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Does Contingent Repayment in Microfinance Help the Poor During Natural Disasters?

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Abstract

Microfinances in Bangladesh introduced a contingent repayment system beginning in 2002, which allowed rescheduling of savings and installments during natural disasters for affected members. This paper is one of the first attempts to evaluate the system employing a unique dataset. In using evidence from a flood in 2004, I find that rescheduling plays the role of a safety net by decreasing the probability that people skip meals during negative shocks by 5.1%. This effect is even higher on the landless and females. This study attempts to contribute to the issue regarding the poverty reduction effect of Microfinances.

JEL Codes: O16, O22, O53, G21
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1. Introduction

This study evaluates a newly introduced contingent repayment system in Microfinance Institutions (MFIs) using a unique dataset. The standard repayment system of MFIs is frequent and strict, and negative shocks occurring after loan disbursements sometimes causes a repayment burden upon borrowers (Zeller et al. 1999). Therefore, there has long been a concern about how flexible loans combined with insurance can work as a safety net for the poor. To overcome this problem, most MFIs in Bangladesh have been introducing a contingent repayment system since 2002, which allows rescheduling of repayment during natural disasters for disaster-affected members (Dowla and Barua 2006).

The goal of this paper is to use a unique dataset to examine the determinants and consequences of rescheduling. A number of articles describe the importance of rescheduling in MFIs and its efficient implementation (Ledgerwood 1998; Norell 2001; Meyer 2002), but no previous studies examine the issue because of a lack of available data. This study is one of the first attempts to evaluate the contingent repayment system.

This study also fills a gap in the literature by investigating the poverty reduction effect of MFIs during natural disasters.[1] The existing literature on the issue is limited, despite its practical importance in designing a poverty reduction policy. This paper employs a dataset collected after a nation-wide flood in 2004. That resulted in many MFIs being rescheduled simultaneously for the first time. The dataset shows that 39% of MFI members were allowed to reschedule during the flood.

[1] However, this study is not the first study to examine the performance of MFIs during natural disasters. For further discussion regarding the issue, see Khandker (2007) and Khan and Kurosaki (2007).

This paper finds that rescheduling helps flood victims ensure food consumption. Rescheduling is found to decrease the probability that people skip meals by 5.1% during negative shocks. Furthermore, the impact is larger on the poor than on the rich, and larger on females than on males. In the absence of rescheduling, the repayment burden increases the probability that females skip meals by 5.5%, while the corresponding change in probability is only 3.5% for males. Thus, although MFI memberships may improve the intra-household bargaining power of women (Van Tassel 2004; Pitt et al. 2006), they still suffer from the burden of repayment more than men during negative shocks.

It is important to study the heterogeneous rescheduling impact within a household. Previous studies find that females and children are more likely to experience decreases in nutrition intake than working-age males during negative shocks (Behrman 1988; Behrman and Deolalikar 1990). However, Pitt et al. (2003) show that credit provided to females by MFIs improves the nutrition intake of children. It is also theoretically plausible that food consumption of productive and/or favored members becomes more sensitive to income fluctuations than the other members (Mangyo 2007).

This paper attempts to contribute to the literature regarding the poverty reduction effects of MFIs particularly by smoothing consumption. A number of previous empirical studies examine the impacts of MFI membership on capital accumulation, consumption, nutrition intake and income.[2] Also, Morduch (1998) and Chemin (2008) use a case study of Bangladeshi MFIs before introducing the contingent repayment

[2] For example, Pitt and Khandker (1998), Pitt et al. (2003), and Tedeschi (2008) find positive impacts of MFI participation on households' outcomes. Coleman (1999), however, shows that MFI membership does not necessarily improve members' livelihoods, and it even increases the demand for moneylenders possibly because of the repayment burden to MFIs.

system to show that MFI membership can mitigate fluctuations in consumption over time. However, Armendariz de Aghion and Morduch (2005: 222) claim that there is no consensus on whether MFIs with the standard repayment system actually reduce poverty, despite a number of previous attempts. This is attributed to the difficulty of controlling for the endogeneity of self-selection into MFI membership. While this study does not examine the long-term impact of MFI membership, it finds that the contingent repayment system, compared to the frequent repayment system, plays the role of a safety net during natural disasters.

This paper begins with the first part of Section 2, which describes features of Bangladeshi floods and the repayment system of MFIs, while the second part describes the dataset. In Section 3, the empirical strategies are discussed and Section 4 shows the results. Section 5 is the conclusion of this paper.

