yamano, 2017). The survey employed a multi-stage sampling method to select the divisions, districts, and villages (Yamano et al., 2014). RMS panel data includes an initial 1,500 households surveyed in 2014 from 16 districts in six divisions of Bangladesh (Table I). Of the 1,500 households in revisited areas, 1,485 were re-interviewed in 2017, which provides an attrition rate of less than 1 per cent between 2014 and 2017. Therefore, the study ended using a balanced panel of 1,485 households surveyed in both rounds for a total of 2,970 observations. The RMS survey provides high quality data on household characteristics, plot characteristics, rice production and marketing, climate stress characteristics, mobile phone ownership, and access to agricultural information.

TABLE I

DISTRIBUTION OF THE SAMPLE HOUSEHOLDS

Division	Districts	Number of upazilas	Number of villages	Number of households	Number of samples used in the analysis[1]
Barishal	Barguna	4	8	80	80
	Barishal	6	12	120	120
	Bhola	6	12	120	119
	Jhalokati	3	6	60	60
	Pirojpur	3	6	60	60
Chattogram	Chandpur	2	4	40	40
	Chattogram	8	16	160	159
Dhaka	Manikganj	5	10	100	99
	Shariatpur	4	8	80	80
Khulna	Jhenaidah	4	8	80	80
	Satkhira	5	10	100	100
Rajshahi	Bogura	5	10	100	100
	Natore	4	8	80	76
	Rajshahi	6	12	120	113
Rangpur	Kurigram	5	10	100	99
	Thakurgaon	5	10	100	100
Total	**16**	**75**	**150**	**1,500**	**1,485**

Notes: The data source is the 2014 and 2017 Rice Monitoring Survey (RMS) Household Survey Data, International Rice Research Institute (IRRI).[1] For a balanced panel, the samples are excluded, which were unavailable in the second-round survey.

3.2 Descriptive Statistics

The use of mobile phones has rapidly expanded in rural Bangladesh. The pattern of access to agricultural information by households in our sample during the study period is shown in Table II. In 2014, about 22 per cent of households had access to information through mobile phones; by 2017, this share had increased to 26 per cent. Figure 1 shows the disaggregated access to agricultural information by household. Among all types of information received, agricultural input and output price information were the most common. Households seek information relating to agricultural practices, i.e., crop damages, agricultural machinery information, etc. They also had access to other types of information, such as new rice varieties and weather information. Making and receiving calls, exchanging text messages, and receiving information from friends, business partners, agriculture extension officers, farmer groups, non-government oranisations (NGOs), and government organisations (GOs) were all part of the household's access to information.

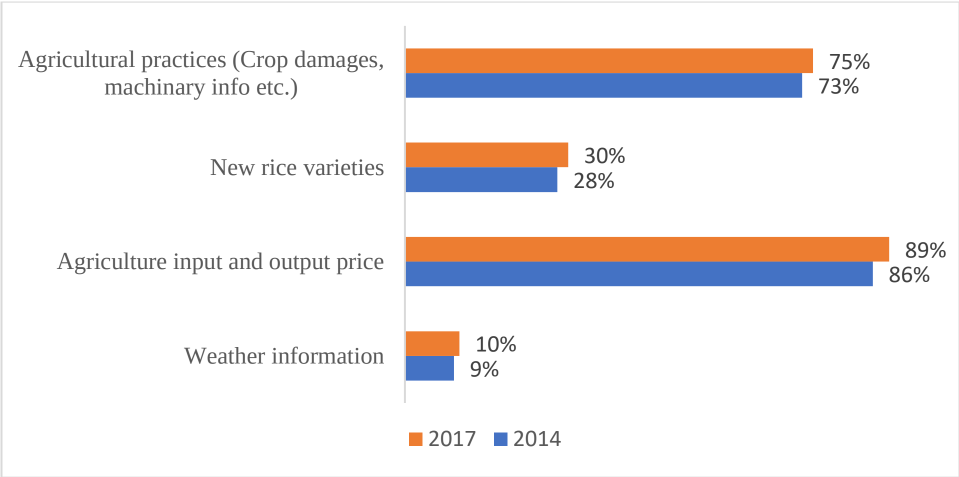
TABLE II

SAMPLE HOUSEHOLDS ACCESS TO AGRICULTURAL INFORMATION THROUGH MOBILE PHONES (N=1485)

