

Mobile money mitigates the negative effects of weather shocks:
Implications for risk sharing and poverty reduction in Bangladesh

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Abstract

To cope with weather shocks, financial services have the potential to serve as formal or informal insurance. However, rural financial inclusion faces challenges related to transaction costs. Mobile money is a financial innovation that enables individuals to transfer and store money quickly, safely, and at a low cost without internet. We examine the impact of these mobile money services on food and non-food consumption in response to weather shocks. Moreover, we investigate whether there is an increase in remittances received via mobile money as a response to the shocks. We utilize a nationally representative household survey combined with historical granular monthly precipitation data. By employing fixed effect and instrumental variable approaches, we find that mobile money compensates for the negative effect of rainfall shocks. Heterogeneity analysis reveals that mobile money enables geographically disadvantaged and poor households to smooth out their food consumption during droughts, while rich households smooth their non-food consumption during floods. We also discover evidence that mobile money, likely through increased overseas remittances, contributes to improved household welfare compared to non-users of mobile money. These findings have implications for how mobile money reshapes formal and informal insurance mechanisms to mitigate the impacts of weather shocks in developing economies.

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1. Introduction

Frequent weather shocks stemming from global climate change are significant for rural and poor household. Floods deprive households' assets and agricultural production, resulting in reduction of household income. Moreover, droughts substantially reduce crop yields, inducing food insecurity. For example, South Asian countries have been confronting climate risk such as extreme floods and cyclone. The vagaries of South Asian summer monsoon rainfall on short and long timescales impact the lives of more than one billion people (Turner & Annamalai, 2012). To cope with the climate shocks, adaptive strategies are urgently needed. Existing literature points to the potential effectiveness of financial services, such as microfinance and weather index insurance, in response to the shocks (Barnett & Mahul, 2007; Kono & Takahashi, 2010).

Rural financial services challenge transaction cost that render markets for financial services costly or missing (Benami & Carter, 2021). The emerging digital technologies (for e.g., mobile money (MM), digital credit scoring, and earth observation) can reshape rural markets for savings, credit, and insurance services, especially in developing countries (Benami & Carter, 2021). In terms of mobile technology, mobile phone has been widely used in developing countries contributing to economic development. Bangladesh also has experienced expansion of mobile phone subscription (Matsuura, Islam, & Tauseef, 2023). With increasing access to mobile phones across the world, mobile money services have been growing in popularity, enabling users to deposit, transfer, and withdraw funds from a digital account without owning a bank account (Suri, et al., 2023). Mobile money dramatically reduces transaction costs, while improving the convenience, security, and time taken for transactions. (Suri, et al., 2023). Since mobile money allows individuals to transfer and store funds using short message services without internet and overcomes the challenges of formal insurance, it is important that we examine how mobile money can help households smooth their consumption in Bangladesh where the number of mobile cellular subscriptions per 100 people is over 100 in 2020 but the ratio of individual internet users remains only 25 % in 2020 (see Figure 1).

In this study, we look at three primary research questions: (1) What is the relationship between mobile money adoption and households' ability to smooth consumption in response to weather shocks? (2) Are there heterogeneous effects between mobile money and consumption smoothing in response to weather shocks from the viewpoint of spatial inequality and poverty status? Bangladesh has one of the highest poverty rates among South Asian countries and is particularly prone to flooding (World Bank, 2018). Given that poor households are especially

vulnerable to weather shocks, this question is of particular interest. (3) What is the mechanism by which households can mitigate the negative impact of the weather shocks through the adoption of mobile money? To these ends, we use a recently collected longitudinal dataset on Bangladeshi household, combining with granular monthly precipitation data.

There is substantial literature looking at the relationship between mobile money and consumption smoothing in response to economic shocks. Jack and Suri (2014) and Riley (2018) find that mobile money has changed risk sharing by allowing users to send and receive remittances in cases of negative shocks to the household. Moreover, Tabetando & Matsumoto (2020), Ahmed & Cowan (2021) and Abiona & Koppensteiner (2022) find that mobile money adopter households are able to maintain their investments in human capital beyond household consumption. The mechanism behind the use of mobile money for informal and formal insurance has also been well documented. Jack & Suri (2014), Riley (2018), and Tabetando & Matsumoto, (2020) show that the underlying mechanism is an increase in remittance receipt. In addition, adoption of mobile money facilitates the receipt of social protection transfers that likely improves the resilience of these households (Aker, Boumnijel, McClelland, & Tierney, 2016; Abiona & Koppensteiner, 2022).

The contribution of this paper is threefold. First, we provide novel evidence that mobile money services enable geographically disadvantaged households to smooth their food consumption in response to droughts as well as their non-food consumption in response to floods, combining a nationally representative household survey and historical precipitation grid data. It also indicates that the results have greater internal and external validity in the literature, especially for South Asian settings. Second, the present study shows that relatively poorer households can smooth their consumption, same as geographically disadvantaged households. Finally, we find that the likely mechanism that improves household resilience against economic shocks is through the increased likelihood of receiving remittance due to use of mobile money.

The rest of the paper is organized as follows. Section 2 describes the data source and key variables that are of interest. In the next section, we present the identification strategy and empirical specification used in the analysis. Section 4 discusses the results. Finally, Section 5 provides concluding remarks and policy implications.

