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Mobile Money Mitigates the Negative Effects of Weather Shocks: Implications for Risk Sharing and Poverty Reduction in Bangladesh

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6.1 Introduction

Frequent weather shocks stemming from global climate change are significant for rural and poor households. Floods deprive households' assets and agricultural production, resulting in a reduction of household income. Moreover, droughts substantially reduce crop yields, inducing food insecurity. For example, South Asian countries confront various climate risks such as extreme floods and cyclones with the idiosyncrasies of summer and monsoon rainfall having short- and long-term impacts on the lives of more than 1 billion people (Turner and Annamalai 2012). To cope with 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 and Mahul 2007; Kono and Takahashi 2010).

Rural financial services challenge transaction costs that render markets for financial services costly or missing (Benami and Carter 2021). The emergence of digital technologies such as mobile phones and mobile or digital money recreate rural markets for savings, credit, and insurance services, especially in developing economies (Benami and Carter 2021). In recent years, mobile phones have been widely adopted in developing countries contributing to economic growth. Bangladesh has also experienced an expansion of mobile phone subscriptions (Matsuura, Islam, and Tauseef 2023). This in turn has led to the development of

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mobile money services enabling people to transfer, deposit, and withdraw money from an online account without having a bank account (Suri et al. 2023). Mobile money greatly reduces transaction costs, while enhancing the convenience, security, and time taken for transactions. (Suri et al. 2023). Since mobile money allows people to transfer and deposit money using short message services without access to the 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 was over 100 in 2020, but the ratio of individual internet users remained at only 25% in 2020 (Figure 6.1).

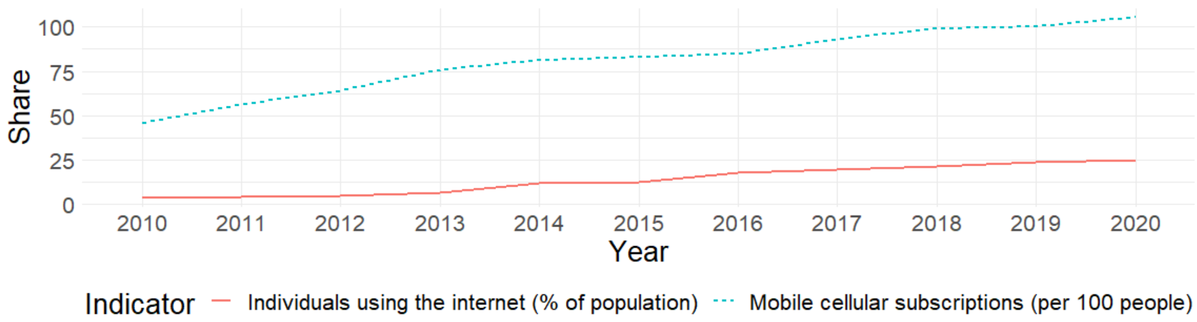
In this chapter, we look at three primary research questions: First, what is the relationship between mobile money adoption and a household's ability to smooth consumption in response to weather shocks? Second, are there heterogeneous effects between mobile money and consumption smoothing in response 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 (Islam, Newhouse, & Yanez-Pagans, 2021). Given that poor households are especially vulnerable to weather shocks, this question is of particular interest. Third, 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 utilize a recently collected longitudinal dataset on Bangladeshi households and combine with granular monthly precipitation data.

There is a rich body of 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 varied risk sharing by allowing users to send and receive remittances in cases of negative economic events to the household. Moreover, Tabetando and Matsumoto (2020), Ahmed and Cowan (2021), and Abiona and Koppensteiner (2022) find that mobile money users are able to sustain 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 and Suri (2014), Riley (2018), and Tabetando and Matsumoto (2020) show that the fundamental mechanism is an increase in remittance receipts. In addition, the adoption of mobile money facilitates the receipt of social protection transfers that likely improves the resilience of these households (Aker et al. 2016; Abiona and Koppensteiner 2022).

The contribution of this chapter 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 nonfood consumption in response to floods, combining a nationally representative household panel 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, we show that relatively poorer households can smooth their consumption, the same as geographically disadvantaged households. Finally, we find that the likely mechanism that improves household resilience against economic shocks is through an increased likelihood of receiving remittances due to the adoption of mobile money.