Access to ag. information through mobile phones	2014		2017		Pooled sample	
	number	%	number	%	number	%
Yes	332	22.36	390	26.26	722	24.31
No	1,153	77.64	1,095	73.74	2,248	75.69

Notes: Computed by the author based on the 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI).

FIGURE 1: **Types of Agricultural Information Access by the Farmers (n=722)**



Farmers have endured crop losses due to climate stress (Table III). In 2014, almost 33 per cent of households in the sample experienced crop loss due to the submergence of their rice plots, which was 44 per cent of the total sample in 2017. In 2014 and 2017, households also suffered crop loss due to drought or salinity on their plots.

TABLE III

EXPERIENCE CROP LOSS DUE TO CLIMATE STRESS (N=1,485)

Climate stress	2014		2017		Pooled sample	
	number	%	number	%	number	%
Submergence	494	33.27	650	43.77	1,144	38.52
Drought	221	14.88	208	14.01	429	14.44
Salinity	101	6.8	143	9.63	244	8.22

Notes: Computed by the author based on the 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI).

The socio-economic characteristics of agricultural information users and non-users are reported in Table IV. Those who have access to agricultural information have larger landholdings and household sizes and are younger and more educated than those who do not. At the 1 per cent level, all of the differences are statistically significant. Table V presents descriptive statistics for the welfare outcome variables of the econometric analysis. The selected indicators for the welfare outcomes are household per capita rice available for consumption from own production, household per capita asset holdings, and the rice yield. Household asset holdings value includes the value of household physical assets, including short- and medium- term productive assets. We use an adult equivalent to compute the per capita values. Households with access to agricultural information have higher household asset values and yields than those who do not. Rice consumption from own production is also higher in the case of households that have access to agricultural information, with statistically significant differences.

TABLE IV

SOCIO-ECONOMIC CHARACTERISTICS OF THE SAMPLE FARMERS (ACCESS TO AGRICULTURAL INFORMATION THROUGH MOBILE PHONE)

	2014		2017		Pooled sample	
	Yes	No	Yes	No	Yes	No
Male household head (dummy)	0.81* (0.022)	0.85 (0.010)	0.93*** (0.013)	0.86 (0.010)	0.87 (0.007)	0.85 (0.012)
Age of household head (years)	43.02*** (0.708)	45.42 (0.381)	45.67** (0.667)	47.54 (0.397)	44.45*** (0.487)	46.44 (0.276)
Education of household head (years)	7.67*** (0.242)	5.35 (0.117)	7.53*** (0.224)	5.47 (0.125)	7.60*** (0.164)	5.41 (0.086)
Household size (No.)	6.00*** (0.134)	5.64 (0.066)	5.93** (0.146)	5.64 (0.075)	5.96*** (0.010)	5.64 (0.049)
Landholdings (decimal)	295.40*** (15.21)	132.75 (4.314)	270.37*** (13.521)	132.13 (4.427)	280.50*** (10.114)	132.45 (3.089)
Distance to market (km)	2.16 (0.110)	2.11 (0.055)	2.12 (0.098)	2.12 (0.058)	2.13 (0.073)	2.11 (0.039)
No. of plots	2.80*** (0.115)	2.33 (0.048)	3.06*** (0.103)	2.47 (0.055)	2.94*** (0.077)	2.40 (0.036)
Crop loss due to climate stress (dummy)	0.36** (0.026)	0.43 (0.015)	0.57 (0.025)	0.53 (0.015)	0.47 (0.019)	0.48 (0.010)

Notes: Computed by the author based on the 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI). Mean values are shown with standard errors in parentheses. Differences in means between two groups ("Yes" and "No") are tested for statistical significance. Significance levels: 10%*, 5%**, 1%***.

