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 climate 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. We examine the impact of these mobile money services on food and non-food consumption following weather shocks. Moreover, we investigate whether there is an increase in received remittances via mobile money as a response to these shocks. To achieve this, 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. Our analysis of heterogeneity shows that mobile money enables geographically disadvantaged or poor households to smooth out their food consumption during droughts, as well as 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).

However, rural financial services challenges transaction cost that render markets for financial services costly or missing (Benami & Carter, 2021). The emerging digital technologies (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, 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 25 % in 2020 as shown in 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 negative economic 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? Given that poor households are particularly vulnerable to weather shocks, and that the poverty rate in Bangladesh is among the highest in South Asian countries that are prone to flooding (World Bank, 2018), 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 newly available 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 maintan their investments in human capital beyond household consumption. The mechanism behind the mobile money for informal and formal insurance has been well documented as well. Jack & Suri (2014), Riley (2018) and Tabetando & Matsumoto, (2020) show that the underlying mechanism is an increase in remittance receipt. In addition, social protection is more likely to be received by household who uses mobile money services (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 the relatively poorer households can smooth their consumption, same as geographically disadvantaged households. Finally, we find that the mechanism proposed in this study is that mobile money allows the user access to remittances from foreign countries when they face the economic shocks.

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.

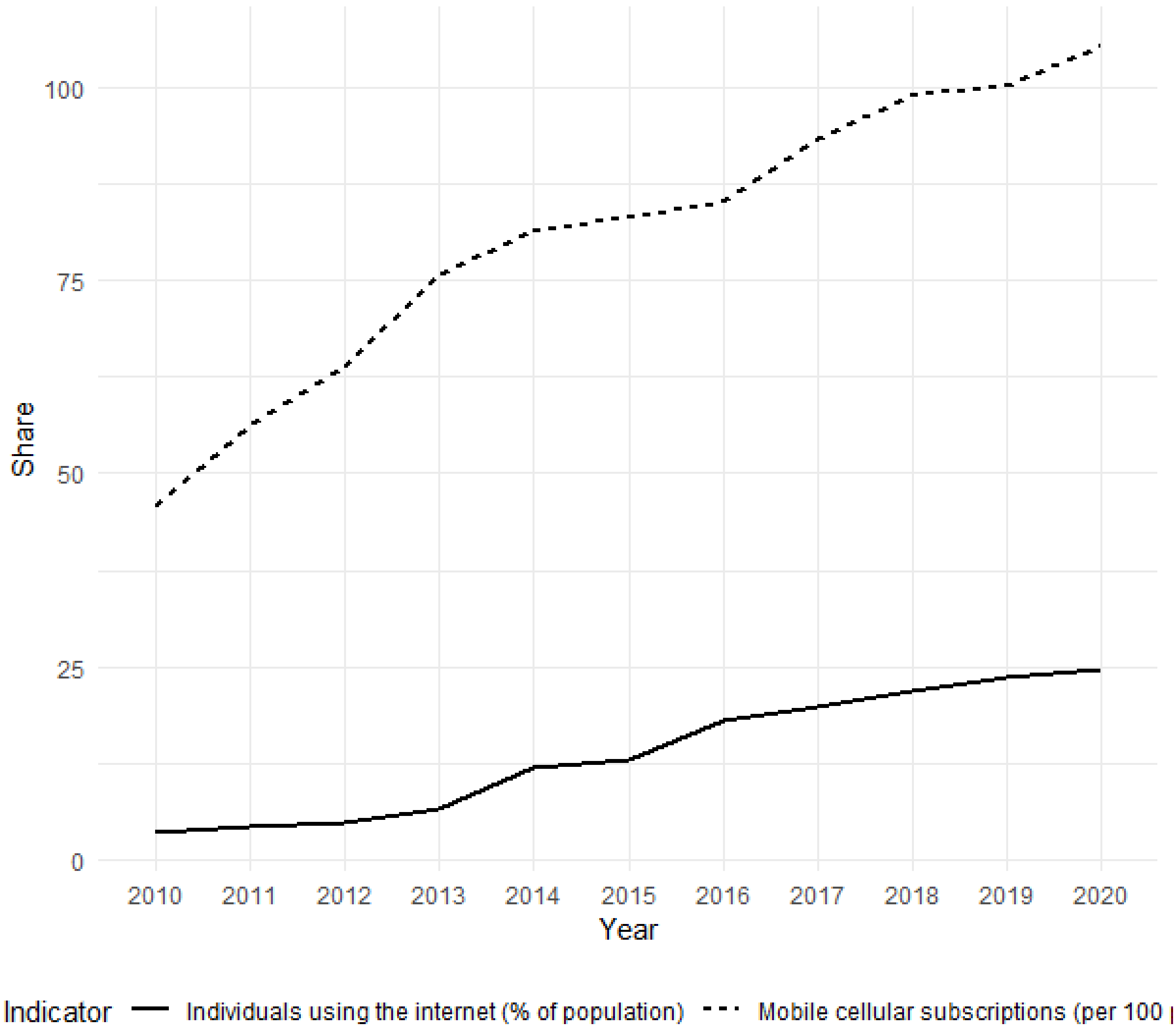

Figure 1 Mobile phone subscription and internet users in Bangladesh

Source: World Bank (2023)

2. Methodology

2.1. Data

We use 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 panel[1]. 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.