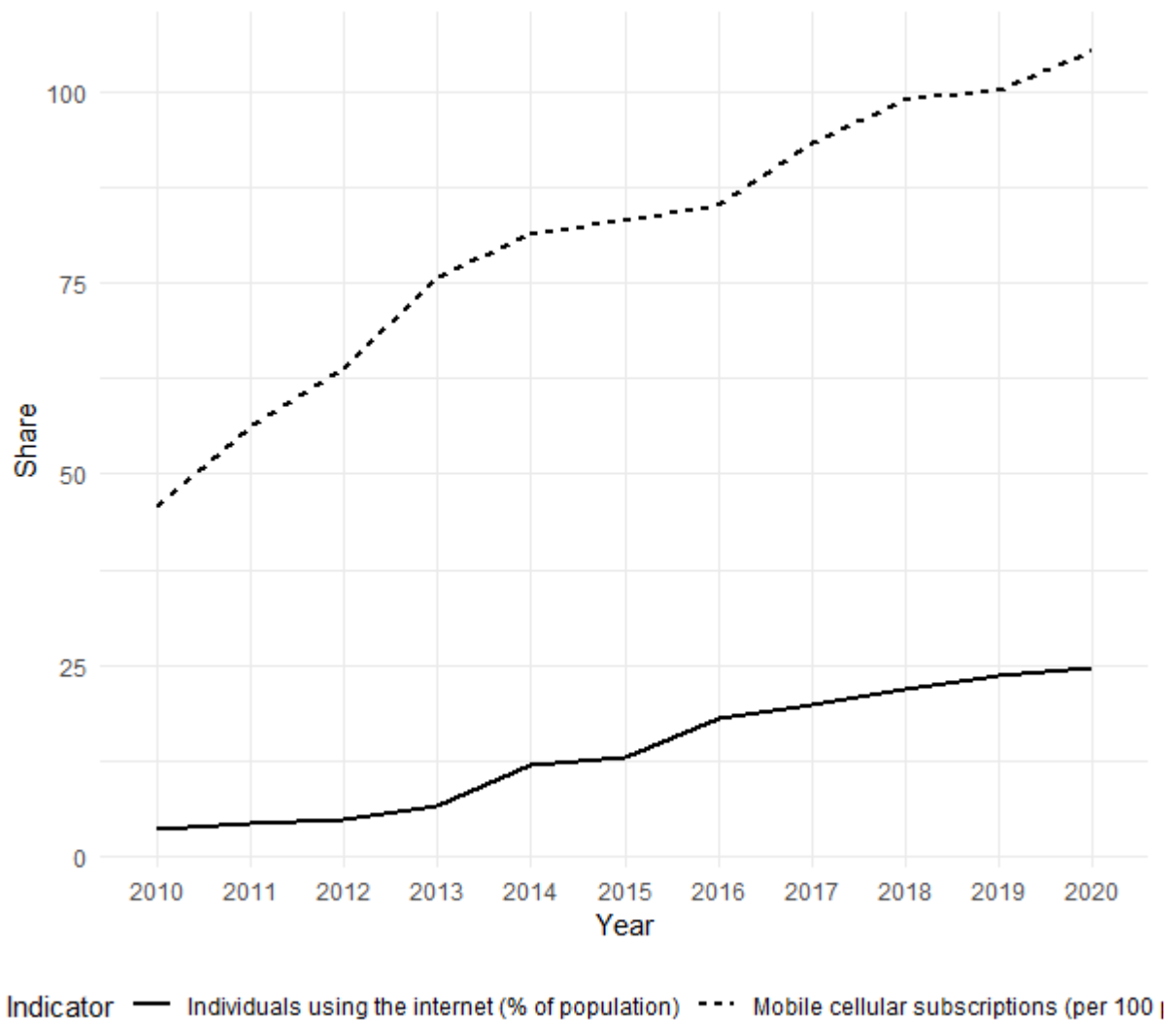


Figure 1 Mobile phone subscription and internet users in Bangladesh

Source: World Bank (2023) Note: Calculated by authors.

2. Methodology

2.1. Data

We use data from the Bangladesh Integrated Household Survey (BIHS), which is a nationally representative rural household panel survey carried out by International Food Policy Research Institute in 2015 and 2018-2019 (from here on 2019) in seven division. The sample design of the BIHS followed a two staged stratified sampling method. Following the sampling framework developed from the community series of the 2001 Population and Housing Census of Bangladesh, primary sampling units (PSUs) were randomly selected in the first stage and random selection of households within each PSU constitute the second stage (Ahmed & Tauseef, 2022). Although BIHS has three rounds, we focus on our analysis on this two-period

panel¹. For this study, we use the balanced subsample of rural households included in both survey rounds, resulting in 9,860 observations from 4,930 households as shown in Table 1. Figure 2 shows the poverty rate of seven divisions of Bangladesh. The poverty rate is found to be the most severe in Rangpur Division compared to the rest of Bangladesh, which is consistent with Khandker (2012); Matsuura, Islam, & Tauseef (2023). Rajshahi and Sylhet Divisions which are northern part of Bangladesh and also historically more neglected and poor (Hossain, et al., 2019; Agricultural Extension in South Asia, 2018). Rural livelihoods in this region are heavily dependent on agriculture. In the following sections, we discuss how much mobile money mitigate the negative effect of weather shocks in Rangpur division compared to the rest of Bangladesh.