2. Background and Data

The 2004 Flood and the Contingent Repayment Structure in MFIs

MFIs receive attention from academic and non-academic circles because of their high repayment rates and their unique repayment structure.[3] One feature of standard MFI loans is frequent repayment: once a MFI member borrows from his/her MFI, the amount to be repaid is divided into approximately 40 to 50 weekly installments. He/She is required to pay tightly scheduled weekly installments beginning soon after the loan disbursement. Also, members must attend member meetings and deposit money into a saving account at their MFIs every week, regardless of whether they have debt. All transactions, such as loan disbursements, payments of installments, and

[3] For a comprehensive discussion of MFIs and their repayment structures, see Armendariz de Aghion and Morduch (2005).

deposits, must be implemented at the member meeting place rather than the borrowers' home (Armendariz de Aghion and Morduch 2005: 137). Borrowers who default on their loans are excluded from future access to credit. If borrowers cannot repay their installments on time, they have to ask the other members in the joint-liability group to reimburse the repayment.[4] Therefore, the joint liability system can play the role of a state contingent repayment system (Townsend 2003), but it does not work during covariate shocks such as natural disasters (Khan and Kurosaki 2007).

Bangladesh is one of the most disaster-prone countries in the world and floods after the planting seasons are clearly the largest risk to household income. In recent decades severe floods have inundated the country in 1974, 1988, 1998, 2004, and 2007. The flood in 1998, inundating 68% of the country, was particularly severe and negatively affected income and assets of MFI members, causing repayment burdens.

Learning from the 1998 flood, most MFIs in Bangladesh have been introducing a contingent repayment structure since 2002. This new repayment structure allows rescheduling of weekly repayments and deposits during disasters without charging additional interest.[5] Indebted MFI members are allowed to reschedule both savings and loan installments, while those who do not have debt postpone only saving deposits. MFIs have also switched loan contracts from joint liability to individual lending (Dowla and Barua 2006).

The first nation-wide flood since the introduction of the contingent repayment structure occurred in July 2004, affecting 39 out of 64 districts of the country. MFIs

[4] A number of studies theoretically explain that this joint liability structure results in high repayment rates (Besley and Coate 1995, Ghatak and Guinnane 1999). On the contrary, Gine et al. (2006) find that the joint liability would even increase risky investments. Also, Kono (2006) finds that the joint liability increases the default rates.
[5] Natural disasters might affect borrowers' solvency as well as their liquidity. However, the new repayment system allows only rescheduling.

postponed collecting weekly saving deposits and debt installments when the flood started. The government of Bangladesh also initiated the Vulnerable Group Feeding (VGF) and Gratuitous Relief (GR) programs that aimed at providing victims with food and agricultural inputs, such as seed and fertilizer. However, most of them started in September and October: two months after the flooding began. Also, since floods are a type of covariate shocks, it is difficult to cope with the shocks by risk sharing among the villagers, increasing the importance of rescheduling. Therefore, a small amount of rescheduling can potentially have large consequences particularly at the beginning of the flood.

The rescheduling was targeted to members who had difficulty in 1) attending the member meetings, and 2) paying for savings and installments. MFIs choose beneficiaries of rescheduling on an individual or group basis. This approach makes better use of the limited financial resource of MFIs than rescheduling all loans in affected areas. It requires, however, officers to visit all affected MFI members during disasters and observe the members' flood damage, causing significant administrative and monitoring costs. This tradeoff between the two targeting approaches is a common problem in the poverty targeting literature (Coady et al. 2004). The following section provides summary statistics regarding the flood damage and rescheduling.

Data Description

This study employs a unique dataset collected from 326 Bangladeshi households including both MFI members and non-members that has some distinct characteristics from other household surveys. First, it includes data on rescheduling treatments

collected using MFI members' bankbooks. The use of the bankbooks alleviates the possibility of recall bias, which is common in retrospective surveys. Second, the survey was conducted one year after the 2004 flood, the first flood in which most MFIs allowed members to reschedule.[6]

This dataset is a follow-up survey of the International Food Policy Research Institute (IFPRI). IFPRI collected data from 757 households in 1998, 1999 and 2004 to examine the 1998 and the 2004 flood (Del Ninno et al. 2001). The IFPRI dataset followed the multistage stratified random sampling methodology for seven districts that were selected depending on their economic status and the flood intensity: Chandpur, Manikganj, Magura, Barisal, Sunamganj, Narsingdi, and Madaripur. In the second stage, IFPRI randomly sampled one Thana from each district and three unions from each of those Thanas.[7] In the next stage, about six villages from each union and two clusters from each of the villages were randomly selected. Approximately three households from each cluster were chosen depending on the village size.