The rest of the chapter is structured in the following manner. Section 6.2 describes the data source and key variables of interest. Section 6.3 presents the identification strategy and empirical specification used in the analysis. Section 6.4 discusses the empirical results, while Section 6.5 provides concluding remarks and policy implications.

Figure 6.1: Mobile Phone Subscription and Internet Users in Bangladesh



Source: Calculated by authors from (World Bank, 2022).

6.2 Methodology

6.2.1 Data

We use data from the Bangladesh Integrated Household Survey (BIHS), which is a nationally representative rural household panel survey carried out by the International Food Policy Research Institute in 2015 and 2018–2019 (from here on 2019) in seven divisions. The sampling strategy of the BIHS followed a two-staged stratified sampling method. Following the sampling framework from the community series of the 2001 Population and Housing Census of Bangladesh, the first stage constituted a selection of primary sampling units or villages after which households were randomly selected for survey interview from each selected primary sampling unit in the second stage (Ahmed and Tauseef 2022). Although the

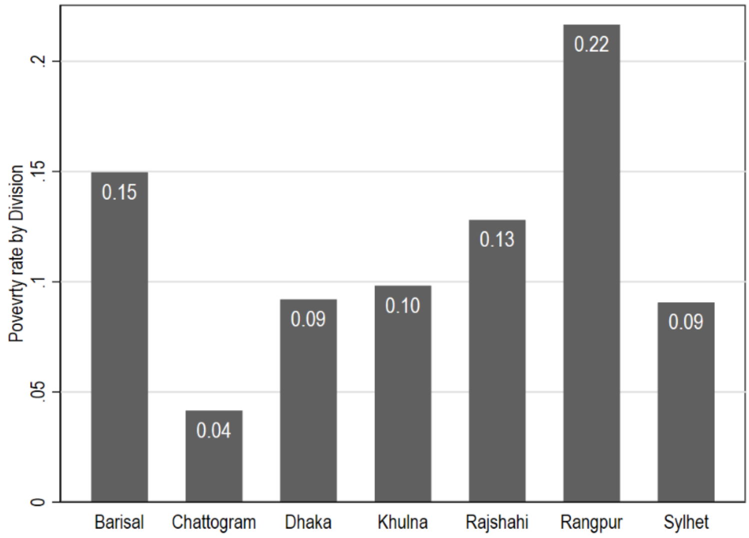
BIHS has three rounds, we focus our analysis on this two-period panel.[2] For our study, we use the balanced panel included in both survey rounds, resulting in 9,860 observations from 4,930 households as shown in Table 6.1. Figure 6.2 shows the poverty rate of seven divisions of Bangladesh. The poverty rate is found to be most severe in Rangpur Division compared to the rest of Bangladesh, which is consistent with studies by Khandker (2012) and Matsuura, Islam, and Tauseef (2023). Rajshahi and Sylhet divisions are situated in the northern part of Bangladesh and are 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 mitigates the negative effect of weather shocks in poor sections of the country like Rangpur Division compared to the rest of Bangladesh.

On the other hand, to generate indicators of weather shocks, we use data collected by the Bangladesh Meteorology Department, which include monthly rainfall 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 issues of data availability, we transformed the grid weather data into 64 district-level. Following Hossain et al. (2018), weather information is divided into two seasons: (i) rabi, from March to November; and (ii) kharif, from December to February. In this chapter, we use only data from the kharif season since the rainfall shock variable in the rabi season is not significantly associated with household welfare.[3]

Figure 6.1: Poverty Rate by Division

[2] The 2011–2012 wave is part of the BIHS but does not have information on mobile money. Because we cannot remove that some households nevertheless were already early adopters in 2011, we cannot use the 2011–2012 wave of the BIHS by assuming that no one had access to mobile money.

[3] The results are available on request.



Source: Calculated by authors from BIHS 2015 and 2019.

6.2.2 Description of Key Variables

In this chapter, we define "shock" in two ways: (i) a rainfall shock and (ii) a self-reported shock. First, we define a rainfall shock as used in Makate et al. (2022):

$$Rainfall\ shock_{dt} = \frac{rain_{dt} - \overline{rain_d}}{\sigma_{rain_d}} \tag{1}$$

where $Rainfall\ shock_{dt}$ is a rainfall shock measure for a cluster (district) (d), in the kharif season in the year (t), which is from March to November for the two main rice seasons, *Aus* and *Aman* (Matsuura, Luh, and Islam 2023). Moreover, $rain_{dt}$ is the observed precipitation 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.