On the other hand, to generate indicators of weather shocks, we use data taken from the Bangladesh Meteorology Department, which includes monthly precipitation and temperature from March 1996 to February 2019 on a global grid using units of 0.5-degree latitude by 0.5-degree longitude. Due to the data availability, we transformed the grid weather data into 64 district-level. Following Hossain et al. (2018), weather data are compiled into two seasons: (1) Rabi, from March to November; and (2) Kharif, from December to February. In this paper, we

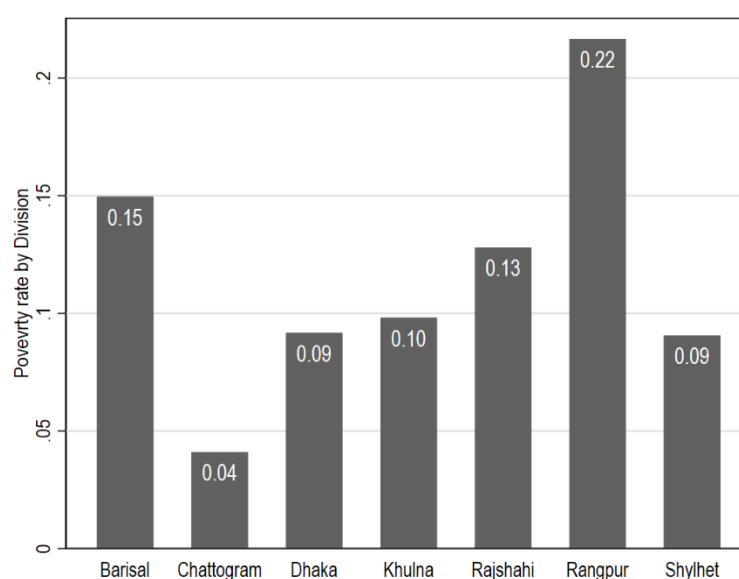


Figure 2 Poverty rate by Division

Source: BIHS2015 and 2019. Note: Calculated by authors

use only the Kharif season variable because the rainfall shock variable is not significantly

¹The 2011-2012 wave is part of the BIHS but does not contain information on mobile money. Because we cannot exclude that some households nevertheless were already early adopters in 2011, we cannot use the 2011–2012 wave of the BIHS by assuming that no household had access to mobile money

associated with household welfare².

2.2. Description of key variables

In this paper, we define “*Shock*” in two ways: (1) a rainfall shock and (2) a self-reported shock. First, we define a rainfall shock as used in Makate, Angelsen, Holden, & Westerngen (2022):

$$Rainfall\ shock_{dt} = \frac{rain_{dt} - \overline{rain_d}}{\sigma_{rain_d}} \quad (1)$$

where $Rainfall\ shock_{dt}$ is a rainfall shock measure for a cluster (district) (d), in Kharif season in the year (t), which is from March to November for two main rice season, Aus and Aman (Matsuura, Luh, & Saiful, 2023). Moreover, $rain_{dt}$ is the observed rainfall for the defined season, $\overline{rain_d}$ is the average seasonal rainfall for the district (d) over the 20 years, and σ_{rain_d} is the standard deviation of rainfall during the same period.

An alternative definition of a self-reported shock is that it is equal to 1 if households lose crops, livestock, production assets, or consumption assets due to flood or cyclone, 0 otherwise.

Our main explanatory variable of interest is mobile money usage. We consider a household to be a mobile money user if at least one member uses a mobile money agency during a particular survey year. Mobile money user is captured through a binary variable at the household level.

To measure the household welfare, the per capita value of monthly food consumption and non-food consumption are used. By decomposing the household consumption, we can distinguish how households smooth their food and non-food consumption in response to shocks with mobile money adoption.

2.3. Descriptive statistics

Table 1 shows the summary statistics for the analysis sample. The number of mobile money users increase from 506 in 2015 to 2254 in 2019, which is nearly half of the sample in 2019. Per capita monthly food expenditure decreases over the survey period in both mobile money users and non-users. Rainfall shock is negative overall indicating droughts, regardless of mobile money users or not. In 2015, about 2.2% in mobile money user and 2.8% in non-user households self-report to losing crops, livestock, production assets, or consumption assets due to flood or cyclone in the survey year. However, the probability of self-reported weather shocks decreases in 2019.

² The results are available upon requests.

As for socioeconomic variables to be controlled in the analysis, female headed households are less likely to use mobile money services. The average years of schooling of household heads using mobile money is 5.23 years in 2015 but falls to 4.52 in 2019. One likely reason for this is the rapid expansion of mobile money services across the country which enabled even poorer and less educated segments of the population to avail such services. We generated a wealth index of assets using principal component analysis (PCA) since the value of assets owned was not asked in all the waves of the survey. Different components of wealth, such as ownership of radio, TV, telephone, computer, animal cart, bicycle, motorbike or refrigerator, and a car or truck are used for the calculation³.

³ The datasets are available at <https://www.ifpri.org/blog/ifpris-bangladesh-integrated-household-survey-bihs-second-round-dataset-now-available>.