The data in this paper was collected only once in December 2005 from three out of the seven IFPRI-survey districts, Chandpur, Manikganj, and Magura, that were selected based on flood severity, poverty level, geographical characteristics, and diffusion of MFIs. According to Centre for Policy Dialogue (2005: pp16), the flood intensity was categorized into five levels: "very severe" including Sunamganj, "severe" including Narsingdi, Manikganj, and Chandpur, "moderate" including Madaripur, "normal" such as Barisal, and "not flooded" including Magura. Since Sunamganj is too different from the other districts in terms of geography, economy, and flooding patterns, I

[6] Only a few MFIs allowed rescheduling of installments during the previous flood in 1998.

[7] Thanas and unions are administration units of Bangladesh; a union consists of some villages, and each Thana includes multiple unions.

dropped the area from my study sites. Out of the three "severely affected" districts, I chose Chandpur and Manikganj because Narsingdi is quite similar to Manikganj in terms of poverty level, agricultural patters, and geography. Finally, I chose Magura as a control group.[8] This survey succeeded in interviewing 326 out of 335 households that IFPRI surveyed in 2004.[9] My questionnaire covered the magnitude of flood damage, basic demographic characteristics, labor and non-labor incomes, asset holdings, savings, MFI memberships, rescheduling treatments, and food consumption from January 2004 until December 2005.

In the December 2005 survey, retrospective information was collected, based on recall, for four sub-periods preceding December 2005: mid-January to mid-July 2004, mid-July to mid-November 2004 (during the flood), mid-November 2004 to mid-July 2005, and mid-July to December 2005. From this retrospective information, a pseudo-panel dataset was compiled. Each period corresponds to the agricultural calendar in Bangladesh. However, the data of the dependent variable -- individual meal frequencies -- was collected only before and during the flood periods. Also, since the focus of this paper is to examine rescheduled and non-rescheduled MFI members, this paper uses only 148 households that were MFI members during the flood period. Therefore, the empirical analysis uses a two-period balanced panel data consisting of 148 households, of which 58 were rescheduled during the flood. The household-level observations include 737 observations of individuals over the age of

[8] Chandpur lies downstream of three major rivers so the flood affected this area the most severely of the three. Manikganj is also adjacent to the major rivers, and damage in this area was also severe. Out of the sample households, more than 60% of the households were involved in MFIs. Magura is relatively poor compared to the other study areas, but the damage from the flood was moderate since it is far from the major rivers. More information on the study sites including summary statistics is available from the author upon request.

[9] The attrition is 2.7% and this is mainly because of migration.

two years old.

Table 1 presents the changes in consumption and income level through time to illustrate the impact of the 2004 flood. The monthly labor income during the flood period was approximately 25% lower than the average of non-flood periods. Correspondingly, 39% of MFI members rescheduled during the flood period, while none of the member households were rescheduled during the pre-flood period. The average duration of rescheduling was 2.72 weeks and the average amount was 490 Taka (Tk). Given that the seasonal labor income during the flood period was 9436 Tk, the amount of rescheduling was equal to approximately 5.2% of labor income.[10] The table also reports that around 20% of people reduced their meal frequency during the period of the flood. In particular, working-age females tended to skip meals more often than other individuals.

Table 2 compares household characteristics during the flood between the rescheduled and non-rescheduled members. The rescheduled members were more flood-affected and poorer than the non-rescheduled ones in terms of income and asset holdings. Also, 30% of people reduced meal frequency in the rescheduled households, while the corresponding statistics for the non-rescheduled households was only 11%. These distinctions in household and individual characteristics are statistically significant.

Figure 1 depicts the fractions of individuals skipping meals during the flood by age. Since the dataset includes few observations aged over 50, I mainly discuss individuals under 50. For both males and females, those around the age of 41 to 45 skipped meals the most frequently. It also shows that a gender gap does not appear in the young

[10] Average monthly labor income is 2359Tk and the flood period includes four months.

generation. The gap becomes the most prominent in their late 20's and early 30's, while it then becomes moderate in elder generations again.