On the other hand, we define self-reported shock as equal to 1 if households lose crops, livestock, production assets, or consumption assets due to flood or cyclone, and 0 otherwise.

Our main independent variable of interest is mobile money use. We consider a household to be a mobile money user if at least one member used a mobile money agency during a particular survey year. Mobile money users are captured through a dummy variable at the household level.

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

2.2.3 Descriptive Statistics

Table 6.1 shows the summary statistics for the analysis sample. The number of mobile money users increase from 506 in 2015 to 2,254 in 2019, which is nearly half of the sample in 2019. The per capita monthly food expenditure decreases over the survey period in both mobile money users and nonusers. Rainfall shock is negative overall indicating droughts, regardless of mobile money use. In 2015, about 2.2% of mobile money users and 2.8% of nonuser 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.

As for socioeconomic variables to be controlled in the analysis, households headed by females are less likely to use mobile money services. The average years of schooling of household heads using mobile money was 5.23 years in 2015 but fell to 4.52 in 2019. One likely reason for this is the rapid expansion of mobile money services across the country that enabled even poorer and less educated segments of the population to avail of such services. We generate a wealth index of assets using principal component analysis since the value of assets owned was not collected in all the rounds of the BIHS. Various components of wealth, such as ownership of radios, televisions, telephones, computers, animal carts, bikes, motorbikes or fridges, and cars or trucks are used for the calculation.[4]

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

Table 6.1: Summary Statistics

Variables	2015						2019					
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
	MM User			Nonuser			MM user			Nonuser		
Per capita monthly food expenditure (Tk)	506	1,871.94	927.34	4,424	1,713.74	1,036.62	2,254	1,735.95	890.95	2,676	1,691.35	907.09
Per capita monthly non-food expenditure (Tk)	506	1,784.94	1326.00	4,424	1,269.84	1,086.23	2,254	1,651.38	1,178.99	2,676	1,447.58	1,167.32
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
Temperature shock in kharif season	506	0.01	0.00	4,424	0.01	0.00	2,254	-0.00	0.00	2,676	-0.00	0.00
Temperature shock in rabi season	506	0.01	0.01	4,424	0.01	0.01	2,254	0.00	0.02	2,676	0.00	0.01
Domestic remittances(Tk)	506	9,676.63	31,879.29	4,424	3,477.74	15,848.32	2,254	9,855.80	43,777.77	2,676	6,101.96	22,944.88
Foreign remittances	506	2,981.59	27,037.80	4,424	946.84	11,724.94	2,254	6,204.21	33,721.53	2,676	4,660.32	72,604.28
Total household income (Tk)	506	2,766,445.9	281.891.7	4,424	181,344.60	218,739.50	2,254	296,410.3	536,127.1	2,676	192,815	199,381.4
Female household	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 household	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
Years of education of household	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

MM = mobile money, Obs = observation, SD = standard deviation.

Note: Per capital monthly food and nonfood expenditure, the value of domestic and foreign remittances, and total household income are deflated to the real value of the taka in 2011. Wealth index is calculated by the principal component analysis of asset variables, following (Vyas and Kumaranayake 2006). The asset variables include trunks, stoves, beds, electric fans, televisions, motorcycles, horses, cows, ducks, computers, printers, etc. The whole list of asset variables is available from https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/BXSYEL

Source: Calculation by authors from BIHS 2015 and 2019.

6.3 Empirical Methodology

In this section, we describe our empirical strategy to elicit (i) the impacts of mobile money on consumption smoothing by comparing the response of mobile money adopters and non-adopters to rainfall and self-reported shocks, (ii) the response of remittance receipts of mobile money adopter households to weather shocks, and (iii) the heterogeneous effect of mobile money adoption on consumption smoothing.

Mobile money is believed to enable households to send and receive money more easily due to the reduction of transaction costs. Therefore, we hypothesize that mobile money services allow households to do risk sharing even if they experience significant weather shocks adversely affecting their livelihood. The mechanism proposed in this study is remittances. Remittances allow family members to better smooth their consumption in the face of adverse shocks. In the empirical analysis, we look at whether the amount of remittance increases in response to weather shocks thanks to mobile money adoption. In the following subsections, we show how our hypothesis is tested by econometrics methods.