Table 1 Summary statistics

Variables	2015						2019					
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
	MM User			Non-user			MM user			Non-user		
Per capita monthly food expenditure (taka)	506	1871.94	927.34	4,424	1713.74	1036.62	2,254	1735.95	890.95	2,676	1691.35	907.09
Per capita monthly food expenditure (taka)	506	1784.94	1326.00	4,424	1269.84	1086.23	2,254	1651.38	1178.99	2,676	1447.58	1167.32
Rainfall shock	506	-1.71	1.03	4,424	-1.60	1.06	2,254	-1.66	1.36	2,676	-1.47	1.30
Self-reported shock	506	0.02	0.15	4,424	0.03	0.16	2,254	0.02	0.13	2,676	0.02	0.13
Domestic remittance (taka)	506	9676.63	31879.29	4,424	3477.74	15848.32	2,254	9855.80	43777.77	2,676	6101.96	22944.88
Foreign remittance (taka)	506	2981.59	27037.80	4,424	946.84	11724.94	2,254	6204.21	33721.53	2,676	4660.32	72604.28
Female HH	506	0.15	0.36	4,424	0.18	0.39	2,254	0.19	0.39	2,676	0.22	0.41
Age of HH	506	46.30	13.50	4,424	45.99	13.55	2,254	46.33	12.43	2,676	48.97	13.81
Household size	506	5.24	2.08	4,424	4.89	1.88	2,254	5.88	2.24	2,676	5.21	2.03
Year of education of HH	506	5.23	4.46	4,424	3.25	3.83	2,254	4.52	4.25	2,676	2.83	3.65
Access to irrigation (%)	506	0.48	0.50	4,424	0.45	0.50	2,254	0.47	0.50	2,676	0.45	0.50
Wealth index	506	0.78	2.01	4,424	-0.56	1.86	2,254	0.71	1.88	2,676	-0.41	1.83

Source: BIHS 2015 and 2019.

Note: Calculation by authors. Per capital monthly food and non-food expenditure and the value of domestic and foreign remittances are deflated to real value of 2011. Wealth index is calculated by Principal Component Analysis of asset variables, following (Vyas & Kumaranayake, 2006). The asset variables include trunk, stove, bed, electric fan, television, motorcycle, horse, cow, duck, computer, printer etc. The whole asset variables are available from <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/BXSYEL>.

3. Empirical strategy

In this section, we discuss our empirical strategy to elicit: (1) the impacts of mobile money on risk sharing by comparing the response of the consumption of mobile money users and nonusers to rainfall and self-reported shocks, (2) the responsiveness of remittance receipt of mobile money user household to weather shocks, and (3) the heterogeneous impact of mobile money adoption on the consumption smoothing.

3.1. Empirical specification

We follow the literature we set our regression specification to elicit the impact of shocks on consumption for household with and without mobile money services (Jack & Suri, 2014; Riley, 2018). The econometric specification is as follows:

$$Y_{it} = \beta_1 + \beta_2 Shock_{it} + \beta_3 MM_{it} + \beta_4 MM_{it} \times Shock_{it} + \beta_5 X_{it} + \eta_i + \omega_t \times \gamma_d + \epsilon_{it} \quad (2)$$

where MM_{it} is mobile money adoption at the household level and $MM_{it} \times Shock_{it}$ is the interaction term for mobile money and the shock measure, X_{it} is the vector of household characteristics, η_i , ω_t and γ_d are household, year, and division fixed effect, respectively, and ϵ_{it} is an error term. In the specification, β_4 is the coefficient of interest in our model.

Using this strategy, we can also assess the mechanisms by which mobile money facilitates risk sharing, in particular the role of remittances, by estimating the following version of equation (2):

$$r_{it} = \gamma_1 + \gamma_2 Shock_{it} + \gamma_3 MM_{it} + \gamma_4 MM_{it} \times Shock_{it} + \gamma_5 X_{it} + \eta_i + \omega_t \times \gamma_d + e_{it} \quad (3)$$

where r_{it} is the total value of remittance by mobile money at the household level and $MM_{it} \times Shock_{it}$ is the interaction term for mobile money and the shock measure, e_{it} is an error term, and γ_4 is the coefficient of interest in our model.

3.2. Identification strategy

In this section, we discuss the identification assumptions behind Equations (2) and (3). There are two main self-selection effects with regards to mobile money which could bias our results. The first one is self-selection into using mobile money. Our estimates would be biased if household selection into mobile money use is correlated with unobservable factors that also affect their ability to deal with shocks, creating a spurious positive association between mobile money use and shock smoothing. Given these conditions, the fixed effects (FE) estimator is a better choice because it controls for time-invariant unobserved heterogeneity (Cameron & Trivedi, 2005). However, time-variant unobserved characteristics are not addressed by FE

estimator. To deal with this problem, we use an instrumental variable (IV) approach. For our research question, the IV is expected to influence the decisions on mobile money use but not the outcome variables (per capita food and non-food consumption expenditure).

Motivated by the information sharing and behavior imitation among rural households, (Zheng, Zhou, & Rahut, 2022; Ma & Abudulai, 2020), we calculated the ratio of mobile money users to the number of respondents within a union, which is the smallest administrative unit in Bangladesh, (except for sampled households) as IV. Empirically, we conducted a falsification test to verify the justness of the synthesized IV (Di Falco, Veronesi, & Yesuf, 2011; Zheng, Zhou, & Rahut, 2022). The results are presented in Table A1 in the Appendix, which suggests that the IV has no significant relationship with the household welfare among non-users.

Moreover, to control for observed factors which could be both correlated with mobile money use as well as help a household smooth consumption after an aggregate shock (Riley, 2018), we propose an additional empirical strategy. It extends equations (2) and (3) to include the interactions of the shock with all observable covariates ($X_{it} \times Shock_{it}$) using the following specification:

$$Y_{it} = \alpha_1 + \alpha_2 Shock_{it} + \alpha_3 MM_{it} + \alpha_4 MM_{it} \times Shock_{it} + \alpha_5 X_{it} + \alpha_6 X_{it} \times Shock_{it} + \eta_i + \omega_t \times \gamma_d + \mu_{it} \quad (4)$$

$$r_{it} = \theta_1 + \theta_2 Shock_{it} + \theta_3 MM_{it} + \theta_4 MM_{it} \times Shock_{it} + \theta_5 X_{it} + \theta_6 X_{it} \times Shock_{it} + \omega_t \times \gamma_d + \psi_{it} \quad (5)$$

where X_{it} are the same set of controls described above. μ_{it} and ψ_{it} are error terms, respectively. By controlling for the interaction of the shocks with household characteristics, we alleviate some of the concerns around the interpretation of α_4 and θ_4 , as proposed by Jack & Sur (2014). Equations (4) and (5) represents our preferred specification throughout the article. Because the remittance variable is truncated in zero, Equation (5) is an IV-Tobit regression model while Equation (4) is estimated by two-stage least squares (2SLS). Hence, we are interested in α_4 in equation (4) and θ_4 in equation (5) and interpret and discuss them in the following result section.