Moreover, the weather data are 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 use only the Kharif season variable because the

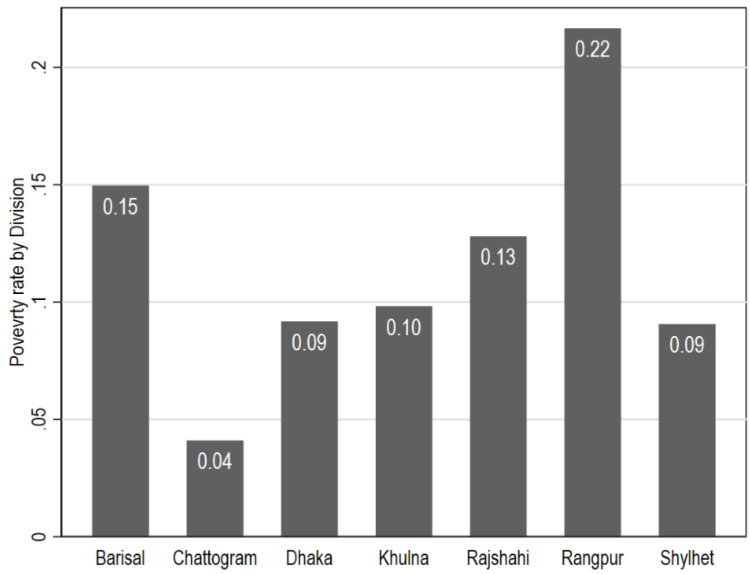

Figure 2 Poverty rate by Division

Source: BIHS2015 and 2019. Note: Calculated by authors

[1]The 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 2009, we cannot use the 2011–2012 wave of the BIHS by assuming that no household had access to mobile money

rainfall shock variable is not singnificantly associated with household welfare[2].

2.2. Description of key variables

In this paper, "*Shock*" has means two definitions, which are a rainfall shock and a self-reported shock. First, we define a rainfall shock as used in Makate, Angelsen, Holden, & Westerngen (2022):

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

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 increases from 506 to 2254 which is about half of the sample in 2019. Per capita food expenditure is the monthly value, and it decreases over time in both mobile money users and non-users. Rainfall shock is negative overall, regardless of mobile money users or not. In 2015, from 2.2 % to 2.8 % households lose crops, livestock, production assets, or consumption assets due to flood or cyclone in the survey year. However, the probability of self-reported shocks decreases in 2019.

As for socioeconomic variables to be controlled in the analysis, female headed households are less likely to use mobile money services. Regarding schooling year of household heads, the

[2] The results are available upon requests.

average schooling year mobile money users in 2015 is 5.23 years but it is 4.517 in 2019. It may be because the mobile money services become common even in less educated groups and widely used in the whole country. We generated a wealth index of assets using principal component analysis (PCA) since the value of assets owned was not asked all the waves of the survey. Different components of wealth, such as radio, TV, telephone, computer, animal cart, bicycle, motorbike or refrigerator, and a car or truck are used for the calculation[3].

[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 Obs	Mean	SD	Obs	Mean	SD	2019 Obs	Mean	SD	Obs	Mean	SD
	User			Non-user			MM user			Non-user		
Per capita food expenditure	506	1871.937	927.340	4,424	1713.741	1036.616	2,254	1735.947	890.950	2,676	1691.350	907.087
Per capita food expenditure	506	1784.938	1326.000	4,424	1269.840	1086.233	2,254	1651.375	1178.993	2,676	1447.580	1167.319
Rainfall shock	506	-1.709	1.027	4,424	-1.601	1.061	2,254	-1.663	1.364	2,676	-1.472	1.305
Self-reported shock	506	0.022	0.146	4,424	0.028	0.164	2,254	0.016	0.127	2,676	0.016	0.126
Female HH	506	0.154	0.362	4,424	0.185	0.388	2,254	0.192	0.394	2,676	0.216	0.411
Age of HH	506	46.301	13.498	4,424	45.989	13.555	2,254	46.331	12.427	2,676	48.974	13.811
Household size	506	5.244	2.081	4,424	4.889	1.882	2,254	5.882	2.242	2,676	5.214	2.029
Schooling year of HH	506	5.230	4.458	4,424	3.250	3.832	2,254	4.517	4.254	2,676	2.834	3.654
Access to irrigation	506	0.475	0.500	4,424	0.445	0.497	2,254	0.472	0.499	2,676	0.449	0.497
Wealth	506	0.776	2.010	4,424	-0.557	1.864	2,254	0.709	1.881	2,676	-0.412	1.834

Source: BIHS 2015 and 2019.