6.3.1 Empirical Specification

We follow the literature to set our regression specification to elicit the effect of shocks on consumption for households using or not using mobile money services (Jack and Suri 2014; Riley 2018). The econometric specification is as follows:

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

Where Y_{it} is the outcome variable which is per capita food/nonfood expenditure, MM_{it} is mobile money adoption at the household level and $MM_{it} \times Shock_{it}$ is the interaction term between mobile money and the shock variables, 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 the strategy, we can also test the mechanisms where mobile money smooths risk sharing—in particular, the role of remittances, by estimating the following model:

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

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 between mobile money and the shock variables, e_{it} is an error term, and γ_4 is the coefficient of interest in our model.

6.3.2 Identification Strategy

In this subsection, we discuss the identifying assumptions behind Equations (2) and (3). There are self-selection problems associated with the adoption of mobile money that could bias our estimates. Our estimates would be biased if a household's selection of the use of mobile money is correlated with unobservable factors that also impact their capacity to deal with shocks, creating a pseudo positive association between mobile money adoption and shock smoothing. Given the conditions, the fixed effects (FE) estimator is a more suitable choice because it controls time-invariant unobserved characteristics (Cameron and Trivedi 2005). However, time-variant unobserved characteristics are not addressed by the FE estimator. To overcome this issue, we use an instrumental variable (IV) approach. For our research question, the IV approach is supposed to affect the decisions on mobile money adoption but not the outcome variables (per capita food and nonfood consumption expenditure).

Motivated by social learning among rural households (Zheng, Zhou, and Rahut 2022; Ma and Abudulai 2020), we calculate the share of mobile money users to the number of respondents in a union (the smallest administrative unit in Bangladesh) (except for sampled households) as the IV approach. Empirically, we conducted a falsification test to verify the appropriateness of the created IV (Di Falco, Veronesi, and Yesuf 2011; Zheng, Zhou, and Rahut 2022). The results, presented in Table A6.1, suggests that the IV does not have a significant relationship with household welfare of the nonusers.

Moreover, to account for observed characteristics that could be associated with both mobile money use as well as facilitate a household to smooth consumption in response to an aggregate shock (Riley 2018), we propose an additional empirical strategy. It extends equations (2) and (3) to include the interaction terms of the shock with all observable explanatory variables ($X_{it} \times Shock_{it}$) using the following model:

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

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

where X_{it} are the same set of controls described above. μ_{it} and ψ_{it} are error terms, respectively. By accounting for the interaction terms between the shocks and household characteristics, we reduce some of the concerns around the interpretation of α_4 and θ_4, as proposed by Jack and Suri (2014). Equations (4) and (5) represent 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 result section.

For Equations (4) and (5) to identify the causal effect of mobile money on risks sharing, we have to assume that the interaction of $MM_{it} \times Shock_{it}$ is exogenous, or uncorrelated with the error ϵ_{it}, conditional on the household FE and the 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 an FE regression for different household characteristics for the self-reported shock and present the results in Table 6.2. We find that self-reported shock is not correlated with other household characteristics, nor with the instrumental variable or mobile money adoption (Table 6.2).

Table 6.2: 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 household	–0.000
	(0.000)
Household size	0.003
	(0.003)
Schooling year of household	–0.003
	(0.002)
Market access (minute)	–0.000
	(0.000)
Asset index	0.000
	(0.002)
Division×Year FE	Yes
Observations	9,860

FE -fixed effect.

Note: Robust standard errors in parentheses. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. Estimated by ordinary least squares.

Source: Calculated by authors.

6.4 Results and Discussions

6.4.1 Empirical Results

Table 6.3 shows the result of our base specification from Equation (2). All regressions include the full sets of household characteristics from Table 6.1. Panel A in Table 6.3 presents the regression results of two-way fixed effect model without IV as robustness check of the results, whereas Panel B in Table 6.3 shows the regression results of the IV–FE model. From Columns (1) to (8) in Panel B, coefficients of interaction terms are what we are most interested in, which are α_4 in equation (3) and θ_4 in equation (4).