TABLE V

HOUSEHOLD ASSET VALUES, OWN RICE CONSUMPTION, AND YIELD (ACCESS TO AGRICULTURAL INFORMATION THROUGH MOBILE PHONE)

	Yes	No
Value of assets (BDT)	10798.24***	6443
	(459.903)	(192.131)
Own rice consumption (Kg/year)	398.61***	346.17
	(11.162)	(5.608)
Yield (ton/hectare)	5.00***	4.74
	(0.061)	(0.037)

Notes: Computed by the author based on the 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI). Mean values are shown with standard errors in parentheses. Differences in means between two groups ("Yes" and "No") are tested for statistical significance. Significance levels: 10%*, 5%**, 1%***.

IV. RESULTS AND DISCUSSIONS

4.1 Access to Agricultural Information

This study identifies various factors that help explain who is likely to have access to agricultural information using the probit function (Table VI). The result shows that specifically, the education of the household head is positively correlated with access to agricultural information. It aligns with the expectation that educated farmers are more active in accessing agricultural information and perhaps are better able to use the information. The probability of access to agricultural information increases with landholdings, as expected. Other variables held the same; households with more land are more likely to access information. Male household heads are more likely to access agricultural information than female household heads. The age of household head and the size of the household do not have any influence on the choice to access agricultural information, but the negative correlation shows young heads of household are more likely to access information. Households located nearer the market are less likely to obtain agriculture-related advice through mobile phone.

The coefficient for crop loss due to climate stress is strongly and positively correlated with access to agricultural information. It indicates that if the farmers experienced more crop loss due to climate stress, they were more likely to access agricultural information over the phone. This result was expected because when they experienced more crop loss, they were more likely to seek information about new technology to better cope with their loss.

TABLE VI

CORRELATED RANDOM EFFECTS PROBIT MODEL OF ACCESS TO AGRICULTURE INFORMATION THROUGH MOBILE PHONES

Variables	Access to agricultural information through mobile phone (yes= 1)	
	Co-efficient	SE
Proportion of village people received services	6.121***	0.651
Age of household head (years)	-0.025	-0.055
Male household head	0.0185	0.319
Education	0.456***	0.064
Household size	0.064	0.052
Land holdings (decimal)	0.747***	0.099
Distance to market (km)	0.647***	0.083
No. of plots	0.171	0.154
Crop loss due to climate stress (yes= 1)	0.401**	0.212
Year 2017	0.813***	0.198
Constant	-15.991***	0.866
Prob> chi^2	0.000	
Number of observations	2970	
Number of households	1485	

Notes: Computed by the author based on the 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI). The mean of time-varying variables and divisional dummies are included in this Correlated Random Effect model. Significance levels: 10%*, 5%**, 1%***. SE is fully robust standard errors.

4.2 Access to Agricultural Information and Household Welfare

The relationship between access to agricultural information and various welfare indicators using correlated random effects models is shown in Table VII. The generalised residual from the first stage model of access to agricultural information is included in the CRE models to test and control for the endogeneity of access to agricultural information [columns (1), (3), and (5) in Table VII]. If the coefficient for the generalised residual is significant, it indicates that access to agricultural information is endogenous.

The findings reveal that access to agricultural information has a positive and significant correlation with the per capita own rice consumption, per capita asset holdings, and yield [columns (1), (3), and (5) in Table VII]. The estimates show that even when controlling all other factors, receivers of agricultural information have a 12 per cent higher yield, 29 per cent higher asset value, and 40 per cent higher own rice consumption than those who do not. Access to information that can increase the yield effect was suggested in previous studies (Casaburi et al., 2014). It is an encouraging result, given that access to information is crucial in increasing productivity, wealth accumulation, and food security in Bangladesh.