3. Estimation Methodology

This section describes the empirical approach measuring the determinants and impacts of rescheduling. Although rescheduling may impact on households in various ways, this study focuses on the individual meal frequency. The use of consumption as an indicator of livelihood is straightforward, and the individual meal frequency is particularly useful in examining the heterogeneous rescheduling impacts within the household. Another advantage with using this variable is that it alleviates the possibility of measurement error caused by the recall bias; it is more accurate to recall the individual meal frequency than the value of individual food consumption (Appleton and Collier 1995: 557).

Considering the absence of a randomized experiment of rescheduling treatment during natural disasters, this paper employs the Recursive Bivariate Probit model which jointly estimates the determinants of rescheduling and the rescheduling impact on individual meal frequency.[11] More specifically, I estimate the following model:

$$\Delta C_{ij} = 1\left[\Delta R_i \alpha + X_i \beta_0 + I_{ij} \beta_1 + u_{ij} > 0\right] \quad (1)$$

$$\Delta R_i = 1\left[Z_i \gamma_0 + X_i \gamma_1 + e_i > 0\right] \quad (2)$$

where ΔC_{ij} takes unity if individual *j* in household *i* took meals less than three times a day during the flood period (the second period), while he/she could take three meals

[11] One might be concerned why this study does not use the amount of rescheduling as the treatment variable. Since higher amount of rescheduling implies higher amount of past loan disbursement, estimating the effect of 1Tk of rescheduling might include both rescheduling effect and past loan disbursement effect.

during the pre-flood period (the first period).[12] ΔR_i takes unity if household *i* was allowed to reschedule at least one saving and/or installment during the flood period; X_i denotes a vector of household characteristics such as asset holdings, flood damage and other control variables; I_{ij} a vector of individual characteristics; Z_i instrumental variables;[13] and finally u_{ij} and e_i indicate residuals of the equations, which follow $E[u_{ij}] = E[e_i] = 0$, $\text{var}[u_{ij}] = \text{var}[e_i] = 1$, and $\text{cov}[u_{ij}, e_i] = \rho$, respectively. The first-differencing of the endogenous variables – the meal frequency and rescheduling – controls for observable and unobservable fixed effects.

A major issue of this specification is endogeneity caused by the fact that MFI officers allowed rescheduling mainly for disaster-affected and poor members. If there is flood damage and/or other time-varying rescheduling determinants that are unobservable to econometricians but observable to MFI officers, it would cause biased results despite the use of first-differencing.

To address the issue, this study takes two approaches. I first present the list of self-reported flood damages obtained from an open-response question in Table 3.[14] This process alleviates the omitted flood damage, because it creates a complete list of the major flood damage the victims suffered. It shows that the main damage includes income, houses, and other assets such as livestock, but not health conditions. Given that the damage to income and assets could be endogenous, this study controls for flood damage by adding the duration of inundation at home in the covariate set *X*.[15] This

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[12] In other words, C_{ijt} takes unity if he/she has less than three meals a day, and $\Delta C_{ij} = C_{ijt} - C_{ijt-1}$. In the dataset, nobody reported more frequent meals during the flood than the pre-flood period.

[13] The covariates X, I, and Z take the values as of the beginning of the flood period.

[14] The survey team let respondents freely answer what kinds of damage they suffered.

[15] The dataset also includes data of the height of inundation, but I use the duration because it has higher variance. Low variation of variables can cause the

affects the damage to houses, livestock, and other assets, and these in turn will decrease income.

I also employ the instrumental variables method in order to mitigate the bias caused by other unobservable determinants of rescheduling. Suitable instrumental variables must be determinants of rescheduling, and must affect the individual meal frequency only through the change in the possibility of rescheduling.

For the instrument, this study utilizes the distance -- from the member's residence to the MFI meeting place -- and its quadratic term. According to my field interviews, MFI officers allowed rescheduling mainly for members who had difficulties in attending the meetings and paying for installments and savings. However, MFIs did not use any concrete criteria, such as asset holdings, to choose beneficiaries of rescheduling. When the flood started, head offices of MFIs picked out affected districts as the first step. At the second step, officers in affected branches visited each member's residence and determined whether rescheduling should be applied. However, where the flood damage was severe and it was dangerous for officers to visit, they abandoned efforts to visit the members and allowed them to reschedule.

The idea is that the further the meeting place was located from members' residences, the more difficult it was for members to attend the meetings during the flood because people were up to their waists in flood water. It was also impossible for the officers to visit members' residences in such a situation. This would, therefore, increase the possibility of rescheduling, but would not affect the livelihoods of households directly.