For equations (4) and (5) to identify the causal effect of mobile money on risk sharing, we must assume that the interaction term $MM_{it} \times Shock_{it}$ is exogenous, or uncorrelated with the error ϵ_{it} , conditional on the household fixed effects, and other control variables. Especially for a self-reported shock as “*Shock*”, it may be systematically correlated with a number of household-level variables. We test this by running a fixed effect regression for different household characteristics for the self-reported shock, the results of which are shown in Table 2. We find that self-reported shock is not correlated with other household characteristics, nor

with the instrumental variable or mobile money adoption (Table 2).

Table 2 Correlates of self-reported shock

	(1) Self-reported shock
Mobile money user	-0.006 (0.005)
Share of households adopting mobile money in the union	-0.001 (0.016)
Female household head	-0.007 (0.008)
Age of HH	-0.000 (0.000)
Household size	0.003 (0.003)
Schooling year of HH	-0.003 (0.002)
Market access (minute)	-0.000 (0.000)
Asset index	0.000 (0.002)
Division×Year FE	Yes
Observations	9,860

Note: Robust standard errors in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Estimated by OLS.

4. Results and discussions

4.1. Empirical results

Table 3 shows the result of our base specification from Equation (2). All regressions include the full sets of household covariates from Table 1. Panel A in Table 3 presents the regression results of two-way fixed effect without IV as robustness checks of the results, whereas Panel B in Table 3 shows the regression results of IV-FE model. From Columns (1) to (8) in Panel B. Coefficients of interaction terms in Panel are variables that we are most interested in, which are α_4 in equation (3) and θ_4 in equation (4).

In Panel A, the shock variables is negatively associated with per capita non-food expenditure in Column (4). It indicates that a one standard deviation positive rainfall shock (indicating a flood) raises the likelihood of a fall in per-capita monthly non-food consumption expenditure by 6.3 percentage points. Moreover, the interaction terms between mobile money user and shocks are positively and statistically significantly associated with per capita monthly non-food expenditure while they are positively but statistically insignificantly associated with per capita monthly food expenditure, regardless of the type of shock. However, the positive and statistically significant signs of the interaction terms indicate mobile money adoption provides incomplete insurance to mobile money user households against rainfall shocks.

In Panel B, the trends of signs of coefficient are robust to the results of Panel A. Results from the full specification are reported in Columns (3), (4), (7), and (8). The rainfall shock in Kharif decreases the per capita monthly food and non-food expenditure while the self-reported shock is not statistically significantly correlated with household welfare. Thus, only rainfall shocks are used in following heterogeneity analysis. In addition, the interaction term between the mobile money user and the rainfall shock is positively and statistically significantly associated with per capita monthly non-food expenditure in Column (4). The magnitude of the coefficient of the interaction term is 0.103 while the magnitude of the coefficient of the interaction term is -0.085. It thus seems that mobile money users overcompensate for the direct negative impact of rainfall shocks. The results are consistent with past studies by Jack & Suri (2014); Riley (2018); Tabetando & Matsumoto (2020); Abiona & Koppensteiner (2022).

Furthermore, in Table 4 we explore the effect using different sub-samples. In Panel A, the sample is divided into two groups which are households in Sylhet, Rangpur, and Rajshahi Division and households in other divisions. The three divisions are relatively far from Dhaka which is capital of Bangladesh. Moreover, Rangpur Division has the highest poverty rates among all the divisions in Bangladesh as seen in Figure 2. Sylhet and Rajshahi Divisions has

ones of the lowest values in the Human Development Index (Subnational HDI 2019, 2023). Therefore, we test if mobile money adoption has heterogeneous effects between less developed areas and more urbanized areas, in terms of economic activity. In Column (1) and (2), we show the opposite results from Table 3. The coefficient of rainfall shock is positively associated with per capita monthly food consumption. It indicates that rainfall below the historical average rainfall (indicating a drought) decreases per capita monthly food expenditure. The plausible explanation is the nature of income sources in those areas. In the three divisions including Rangpur, agrarian sector is dominant compared to the rest of Bangladesh including Dhaka (Khandker, 2012). Their livelihoods heavily rely on crop production. Therefore, drought would significantly affect crop yields, leading to a fall in farm income and, therefore, reduces food consumption expenditure. Thus, the coefficient of the interaction term in Column (1) turns into negative and statistically significant, as opposed to Table 3. It indicates that mobile money users overcompensate for the direct negative impact of drought in Sylhet, Rangpur, and Rajshahi Division. Another plausible reason is that geographically disadvantaged areas usually have poorer connectivity and market access compared to areas near Dhaka. Therefore, non-food goods may not be conveyed from urban areas to the disadvantaged areas. As a result, the coefficient of the interaction term in Column (2) is statistically insignificant, indicating that households using mobile money are not able to make their non-food consumption stable in response to the rainfall shocks. In line with Table 3, Column (4) shows the positive coefficient of the interaction term and negative coefficient of rainfall shock. It implies that mobile money works differently as insurance for consumption smoothing insurance depending on the geographical factors. This is an encouraging result that mobile money has a pro-poor effect and can be promoted in the geographically disadvantaged areas to reduce disparity amongst regions.