TABLE VII

CORRELATED RANDOM EFFECTS MODEL OF THE RELATIONSHIP BETWEEN ACCESS TO AGRICULTURAL INFORMATION THROUGH MOBILE PHONE AND HOUSEHOLD WELFARE

	Value assets[a] (BDT)		Own rice consumption[a] (Kg/year)		Yield[b] (ton/hectare)	
	CF/CRE	CRE	CF/CRE	CRE	CF/CRE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Access to agricultural information (yes=1)	0.292*** (0.081)	0.208*** (0.053)	0.403*** (0.098)	0.181*** (0.065)	0.121*** (0.033)	0.046*** (0.022)
Crop loss due to climate stress (yes= 1)	0.005 (0.043)	0.006 (0.043)	-0.394*** (0.066)	-0.394*** (0.066)	-0.272*** (0.024)	-0.270** (0.024)
Age of household age	-0.009 (0.011)	-0.009 (0.011)	0.002 (0.017)	-0.001 (0.017)	-0.001 (0.006)	-0.001 (0.006)
Male household head	-0.049 (0.067)	-0.047 (0.067)	-0.001 (0.104)	0.005 (0.104)	0.028 (0.037)	0.030 (0.037)
Education (years)	0.014 (0.011)	0.014 (0.011)	0.032** (0.017)	0.032** (0.017)	0.010* (0.006)	0.010* (0.006)
Household size (No.)	-0.084*** (0.011)	-0.083*** (0.011)	-0.070*** (0.017)	-0.069*** (0.016)	0.012** (0.006)	0.012** (0.006)
Landholdings (ha)	0.052*** (0.014)	0.053*** (0.014)	0.006 (0.017)	0.010 (0.017)	-0.026*** (0.006)	-0.025*** (0.005)
Distance to market (km)	-0.009 (0.011)	-0.011 (0.012)	0.026** (0.013)	0.023** (0.013)	0.005 (0.004)	0.004 (0.004)
No. of plots	0.064*** (0.012)	0.065*** (0.012)	0.046*** (0.016)	0.048*** (0.016)	0.030*** (0.005)	0.031*** (0.005)
Year 2017 (dummy)	0.409*** (0.037)	0.411*** (0.037)	-0.528*** (0.058)	-0.522*** (0.058)	-0.074*** (0.021)	-0.072*** (0.021)
Generalised residual	-0.020 (0.015)		-0.055*** (0.018)		-0.019*** (0.006)	
Constant	7.225*** (0.128)	7.195*** (0.126)	6.218*** (0.152)	6.138*** (0.150)	1.556*** (0.050)	1.529*** (0.050)
R^2 overall	0.292	0.291	0.116	0.113	0.217	0.214
Prob> chi^2	0.000	0.000	0.000	0.000	0.000	0.000
No. of observations	2,970	2,970	2,970	2,970	2,970	2,970
No. of households	1,485	1,485	1,485	1,485	1,485	1,485

Notes: Computed by the author based on the 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI). CF= Control Function approach and CRE= Correlated Random Effects model. Columns (1), (3), (5) treat access to agricultural information as endogenous, and Columns (2), (4), (6) treat access to agricultural information as exogenous. BDT= Bangladeshi Taka.
The mean of time-varying variables and divisional dummies are included in this Correlated Random Effect model. [a] Outcome variables are per adult equivalent and given in logarithmic terms and yield[b] variable is given in logarithmic terms. Significance levels: 10%*, 5%**, 1%***. A fully robust bootstrapped standard errors are in parentheses.

Examining other variables, we find land holdings are strongly and positively correlated with wealth accumulation but not with own rice consumption and yield. These results indicate that households with more land stimulate more wealth accumulation. On the other hand, large landholders do not rely on the consumption of their own produced rice. Rather, they sell a large portion of their rice production in the markets. Household size is negatively associated with all the outcome variables, which indicates that a large household has a negative effect on household welfare in rural areas. Other significant covariates are education and year dummies. Where changes in other covariates are significant, these exhibited the expected results.