Note: Calculation by authors. Mean values are shown with standard deviations in parentheses. 100 decimals are equal to 0.4 ha. Per capital food and non-food expenditure are deflated to real value of 2011.

3. Empirical strategy

In this section, we will estimate: (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 by empirical specification of the impact of a shock on consumption for household with and without mobile money services (Jack & Suri, 2014; Riley, 2018). The econometric specification is as follows:

$$Y_{it} = \beta_1 + \beta_2 Shock_{it} + \beta_3 MM_{it} + \beta_4 MM_{it} \times Shock_{it} + \beta_5 X_{it} + \eta_i + \omega_t \times \gamma_d + \epsilon_{\mathrm{it}} \quad (1)$$

where MM_{it} is MM 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. Particularly, 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):

$$r_{it} = \gamma_1 + \gamma_2 Shock_{it} + \gamma_3 MM_{it} + \gamma_4 MM_{it} \times Shock_{it} + \gamma_5 X_{it} + \eta_i + \omega_t \times \gamma_d + \mathrm{e}_{\mathrm{it}} \quad (2)$$

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 (1) and (2). There are two main self-selection effects with regards to mobile money which could bias our results. The first one is self-selection by using mobile money. If household selection into mobile money use is correlated with unobservable factors that affect their ability to deal with shocks that will bias my results, 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 the problem of mobile money adoption, we use instrumental variable (IV) approach. In this study, 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 and help a household smooth consumption after an aggregate shock (Riley, 2018), we propose an additional different strategy. It extends equations (1) and (2) to include the interactions of the shock with all observable covariates ($X_{it} \times Shock_{it}$) using the following specification:

$$Y_{it} = \alpha_1 + \alpha_2 Shock_{it} + \alpha_3 MM_{it} + \alpha_4 MM_{it} \times Shock_{it} + \alpha_5 X_{it} + \alpha_6 X_{it} \times Shock_{it} + \eta_i + \omega_t \times \gamma_d + \mu_{it} \tag{3}$$

$$r_{it} = \theta_1 + \theta_2 Shock_{it} + \theta_3 MM_{it} + \theta_4 MM_{it} \times Shock_{it} + \theta_5 X_{it} + \theta_6 X_{it} \times Shock_{it} + \omega_t \times \gamma_d + \psi_{it} \tag{4}$$

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 (3) and (4) represents our preferred specification throughout the article. Because the remittance variable is truncated in zero, Equation (4) is an IV-Tobit regression model while Equation (3) is estimated by two-stage least squares (2SLS).

For equations (3) and (4) 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. Table 2 shows that it is not correlated with other household characteristics, nor with the instrumental variable or mobile money adoption.

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	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 basic specification from Equation (1). 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, whereas Panel B in Table 3 shows the regression results of IV-FE model. From Columns (1) to (8) in Panel B.

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 to decrease the per-capita non-food consumption by 6.3 percentage points. Moreover, the interaction terms between MM user and shocks are positively and significantly associated with per capita non-food expenditure while they are positively but insignificantly associated with per capita food expenditure, regardless of type of shocks. However, the positive and significant signs of the interaction terms indicate mobile money adoption provides incomplete insurance to 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 food and non-food expenditure while the self-reported shock is not significantly correlated with household welfare. In addition, the interaction term between the MM user and the rainfall shock is positively and significantly associated with per capita 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, Table 4 shows results for different 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 divisions in Bangladesh in Figure 2. Sylhet and Rajshahi Divisions are ones of the lowest 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 food consumption. It indicates that rainfall below the historical average rainfall (indicating a drought) decreases per capita food expenditure. The plausible explanation is the structures of income in those areas. In the three divisions including Rangpur, agrarian sector is dominant compared to the rest of Bangladesh including Dhaka (Khandker, 2012). Therefore, drought would significantly affect farm income and it reduces food consumption. Thus, the coefficient of the interaction term in Column (1) turns into negative and significant, opposed to Table 3. It indicates that mobile money users overcompensate for the direct negative impact of drought in Sylhet, Rangpur, and Rajshahi Division. 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 the inequality.