In Panel A, the shock variables are negatively associated with per capita nonfood 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 nonfood consumption expenditure by 7.2 percentage points. Moreover, the interaction terms between the mobile money user and shocks are positively and statistically significantly associated with per capita monthly nonfood 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 sign on the interaction terms indicate that mobile money use serves as informal insurance to mobile money adopter households against rainfall shocks as seen in Columns (4) and (8).

In Panel B, the trends of signs on the coefficients are similar to the results of Panel A. Results from the full specification are reported in Columns (3), (4), (7), and (8). In Column (3), the coefficient of the interaction term is negative and significant. It indicates that mobile money users seem to be able to smooth a large part of positive rainfall shocks, indicating droughts in the kharif season, on per capita food consumption. Moreover, the rainfall shock in the kharif season decreases the per capita nonfood 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 nonfood expenditure in Column (4). The magnitude of the coefficient of the interaction term is 0.120 while the magnitude of the coefficient of the rainfall shock is –0.098. It thus seems that mobile money adoption overcompensates for the negative effect of rainfall shocks. These results are consistent with past studies by Jack and Suri (2014), Riley (2018), Tabetando and Matsumoto (2020), and Abiona and Koppensteiner (2022).

Furthermore, in Table 6.4 we explore the effect using different subsamples. In Panel A, the sample is divided into two groups which are households in Sylhet, Rangpur, and Rajshahi divisions and households in other divisions. The three divisions are relatively far from Dhaka, the capital of Bangladesh. Moreover, Rangpur Division has the highest poverty rate among all the divisions in Bangladesh as seen in Figure 6.2. Sylhet and Rajshahi divisions have the lowest values in the Human Development Index (Global Data Lab 2019). Therefore, we test whether mobile money adoption has any heterogeneous effect between less developed areas and more urbanized areas, in terms of economic activity. In Columns (1) and (2), we show the results. 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, the agrarian sector is dominant compared to the rest of Bangladesh including Dhaka (Khandker 2012). Their livelihoods rely heavily 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) is negative and statistically significant. It indicates that mobile money adoption overcompensates for the negative effect of drought in Sylhet, Rangpur, and Rajshahi divisions. Another plausible explanation is that geographically disadvantaged areas usually have poorer logistics and market access compared to areas near Dhaka. Therefore, nonfood 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 nonfood consumption stable in response to the rainfall shocks. In line with Table 6.3, Column (4) shows the positive coefficient of the interaction term and negative coefficient of rainfall shock. The plausible reason is that those that live near Dhaka have better logistics, then mobile money can be used for transactions of purchasing nonfood products. 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 subsamples by consumption quota. They are below or above per capita expenditure in 2015. The result in Column (1) shows that the coefficient of the rainfall shock is statistically significant and 0.67, and the coefficient of the interaction term is statistically significant and –0.158. The result suggests that mobile money adoption overcompensates the negative impact of deficient rainfall indicating droughts on food consumption for the poorer households. Moreover, we find significant mitigating effects of mobile money on nonfood consumption for the poorer households in Column (2). The logic behind the effects of mobile money is that poor households' livelihood is more likely to rely predominantly on agriculture, which is highly susceptible to rainfall shocks, especially droughts. Thus, droughts devastate crop yields more than floods do, inducing a more severe effect on food insecurity. This is consistent with Jack and Suri (2014); Tabetando and Matsumoto (2020) and a welcome finding from rural development perspective. From Column (3) and (4), the results for households above median per capita expenditure are presented. While the coefficients in Column (3) are statistically insignificant, the coefficient of rainfall shock is significant and –0.098 and the coefficient of the interaction term is significant and 0.093 in Column (4). It indicates that mobile money adoption mitigates the negative effects of excessive rainfall on nonfood expenditure. The richer 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 poorer and richer households. In Panel C, we also separate the sample into two subsamples, with respect to household income. We find that the results are consistent with the results of Panel B. The result implies that digital connectivity of poor households builds their resilience to weather shocks under climate change.