However, households who access agricultural information have higher own rice consumption, even controlling for climate risk exposure. On the other hand, those who experienced higher crop losses have a significantly lower yield, own rice consumption and asset values, indicating the effect of risk on household welfare. Even controlling for access to information, households registered lower own rice consumption and yield in 2017 than in 2014, which is perhaps an effect of the climate risk. We also check robustness by treating access to agricultural information as exogenous [columns (2), (4), and (6) in Table VII]. The results reveal, to a great extent, that they are similar results and directions. But access to agricultural information gives more prominent results if endogeneity is controlled.

4.3 Who Benefits More from Access to Agricultural Information

A disaggregated estimation of the own rice consumption equation to compare climate-risk vulnerable households with climate-risk non-vulnerable households is presented in Table VIII. The climate-risk vulnerable household is considered if a household experiences crop loss due to at least one of the three climate stresses, i.e., submergence, drought, and salinity.

The estimated coefficients reveal that access to agricultural information increases the own consumption of both groups of households’, i. e., climate-risk vulnerable households and climate-risk non-vulnerable households. However, the benefits that access to agricultural information provides to households' own consumption are higher for those who experience crop loss (climate-risk vulnerable households). This may indicate that these households are more reliant on their own rice consumption and they benefitted more from having access to agricultural information. Thus, it is important to increase access to agricultural information services to support their food security.

TABLE VIII

COMPARISON OF THE CORRELATED RANDOM EFFECTS MODEL ESTIMATION OF OWN RICE CONSUMPTION FOR CLIMATE RISK VULNERABLE AND CLIMATE RISK NON-VULNERABLE HOUSEHOLDS

	Climate-risk vulnerable	Climate-risk non-vulnerable
Access to agricultural information (yes=1)	0.575***	0.264***
	(0.176)	(0.010)
Age of household age (years)	0.016	-0.021
	(0.025)	(0.022)
Male household head (dummy)	-0.044	-0.010
	(0.163)	(0.126)
Education (years)	0.060**	0.011
	(0.028)	(0.019)
Household size (No.)	-0.056**	-0.076***
	(0.026)	(0.020)
Landholdings (ha)	-0.005	0.018
	(0.029)	(0.019)
Distance to market (km)	0.072**	0.007
	(0.026)	(0.013)
No. of plots	0.071***	0.006
	(0.025)	(0.019)
Year 2017 (dummy)	-0.585***	-0.376***
	(0.091)	(0.073)
Generalised residual	-0.098***	-0.021
	(0.032)	(0.019)
Constant	5.776***	6.165***
	(0.298)	(0.159)
R^2 overall	0.113	0.131
Prob> chi^2	0.000	0.000
No. of observations	1416	1554
No. of households	1047	1116

Notes: Computed by the author based on the 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI). The climate-risk vulnerable group is considered if a household experiences crop loss with any of the three climate stresses (submergence, drought or salinity) in their plot (yes=1). The mean of time-varying variables and divisional dummies are included in this Correlated Random Effect model. Significance levels: 10%*, 5%**, 1%***. A fully robust bootstrapped standard errors are in parentheses.

V. CONCLUSIONS AND POLICY IMPLICATIONS

This paper analyses the factors that influence access to agricultural information through mobile phones and their impacts on household welfare indicators using two-round panel data from 2014 and 2017. A control function approach and correlated random effects model are used to control for endogeneity and unobserved heterogeneity. The empirical results show that the proportion of village people who received extension services, larger landholdings, education and larger household size are the variables that increase access to agricultural information through mobile phones. Crop loss results from climate stress exposure prompts farmers to seek out agricultural information. Using indicators of household assets, rice yield and own rice consumption, we estimate the household welfare impacts of access to agriculture information. In particular, households' access to agricultural information is linked to an increase in their own rice consumption, asset accumulation value, and rice yield than those who do not. In addition, the estimates, differentiated by climate-stress vulnerable households, revealed that access to agricultural information has more impact on the climate stress-affected vulnerable groups. The identified relationships are plausible and consistent in terms of economic theory. However, this study is not free of limitations. This study employed observational survey data in which we cannot eliminate reporting bias. Despite these limitations, this study of a large sample size is a nationally representative data of Bangladesh and concludes that agricultural information can contribute significantly to enhancing agricultural productivity and improving food security in rural areas, especially when vulnerable households have access to agricultural information.