In Panel B, the sample is divided into four sub-samples by consumption quota. They are 1st quantile, 2nd quantile, 3rd quantile, and 4th quantile of per capita monthly expenditure in 2015. The result in Column (1) shows that the coefficient of the rainfall shock is statistically significant and 0.156, and the coefficient of the interaction term is statistically significant and -0.251. The result suggests that mobile money adoption overcompensates the negative impact of deficient rainfall indicating droughts on food consumption for the poorest households. However, we find no statistically significant mitigating effects of mobile money on non-food consumption for the poorest households in Column (2). The logic behind the effects of mobile money is that poor households' livelihood is more likely to rely on agriculture which is highly susceptible to rainfall shocks especially droughts. Thus, droughts devastate crop yields than floods, inducing severer food insecurity. This is consistent with Jack & Suri (2014); Tabetando

& Matsumoto (2020) and a welcome finding from rural development perspective. From Column (3) to (6), the results for 2nd and 3rd quantiles of per capita expenditure are presented. However, food and non-food consumption are not affected by rainfall shocks. Finally, Column (7) and (8) show the results of 4th quantile of per capita expenditure which corresponds to the richest households in the sample. While the coefficients in Column (7) are statistically insignificant, the coefficient of rainfall shock is significant and -0.109 and the coefficient of the interaction term is significant and 0.150 in Column (8). It indicates that mobile money adoption overcompensates the negative effects of excessive rainfall on non-food expenditure. The richest households are more likely to have alternative instruments rather than mobile money to smooth their food consumption in response to the rainfall shocks. Thus, mobile money is found to have opposite effects on household welfare for 1st and 4th quantiles of the per capita expenditure distribution.

Table 3 Impact of rainfall shocks on consumption for mobile money users and non-users

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS							
	Rainfall				Self-reported			
	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure
MM user	-0.019 (0.019)	0.042** (0.020)	-0.027 (0.020)	0.042** (0.020)	-0.019 (0.013)	0.007 (0.014)	-0.018 (0.013)	0.009 (0.014)
Interaction	-0.002 (0.009)	0.016* (0.009)	-0.007 (0.009)	0.016* (0.010)	0.082 (0.077)	0.207*** (0.077)	0.106 (0.084)	0.169** (0.086)
Shock	-0.015** (0.007)	-0.060*** (0.007)	0.012 (0.026)	-0.063** (0.027)	-0.040 (0.043)	-0.080* (0.042)	-0.071 (0.176)	-0.140 (0.187)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interaction with shock	No	No	Yes	Yes	No	No	Yes	Yes
Observation	9,860	9,860	9,860	9,860	9,860	9,860	9,860	9,860
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2SLS							
	Rainfall				Self-reported			
	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure
MM user	-0.094 (0.101)	0.322*** (0.109)	-0.109 (0.103)	0.332*** (0.111)	0.011 (0.082)	0.046 (0.082)	0.010 (0.082)	0.051 (0.082)
Interaction	-0.065** (0.028)	0.097*** (0.029)	-0.076** (0.031)	0.103*** (0.032)	0.006 (0.183)	0.362** (0.182)	0.047 (0.211)	0.318 (0.219)
Shock	0.003	-0.086***	0.023	-0.085***	-0.022	-0.112**	-0.050	-0.143

	(0.011)	(0.011)	(0.027)	(0.029)	(0.052)	(0.057)	(0.179)	(0.199)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interaction with shock	No	No	Yes	Yes	No	No	Yes	Yes
Observation	9,860	9,860	9,860	9,860	9,860	9,860	9,860	9,860

Note: Robust standard errors clustered by households in parentheses. Outcome variables are converted into logarithm. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Cragg-Donald Wald F Statistic for the instrumented variables is 69.846. Thus, it rejects the null hypothesis of weak instruments. The interaction term between mobile money user and shocks is instrumented by the interaction term between share of mobile money users and the shocks, which is exogenous in our model. The first stage for 2SLS and the full table of the outcome equations are available upon requests.

Table 4 Heterogeneous effects of the impact of rainfall shocks on consumption for mobile money users and non-users.

Panel A	(1)	(2)	(3)	(4)
	Sylhet, Rangpur, and Rajshahi		Rest of Bangladesh	
	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure
Mobile money user	-0.751*** (0.267)	0.026 (0.231)	0.030 (0.114)	0.394*** (0.129)
Interaction	-0.270*** (0.063)	-0.017 (0.055)	-0.031 (0.039)	0.148*** (0.041)
Rainfall shock	0.154*** (0.058)	-0.041 (0.049)	-0.028 (0.035)	-0.112*** (0.037)
Household FE	Yes	Yes	Yes	Yes
Division×Year	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Interaction with shock	Yes	Yes	Yes	Yes
Observations	3,382	3,382	6,476	6,476
Panel B	(1)	(2)	(3)	(4)
	1st quantile of per capita expenditure in 2015		2nd quantile of per capita expenditure in 2015	
	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure
Mobile money user	-0.361** (0.180)	0.373* (0.194)	0.028 (0.197)	0.649*** (0.231)
Interaction	-0.251*** (0.069)	0.060 (0.064)	-0.064 (0.059)	0.105 (0.064)
Rainfall shock	0.156*** (0.060)	-0.035 (0.050)	0.005 (0.049)	-0.039 (0.060)
Household FE	Yes	Yes	Yes	Yes
Division×Year	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes

Interaction with shock	Yes	Yes	Yes	Yes
Observations	2,464	2,464	2,466	2,466
Panel B	(5)	(6)	(7)	(8)
	3rd quantile of per capita expenditure in 2015		4th quantile of per capita expenditure in 2015	
	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure
Mobile money user	-0.014 (0.198)	0.261 (0.233)	0.225 (0.244)	0.376 (0.245)
Interaction	-0.142** (0.061)	0.003 (0.070)	0.012 (0.062)	0.150** (0.064)
Rainfall shock	-0.001 (0.054)	-0.057 (0.065)	0.001 (0.057)	-0.109* (0.061)
Household FE	Yes	Yes	Yes	Yes
Division×Year	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Interaction with shock	Yes	Yes	Yes	Yes
Observations	2,462	2,462	2,466	2,466

Note: All columns are estimated by 2SLS. Robust standard errors clustered by households in parentheses. Outcome variables are converted into logarithm. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. The interaction term between mobile money user and shocks is instrumented by the interaction term between share of mobile money users and the shocks, which is exogenous in our model. Full regression table is available upon requests.

3.3. Mechanism: Mobile money and remitting network

The proposed mechanism in this paper is that mobile money improves household resilience by facilitating easier flow of remittances from friends and family in other locations in response to a rainfall shock and enable households to smooth consumption. estimates from Equation (5) are reported in Table 5. While the interaction term is statistically insignificant in Column (1), the coefficients of both the interaction term and the rainfall shock are statistically significant in Column (2). It indicates that households that use mobile money are more likely to receive foreign remittance in larger amount through mobile money in response to the rainfall shock, compared to nonuser households. Similar to Tabetando & Matsumoto (2020), it thus appears that mobile money adoption is inducing households to participate in an insurance pool where households transfer and share resources notably in the event of a negative shock.

The result is also consistent with Jack & Suri (2014); Suri & Jack (2016); Riley (2018); Tabetando & Matsumoto (2020); Batista & Vicente (2020). In addition, we add to the literature by distinguishing the effect of domestic vs international remittance using mobile money by noting that international remittance is a much larger source of resilience for households in the face of shocks compared to domestic remittance. As a result, our findings emphasize the importance of remittance from overseas out-migrants and calls for facilitating cross border labor migration.

Table 5 Mechanism for mobile money remittances

	(1) Value of domestic remittance (deflated)	(2) Value of foreign remittance (deflated)
Mobile money user	4142.006 (3.0e+04)	-14496.46 (176143.1)
Interaction	-6.2e+03 (9341.212)	157081.2** (66934.26)
Rainfall shock	2324.829 (7536.756)	-126559.5** (56683.12)
Division×Year	Yes	Yes
Control variables	Yes	Yes
Interaction with shock	Yes	Yes
Observations	9,858	9,858

Note: Robust standard errors clustered by households in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. The interaction term between mobile money user and shocks is instrumented by the interaction term between share of mobile money users and the shocks, which is exogenous in our model. Full regression table is available upon requests.

5. Conclusion and policy implications

Poor households are vulnerable to negative economic shocks, since they are likely to fail to

smooth their consumption in response to the shocks such as rainfall. Bangladesh is extremely prone to floods every year and the climate risk is rising due to the global climate change. Since we need easier and more accessible adaptation strategy against the shocks, mobile money services can be a preferred and suitable options. It is a new and fast-growing technology which can help households insure their consumption against the shocks by providing access to remittances from other locations not affected by the shocks (Riley, 2018). In this work, we provide new and applicable evidence on the consequences of mobile money adoption on household welfare in the context of South Asian countries.

To this end, we use a national representative household panel data set from Bangladesh and a monthly granular precipitation dataset collected by Bangladesh Meteorology Department. Combining the two datasets enable us to estimate the role of the mobile money on consumption smoothing in response to objective and subjective shocks.

Our results show that large rainfall shocks negatively affect food and non-food consumption, but adoption of mobile money can provide much needed resilience to households in mitigating this impact by allowing the easier flow of remittances from foreign countries. However, we do not find that self-reported shocks affect household consumption and mobile money mitigates the effect of the self-reported shocks. We find significant heterogeneity in this effect, with respect to geography and welfare distribution. In geographically disadvantaged divisions, mobile money mitigate the negative effects of droughts on food consumption because agrarian sectors are much more dominant income sources in the areas. Moreover, the effect is found to be consistent for the poorest households. Regarding food consumption, mobile money works as an informal insurance against with droughts for the poorest households. However, mobile money enables the richest households affected by floodings to smooth their non-food consumption. We confirm the mechanism through which mobile money accounts enable risk sharing by looking at flows of remittances after the rainfall shock. We also find suggestive evidence that households with mobile money are more likely to receive overseas remittances in response to the rainfall shocks rather than domestic remittance.

Our findings shed light on the importance of mobile money services as informal insurance and risk sharing, given the frequency of extreme climate events in relation to climate change. Governments and stakeholders are suggested to promote the expansion of mobile money services so that rural households cheaply, quickly, and safely get an option to cope with future weather shocks. Moreover, mobile money services may overcome the spatial inequality and bring a pro-poor effect. The diffusion of mobile money would help poor households and households living far from Dhaka, whose livelihood mainly depends on agriculture, smooth

their food consumption, and share their risks by overseas remittances. This is particularly important in the context of Bangladesh, where many vulnerable rural households confront weather shocks.