Table 6.3: Impact of Rainfall Shocks on Consumption for Mobile Money Users and Nonusers

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS							
	Rainfall				Self-reported			
	Per capita food expenditure	Per capita nonfood expenditure	Per capita food expenditure	Per capita nonfood expenditure	Per capita food expenditure	Per capita nonfood expenditure	Per capita food expenditure	Per capita nonfood expenditure
MM user	–0.015	0.042**	–0.022	0.040*	–0.020	0.005	–0.019	0.005
	(0.019)	(0.020)	(0.020)	(0.020)	(0.013)	(0.014)	(0.013)	(0.014)
Interaction	0.001	0.018*	–0.004	0.017*	0.088	0.193**	0.110	0.152*
	(0.009)	(0.009)	(0.009)	(0.010)	(0.078)	(0.077)	(0.084)	(0.087)
Shock	–0.019***	–0.064***	0.003	–0.072***	–0.042	–0.068	–0.073	–0.102
	(0.007)	(0.007)	(0.026)	(0.027)	(0.043)	(0.041)	(0.176)	(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 nonfood expenditure	Per capita food expenditure	Per capita nonfood expenditure	Per capita food expenditure	Per capita nonfood expenditure	Per capita food expenditure	Per capita nonfood expenditure
MM user	–0.073	0.290***	–0.090	0.302***	–0.000	0.006	0.001	0.009
	(0.103)	(0.109)	(0.105)	(0.112)	(0.084)	(0.084)	(0.084)	(0.084)
Interaction	–0.050*	0.113***	–0.061*	0.120***	0.018	0.322*	0.060	0.279
	(0.029)	(0.030)	(0.032)	(0.033)	(0.184)	(0.178)	(0.212)	(0.218)
Shock	–0.003	–0.095***	0.014	–0.098***	–0.026	–0.096*	–0.057	–0.120

	(0.011)	(0.012)	(0.027)	(0.029)	(0.052)	(0.056)	(0.179)	(0.197)
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
Observations	9,860	9,860	9,860	9,860	9,860	9,860	9,860	9,860

FE =fixed effect, MM = mobile money, OLS = ordinary least squares, 2SLS = two-staged least squares.

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

Source: Calculated by authors.

Table 6.4: Heterogeneous Effects of the Impact of Rainfall Shocks on Consumption for Mobile Money Users and Nonusers

Panel A	(1)	(2)	(3)	(4)
	Sylhet, Rangpur, and Rajshahi		Rest of Bangladesh	
	Per capita food expenditure	Per capita nonfood expenditure	Per capita food expenditure	Per capita nonfood expenditure
Mobile money user	–0.679**	0.044	0.017	0.313**
	(0.279)	(0.249)	(0.118)	(0.129)
Interaction	–0.303***	-0.001	–0.014	0.165***
	(0.065)	(0.056)	(0.044)	(0.045)
Rainfall shock	0.169***	–0.053	–0.038	–0.127***
	(0.061)	(0.050)	(0.034)	(0.038)
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)
	Below median per capita expenditure in 2015		Above median per capita expenditure in 2015	
	Per capita food expenditure	Per capita nonfood expenditure	Per capita food expenditure	Per capita nonfood expenditure
Mobile money user	-0.194	0.421***	0.155	0.332**
	(0.135)	(0.146)	(0.157)	(0.165)
Interaction	–0.158***	0.083*	–0.039	0.093*
	(0.045)	(0.044)	(0.049)	(0.050)
Rainfall shock	0.067*	–0.055	–0.025	–0.098**
	(0.038)	(0.038)	(0.040)	(0.045)
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	4,930	4,930	4,928	4,928

Panel C	(1)	(2)	(3)	(4)
	below median household income in 2015		above median household income in 2015	
	Per capita food expenditure	Per capita nonfood expenditure	Per capita food expenditure	Per capita nonfood expenditure
Mobile money user	-0.087	0.508**	-0.107	0.182
	(0.203)	(0.226)	(0.121)	(0.127)
Interaction	-0.097*	0.151**	-0.036	0.107**
	(0.059)	(0.063)	(0.039)	(0.043)
Rainfall shock	0.027	-0.115**	-0.000	-0.086**
	(0.047)	(0.049)	(0.033)	(0.038)
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	4,936	4,936	4,922	4,922

FE = fixed effect.

Notes: All columns are estimated by 2SLS. Robust standard errors clustered by households in parentheses. Outcome variables are converted into logarithm. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% 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. The full regression table is available on request.

Source: Calculated by authors.