Therefore, the government should digitalise extension services and take the proper initiative to introduce hotline information services to ensure access to timely and reliable information. It can help enhance people's access to information and ultimately reduce the information gap that contributes significantly to food security in rural areas.

REFERENCES

Abdul Latif Jameel Poverty Action Lab. (J-PAL). (2018). Improving extension services to increase smallholder productivity. *J-PAL Policy Insights*. https://doi.org/10.31485/pi.2260.2018

Afrad, S. I., Wadud, F., & Babu, S. C. (2019). Reforms in agricultural extension service system in Bangladesh. In *Agricultural Extension Reforms in South Asia*. https://doi.org/10.1016/b978-0-12-818752-4.00002-3

Aker, J. C. (2010). Information from markets near and far: Mobile phones and agricultural markets in Niger. *American Economic Journal: Applied Economics*, *2*(3), 46–59. https://doi.org/10.1257/app.2.3.46

Aker, J. C. (2011). Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics*, *42*(6), 631–647. https://doi.org/10.1111/j.1574-0862.2011.00545.x

Aker, J. C., & Ksoll, C. (2016). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *Food Policy*, *60*, 44–51. https://doi.org/10.1016/j.foodpol.2015.03.006

Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa Working Paper 211. Center for Global Development, (June).

Baumüller, H. (2013). Mobile technology trends and their potential for agricultural development. *ZEF Working Paper 123.*

BBS. (2018). 45 years agriculture statistics of major crops (Aus, Amon, Boro, Jute, Potato & Wheat). Bangladesh Bureau of Statistics (BBS) Statistics and Informatics Division (SID). January, 1–216.

Camacho, A., & Conover, E. (2010). The impact of receiving price and climate information in the agricultural sector. *Documento CEDE*, 2010–40.

Casaburi, L., Kremer, M., Mullainathan, S., & Ramrattan, R. (2014). Harnessing ICT to increase agricultural production: Evidence from Kenya. *Harvard University*.

Chamberlain, G. (1984). Chapter 22 Panel data. *Handbook of Econometrics*, *2*, 1247–1318. https://doi.org/10.1016/S1573-4412(84)02014-6

Cohn, A. S., Newton, P., Gil, J. D. B., Kuhl, L., Samberg, L., Ricciardi, V., Manly, J. R., & Northrop, S. (2017). Smallholder agriculture and climate change. *Annual Review of Environment and Resources*, *42*, 347–375. https://doi.org/10.1146/annurev-environ-102016-060946

Cole, S., & Fernando, A. N. (2012). The value of advice: Evidence from mobile phone-based agricultural extension. *Harvard Business School Working Paper# 13-047*.

Daum, T. (2018). ICT applications in agriculture. In *Encyclopedia of Food Security and Sustainability* (Vol. 1). https://doi.org/10.1016/B978-0-08-100596-5.22591-2

Duncombe, R., & Boateng, R. (2009). Mobile phones and financial services in developing countries: A review of concepts, methods, issues, evidence and future research directions. *Third World Quarterly*, *30*(7), 1237–1258. https://doi.org/10.1080/01436590903134882

Furuholt, B., & Matotay, E. (2011). The developmental contribution from mobile phones across the agricultural value chain in rural Africa. *The Electronic Journal of Information Systems in Developing Countries*, *48*(1), 1–16. https://doi.org/10.1002/j.1681- 4835.2011.tb00343.x

Gates, B. (2016). Why the future is bright for the world's poorest farmers? Technology is transforming agriculture and the fight against poverty. https://www.gatesnotes.com/Development/The-Future-of-Farming

IFPRI. (2016). *Bangladesh integrated household survey 2015*. International Food Policy Research Institute.

Imbens, G., & Wooldridge, J. (2007). *"What's new in econometrics" Lecture 5*. NBER.