However, these instrumental variables might be correlated to unobservable poverty factors and flood intensity, given a possibility that the locations of meeting places are

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multicolinearity and make estimation results unstable, particularly in nonlinear specifications such as the Bivariate Probit model.

not randomly determined. For instance, Zeller et al. (1999) find that branches of MFIs tend to be constructed where access to transportation and electricity infrastructure is good. If this tendency is applicable to the location choice of member meetings, members living far away from the meeting place might presumably live where access to the infrastructure is poor, such as a riverside. Also, such marginal areas might be more flood-affected, and more importantly, might suffer from poor access to food markets, causing upward bias. To address the concerns, I include geographical characteristics of residences, such as the number of markets and self-employed shops in the union community, distance to rivers, and distance to paved roads into the covariates.[16]

The distance to meeting places might also play a role in the screening of MFI memberships. Members who attend the meetings from far away might be young and physically healthy enough to walk the long distance, and might not have to stay at home for housekeeping or childcare. To deal with these potential issues, I also control for the household head and demographic characteristics.[17]

A third potential issue with the instruments is that the distance might be correlated to characteristics of the particular MFIs. Members commuting a long distance might be members of small local MFIs that have only a few members, and therefore each member has to commute long distances to attend the meetings. Another possibility is that such members join MFIs whose group size is large. If MFI members form a large group compared to the number of total members in the village, the total number of

[16] Recall that a union is an administration unit in Bangladesh. Each union includes multiple villages. Since data on access to markets and self-employed shops is not included in my data, I employ the data from the IFPRI survey.

[17] Also, one might be concerned that members commuting the long distance might be more likely to be Hindu and/or male, given that Muslim law prohibits unmarried women to walk alone. However, this possibility is negligible because most MFI members in Bangladesh are married women.

available groups in the village will be small, and therefore each member might have to attend the meetings from far away. These MFI characteristics might be correlated to the level of social capital which may affect food security in the face of negative shocks.

It is, however, inadequate to address these possibilities by adding MFI group characteristics into the covariates, since these would be endogenously determined by households. Instead, I compare the average distance to meeting places [1] between major and local MFIs, and [2] between MFIs forming large and small groups. Table 4 reports that neither of them rejects the null that the average distance is the same between the two groups, implying that this issue is negligible.

Finally, if members attend the meetings from far away during the flood, it might cause them to be sick, affecting their meal frequency and causing upward bias. Table 3 is helpful in addressing the issue again. None of the MFI households report an incidence of ill-health/injury as a major shock during the flood. The individual-level data also report few incidences of ill-health (not reported in tables). This study further discusses the adequacy of the instrumental variables in the appendix. Another potential concern regarding this dataset is its small sample size, which is common for uniquely collected datasets. This study also addresses this concern in the appendix.

4. Estimation Results

Determinants of Rescheduling

Table 5 presents the results of the equation (2) examining the determinants of rescheduling. The estimation has 629 observations for individuals aged 2 and over.[18]

[18] Observations of individuals less than two years of age were dropped, since their meal frequencies are irregular. Also, some observations are dropped because of the missing values in the data on the number of markets and self-employed shops.

The covariates include the valid instruments of distance to the meeting place and its quadratic term, the duration of inundation, asset holdings, demographics, household head and geographical characteristics, and district-level fixed effects. I employ household-level cluster-adjusted robust standard errors to address the possible correlation of residuals within a household, given that the rescheduling is a household-level treatment.

Table 5 shows that members living far away from the meeting place are more likely to have the opportunity to reschedule, which is consistent with the discussion in Section 3. Individuals living 100m away from the meeting place were 6.6% more likely to reschedule on average. The bottom row of the table rejects the null that the coefficients of instrumental variables are jointly zero, rejecting the possibility of weak instruments. A similar result is shown in the coefficient of distance to paved roads: a 100m increase in the distance raises the probability of rescheduling by 1.54%.[19] The transportation cost to attend member meetings increases the possibility of rescheduling.

It is also found that rescheduling is targeted to those who have less grain storage. A 1000 Tk of grain storage holding reduces the probability by 15.5%.[20] This significant and high marginal effect is likely because it directly affects food consumption and the subsistence nutrition intake. It therefore is expected to be an important determinant. However, the coefficient of the duration of inundation at home and non-land productive assets – such as livestock, rickshaws, and fishing equipments –

[19] One might be concerned that the distance to paved roads would be a more important determinant of rescheduling and a better option of the instruments. However, the distance to roads could directly affect the meal frequency through, for example, the occupation choice. Therefore, it is less likely to satisfy the exclusion restriction.