In Panel B, the sample is divided into two samples. One is the sample below baseline median per capita expenditure in 2015. Another one is the sample above baseline median per capita expenditure in 2015. The results in Column (1) and (2) suggest that mobile money adoption attenuates the impact of rainfall shocks on food and non-food consumption for relatively poor households while we find no significant effects for relatively rich households. This is consistent with Jack & Suri (2014); Tabetando & Matsumoto (2020). We also find the various functions of mobile money for the poor households. On the one hand, Column (1) suggests that mobile money mitigates the negative effect of drought on food consumption. On the other hand, Column (2) suggests that mobile money mitigate the negative effect of flood on non-food consumption. This is also a welcome finding from rural development perspective.

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	0.042**	-0.027	0.042**	-0.019	0.007	-0.018	0.009
	(0.019)	(0.020)	(0.020)	(0.020)	(0.013)	(0.014)	(0.013)	(0.014)
Interaction	-0.002	0.016*	-0.007	0.016*	0.082	0.207***	0.106	0.169**
	(0.009)	(0.009)	(0.009)	(0.010)	(0.077)	(0.077)	(0.084)	(0.086)
Shock	-0.015**	-0.060***	0.012	-0.063**	-0.040	-0.080*	-0.071	-0.140
	(0.007)	(0.007)	(0.026)	(0.027)	(0.043)	(0.042)	(0.176)	(0.187)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division×Year	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	0.322***	-0.109	0.332***	0.011	0.046	0.010	0.051
	(0.101)	(0.109)	(0.103)	(0.111)	(0.082)	(0.082)	(0.082)	(0.082)
Interaction	-0.065**	0.097***	-0.076**	0.103***	0.006	0.362**	0.047	0.318
	(0.028)	(0.029)	(0.031)	(0.032)	(0.183)	(0.182)	(0.211)	(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	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. Full regression table is 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***	0.026	0.030	0.394***
	(0.267)	(0.231)	(0.114)	(0.129)
Interaction	-0.270***	-0.017	-0.031	0.148***
	(0.063)	(0.055)	(0.039)	(0.041)
Rainfall shock	0.154***	-0.041	-0.028	-0.112***
	(0.058)	(0.049)	(0.035)	(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)
	Below baseline median per capita consumption in 2015		Above baseline median per capita consumption in 2015	
	Per capita food expenditure	Per capita non-food expenditure	Per capita food expenditure	Per capita non-food expenditure
Mobile money user	-0.201	0.424***	0.134	0.402**
	(0.132)	(0.143)	(0.155)	(0.169)
Interaction	-0.163***	0.081*	-0.043	0.073
	(0.044)	(0.044)	(0.042)	(0.045)
Rainfall shock	0.064*	-0.039	-0.010	-0.097**
	(0.039)	(0.038)	(0.039)	(0.044)
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	4,812	4,812	5,046	5,046

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 allows remittances to be sent in larger amount by friends and family in other locations in response to the rainfall shock and that this allows consumption smoothing. The results from estimating Equation (4), are reported in Table 5. While the interaction term is insignificant in Column (1), the coefficients of both the interaction term and the rainfall shock are 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. As 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 consistent with Jack & Suri (2014); Suri & Jack (2016); Riley (2018); Tabetando & Matsumoto (2020); Batista & Vicente (2020). In addition, we add to the literature by distinguishsing the type of remittance using mobile money. As a result, our findings emphasize the importance of remittance from overseas out-migrants.

Table 5 Mechanism for mobile money remittances

	(1) Value of domestic remittance (deflated)	(2) Value of foreign remittance (deflated)
Mobile money user	4142.006	-14496.46
	(3.0e+04)	(176143.1)
Interaction	-6.2e+03	157081.2**
	(9341.212)	(66934.26)
Rainfall shock	2324.829	-126559.5**
	(7536.756)	(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, then are likely to fail to smooth their consumption in response to the shocks such as rainfall shocks. Bangladesh is one of the flooding prone countries 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 are preferred and suitable options. They are 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 appropriate evidence on the consequences of the mobile money adoption on the welfare of households in the setting 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.

In this paper, we show large rainfall shocks negatively affect food and non-food consumption, but that mobile money can mitigate this impact by allowing the easy receiving of remittances from foreign countries. However, we do not find the consistence that self-reported shocks affect household consumption and mobile money mitigates the effect of the self-reported shocks. This effect has heterogeneities, in terms of geography and poverty status. In the 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 poorer households. Regarding food consumption, mobile money works as an informal insurance against with droughts for poorer households. Furthermore, mobile money enables the poorer 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 and non-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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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	-0.001
	(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 logarithm. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.