Jack, K., & Tobias, J. (2017). Seeding success: Increasing agricultural technology adoption through information. *IGC Brief* (December), 1–8. Retrieved from https://www.theigc.org/wp-content/uploads/2017/12/IGCJ5833-Agriculture-growth-brief-171214-Web.pdf

Jensen, R. (2007). The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector. *Quarterly Journal of Economics*, *122*(3), 879–924. https://doi.org/10.1162/qjec.122.3.879

Kikulwe, E. M., Fischer, E., & Qaim, M. (2014). Mobile money, smallholder farmers, and household welfare in Kenya. *PLoS ONE*, *9*(10). https://doi.org/10.1371/journal.pone.0109804

Mittal, S., & Mehar, M. (2012). How mobile phones contribute to growth of small farmers? evidence from India. *Quarterly Journal of International Agriculture*, *51*(3), 227–244.

Mittal, S., Mehar, M., & Hariharan, V. K. (2019). Information and communication technologies for strengthening extension services to reach the last mile in India. *Agricultural Extension Reforms in South Asia*, 255–274. https://doi.org/10.1016/B978-0-12-818752-4.00013-8

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, *46*(1), 69–85.

Nakasone, E., & Torero, M. (2016). A text message away: ICTs as a tool to improve food security. *Agricultural Economics (United Kingdom)*, *47*, 49–59. https://doi.org/10.1111/agec.12314

OCHA. (2014). Weathering climate change effects with stress-tolerant rice varieties. Reliefweb. News and Press Release, Government of the United States of America. https://reliefweb.int/report/bangladesh/weathering-climate-change-effects-stress-tolerant-rice-varieties

Ogunniyi, M. D., & Ojebuyi, B. R. (2016). Mobile phone use for agribusiness by farmers in Southwest Nigeria. *Journal of Agricultural Extension*, *20*(2), 172–187.

Ragasa, C., & Mazunda, J. (2018). The impact of agricultural extension services in the context of a heavily subsidized input system: The case of Malawi. *World Development*, *105*, 25–47. https://doi.org/10.1016/j.worlddev.2017.12.004

Rahman, M. S., Haque, M. E., & Afrad, M. S. I. (2020). Utility of mobile phone usage in agricultural information dissemination in Bangladesh. *East African Scholars Journal of Agriculture and Life Sciences*, *4472*(6). https://doi.org/10.36349/EASJALS.2020.v03i06.020

Rahman, T., Ara, S., & Khan, N. A. (2020). Agro-information service and information-seeking behaviour of small-scale farmers in rural Bangladesh. *Asia-Pacific Journal of Rural Development*, *30*(1–2), 175–194. https://doi.org/10.1177/1018529120977259

RMS. (2019). Rice monitoring survey in Bangladesh. International Rice Research Institute (IRRI). Los Banos, The Philippines.

Sadoulet, E., & De Janvry, A. (1995). Quantitative development policy analysis. Baltimore, MD: Johns Hopkins University Press.

Smith, R. J., & Blundell, R. W. (1986). An exogeneity test for a simultaneous equation Tobit model with an application to labor supply. *Econometrica*, *54*(3), 679. https://doi.org/10.2307/1911314

Verkaart, S., Munyua, B. G., Mausch, K., & Michler, J. D. (2017). Welfare impacts of improved chickpea adoption : A pathway for rural development in Ethiopia ? *Food Policy*, *66*, 50–61. https://doi.org/10.1016/j.foodpol.2016.11.007

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Wooldridge, J. M. (2014). Quasi-maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables. *Journal of Econometrics*, *182*(1), 226–234.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, *50*(2), 420–445.

Yamano, T., Malabayabas, M. L., Panda, A., & Gupta, I. (2014). *Rice monitoring survey 2014 in Bangladesh.* Mimeograph. Los Banos, Philippines: International Rice Research Institute.

Yamano, T. (2017). *Rice monitoring survey: South Asia*. Harvard Dataverse V1. https://doi.org/10.7910/DVN/0VPRGD .