Reference

- Abiona, O., & Koppensteiner, M. (2022). Financial Inclusion, Shocks, and Poverty. *Journal of Human Resources*, 57(2), 435-464. doi:<https://doi.org/10.3368/jhr.57.2.1018-9796R1>
- Agricultural Extension in South Asia. (2018, January 23). *Agricultural Extension in South Asia*. Retrieved from Agricultural development in North West Bangladesh: <https://www.aesanetwork.org/agricultural-development-in-north-west-bangladesh/>
- Ahmed, A., & Tauseef, S. (2022). Climbing up the Ladder and Watching Out for the Fall: Poverty Dynamics in Rural Bangladesh. *Social Indicators Research*, 160, 309-340.
- Ahmed, H., & Cowan, B. (2021). Mobile money and healthcare use: Evidence from East Africa. *World Development*, 141, 105392. doi:<https://doi.org/10.1016/j.worlddev.2021.105392>
- Aker, J., Boumnijel, R., McClelland, A., & Tierney, N. (2016). Payment Mechanisms and Antipoverty Programs: Evidence from a Mobile Money Cash Transfer Experiment in Niger. *Economic Development and Cultural Change*, 65(1), 1-37.
- Barnett, B., & Mahul, O. (2007). Weather Index Insurance for Agriculture and Rural Areas in Lower-Income Countries. *American Journal of Agricultural Economics*, 89(5), 1241-1247. doi:<https://doi.org/10.1111/j.1467-8276.2007.01091.x>
- Batista, C., & Vicente, P. (2020). Improving access to savings through mobile money: Experimental evidence from African smallholder farmers. *World Development*, 104905.
- Benami, E., & Carter, M. (2021). Can digital technologies reshape rural microfinance? Implications for savings, credit, & insurance. *Applied Economic Perspectives and Policy*, 43, 1196-1220.
- Cameron, A., & Trivedi, P. (2005). *Microeconometrics Methods and Applications*. Cambridge: Cambridge University Press.
- Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829-846.
- Hossain, M., Qiam, L., Arshad, M., Shahid, S., Fahad, S., & Akhter, J. (2019). Climate change and crop farming in Bangladesh: an analysis of economic impacts. *International Journal of Climate Change Strategies and Management*, 11(3), 424-440.
- Jack, W., & Suri, T. (2014). Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution. *American Economic Review*, 104(1):183-223.
- Khandker, S. (2012). Seasonality of income and poverty in Bangladesh. *Journal of Development Economics*, 97, 244-256.
- Kono, H., & Takahashi, K. (2010). MICROFINANCE REVOLUTION: ITS EFFECTS,

- INNOVATIONS, AND CHALLENGES. *The Developing Economies*, 48(1), 15-73.
doi:<https://doi.org/10.1111%2Fj.1746-1049.2010.00098.x>
- Ma, W., & Abudulai, A. (2020). Impact of Internet use on economic well-being of rural households: Evidence from China. *Review of Development Economics*, 24(2), 503-523.
- Makate, C., Angelsen, A., Holden, S., & Westerngen, O. (2022). Crops in crises: Shocks shape smallholders' diversification in rural Ethiopia. *World Development*, 159, 106054.
doi:<https://doi.org/10.1016/j.worlddev.2022.106054>
- Matsuura, M., Islam, A., & Tauseef, S. (2023). Mobile Phone Ownership, Income Diversification, and Poverty Reduction in Rural Bangladesh. *IDE Discussion Paper*, 875.
doi:<https://dx.doi.org/10.2139/ssrn.4176609>
- Matsuura, M., Luh, Y.-H., & Saiful, A. (2023). Weather shocks, livelihood diversification, and household food security: Empirical evidence from rural Bangladesh. *Agricultural Economics*, 00, 1-16. doi:<https://doi.org/10.1111/agec.12776>
- Riley, E. (2018). Mobile money and risk sharing against village shocks. *Journal of Development Economics*, 135, 43-58.
- Subnational HDI 2019. (2023). Retrieved 05 26, 2023, from Global Data Lab:
https://globaldatalab.org/shdi/shdi/BGD/?levels=1%2B4&interpolation=1&extrapolation=0&nearest_real=0&years=2019
- Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, 354(6317), 1288-1292. doi:<https://doi.org/10.1126/science.aah5309>
- Suri, T., Aker, J., Batista, C., Callen, M., Ghani, T., Jack, W., . . . Sukhtankar, S. (2023, February). Mobile Money. *VoxDevLit*, 2(2).
- Tabetando, R., & Matsumoto, T. (2020). Mobile money, risk sharing, and educational investment: Panel evidence from rural Uganda. *Review of Development Economics*, 24, 84-105. doi:<https://doi.org/10.1111/rode.12644>
- Turner, A., & Annamalai, H. (2012). Climate change and the South Asian summer monsoon. *Nature Climate Change*, 2, 587-595.
- Zheng, H., Zhou, Y., & Rahut, D. (2022). Smartphone use, off-farm employment, and women's decision-making power: Evidence from rural China. *Review of Development Economics*, 1-27. doi:<https://doi.org/10.1111/rode.12966>

Table A 1 Test of validity of the selection instruments

	(1) Per capita food expenditure	(2) Per capita non-food expenditure
Share of households adopting mobile money in the union	0.029 (0.064)	-0.001 (0.062)
Household FE	Yes	Yes
Division Year	Yes	Yes
Control variables	Yes	Yes
Observations	5,032	5,032

Note: Robust standard errors clustered by households in parentheses. Outcome variables are converted into logarithm. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.