6.4.2 Mechanism: Mobile Money and Remitting Network

The plausible mechanism presented in this chapter is that mobile money improves household resilience by facilitating easier flow of remittances from friends, relatives, and family in other locations responding to a rainfall shock and, thus, enabling households to smooth consumption. We show this with estimates from Equation (5) that are reported in Table 6.5. 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 using mobile money services are more likely to receive foreign remittance in larger amounts through mobile money in response to the rainfall shock, compared to nonuser households. Similar to Tabetando and Matsumoto (2020), it therefore seems that mobile money use is leading households to engage in an informal insurance structure where households transfer and share resources particularly in the event of a negative shock.

The result is also consistent with Jack and Suri (2014), Suri and Jack (2016), Riley (2018), Tabetando and Matsumoto (2020), and Batista and Vicente (2020). In addition, we add to the literature by distinguishing the effect of domestic versus international remittances using mobile money by noting that international remittances are a much larger source of resilience for households in the face of shocks compared to domestic remittances. It therefore can be assumed that the adoption of mobile money technology is encouraging international remittance flows by reducing the transaction costs associated with this channel. As a result, our findings emphasize the importance of remittances from overseas out-migrants and calls for facilitating cross-border labor migration and ease of regulations encouraging free flow of transfers into the country.

Table 6.5: Mechanism for Mobile Money Remittances

	(1) Value of domestic remittance (deflated)	(2) Value of foreign remittance (deflated)
Mobile money user	3.7e+04	-6.6e+03
	(2.5e+04)	(1.1e+05)
Interaction	–3.2e+03	8.5e+04**
	(7925.436)	(3.9e+04)
Rainfall shock	–2.4e+03	–3.1e+04
	(6309.794)	(3.2e+04)
Division×Year	Yes	Yes
Control variables	Yes	Yes
Interaction with shock	Yes	Yes
Observations	9,860	9,860

Notes: Robust standard errors clustered by households in parentheses. ***Significant at the 1% level.

**Significant at the 5% level. *Significant at the 10% 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.
Source: Calculated by authors.

6.5 Conclusion and Policy Implications

Poor households are more vulnerable to negative economic shocks since they are likely to fail to smooth their consumption in response to shocks such as rainfall. Bangladesh is extremely prone to floods every year and the climate risk is rising due to global climate change. Since we need easier and more accessible adaptation strategies against such shocks, mobile money services can be a preferred and suitable option. It is a novel and rapidly-growing technology that can help households insure their welfare against climatic shocks by giving access to remittances from other locations not affected by shocks (Riley 2018). In this chapter, 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 nationally representative household panel data set from Bangladesh and a monthly granular precipitation dataset collected by the Bangladesh Meteorology Department. Combining the two datasets enable us to estimate the role of mobile money technology on consumption smoothing in response to objective and subjective shocks.

Our results show that large rainfall shocks negatively affect food and nonfood consumption, but the adoption of mobile money can provide much needed resilience to households in mitigating this impact by allowing the easier flow of remittances, especially from foreign countries. However, we do not find that self-reported shocks affect household consumption, and that mobile money mitigates the effect of such self-reported shocks. We find significant heterogeneity in our results, with respect to geography and welfare distribution. We find geographically disadvantaged divisions benefit more from mobile money technology by mitigating the negative effects of droughts on food consumption. Moreover, regarding food consumption, mobile money works as an informal insurance against droughts for the poorer households. It indicates that poorer households' livelihoods and food consumption are more likely to rely on their own agricultural production that is more vulnerable to droughts. However, mobile money enables both poorer and richer households affected by floods to smooth their nonfood consumption. We determine the mechanism, where mobile money enables risk sharing, by increase in remittances received after the rainfall shock, possibly due to a reduction in transaction costs. We also find evidence that households owning mobile money are more likely to receive overseas remittances in response to the rainfall shocks rather than domestic remittances.

Our findings shed light on the importance of mobile money services as informal insurance and risk sharing, given the incidence of extreme climate events related to climate change. Governments and stakeholders should promote the expansion of mobile money services so that rural households can cheaply, quickly, and safely avail an option to cope with future weather shocks. Moreover, mobile money services may help overcome spatial inequality by bringing forth a pro-poor effect. The diffusion of mobile money would help poor households, whose livelihoods mainly depend 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.

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Appendix

Table A6.1: Test of Validity of the Selection Instruments

	(1) Per capita food expenditure	(2) Per capita nonfood expenditure
Share of households adopting mobile money in the union	0.029	-0.001
	(0.064)	(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 a logarithm. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Source: Authors.