[20] The coefficient of grain storage potentially suffers from a possibility of attenuation caused by recall bias. Unlike the other asset holdings, the amount of grain storage fluctuates through time and this might cause a recall bias. Therefore, it would be better to interpret the marginal effect of grain storage as being at least 15.5%.

show expected signs but are statistically insignificant.

Finally, the table also shows some counter-intuitive findings. For instance, the coefficient of owned field is positive and statistically significant, but the significance is marginal and the estimated marginal effect is only 0.05% per 1000Tk of land holdings. Also, households with poor access to the food markets do not intensively benefit from the rescheduling.

Rescheduling Effects on Individual Meal Frequency

The first column of Table 6 presents the result of equation (1) evaluating the impact of rescheduling on individual meal frequency. The main finding of this table is that rescheduling significantly reduces people skipping meals during the flood. The repayment burden in the absence of rescheduling increases the probability that people will skip meals by 5.06 %. It is also found that inundation at home significantly reduces meal frequency.

The table also shows that physical and human assets help people ensure food consumption. Coefficients of grain, owned field, non-land productive assets, and head's education show expected signs and three of them are statistically significant. However, the results show diversified marginal effects on meal frequency across asset categories. As expected, grain storage plays an important role in ensuring food consumption. A 1000 Tk of grain storage reduces the probability of skipping meals by 1.11%, while a 1000Tk increase of non-land productive assets reduces the probability by only 0.25%. Also, the impact of owned field is statistically insignificant. These findings are consistent to Fafchamps et al. (1998) and Kazianga and Udry (2006), who state that people mainly utilize grain storage to ensure their consumption.

The second column focuses on landless households. Since they are poorer and more vulnerable to risks (Foster 1995; Kurosaki 2006), the demand for rescheduling and the expected marginal effect should be high. The table confirms that the rescheduling effect is larger for landless households than for the entire sample. The coefficients of physical assets and heads' education also show the same signs as those of the entire sample.

Finally, the table shows that the correlations between the residuals of two equations are statistically insignificant in both columns, rejecting the necessity of using the instrumental variables. However, the estimation uses the Wald test to test the significance of the correlation. The performance of the Wald test is poor when a small-sample dataset is used. Therefore, I mainly discuss the results from the Bivariate Probit models. I also report results from the single Probit models in the appendix.

Heterogeneous Rescheduling Effects across Gender

Given the fact that females skip meals more frequently than males (Table 1 and Figure 1), I divide the individual observations according to gender, and estimate the rescheduling impact separately. Table 7 shows the heterogeneous rescheduling effect across gender. The absence of rescheduling brings the burden of repayment and significantly reduces the frequency of meals for both males and females. However, females are more likely to sacrifice meals; the marginal effect on females, -5.46 %, is approximately 1.6 times as much as that of males, -3.47%. This finding is consistent with Behrman (1988) and Behrman and Deolalikar (1990). The higher marginal effect on females implies that they might benefit more than males from rescheduling in

ensuring the subsistence level of food consumption and nutrition-intake.

A similar tendency is found in the coefficients of physical and human assets. Households with educated head and more physical assets are less likely to reduce the meal frequency, and the marginal effects on females are larger than those on males. For instance, a 1000Tk of decline in grain storage increases the probability for females by 1.34%, while it increases the probability for males by only 0.76%. However, the coefficient of inundation is counter-intuitively significant only in the first column.

Finally, one might be interested in the rescheduling effects on the young generations. Malnutrition of children in the face of negative shocks is also an important issue in developing countries. It can cause persistent damage in the process of human capital accumulation, compared to shocks in adulthoods. This study, however, does not tackle the issue because of the limitation of data: the number of observations of children is small, and estimations using such a dataset do not show a stable result.

5. Conclusion

MFIs in Bangladesh introduced a contingent repayment system beginning in 2002 that allowed rescheduling of weekly saving and installments during natural disasters. Since there is no datasets on randomized rescheduling treatment during natural disasters, I employ the instrumental variable estimation, finding that rescheduling plays the role of a safety net during negative shocks. In particular, the benefits from rescheduling are higher for vulnerable households than for the rest of the population, and higher for females than for males. It is also found that the determinants of rescheduling include the transportation cost to attend member meetings, and financial ability to pay for savings and installments.

These findings have an implication regarding the poverty reduction effect of MFIs. The impact of MFI membership could be diverse including average consumption, investment, and intra-households bargaining power of members. Morduch (1998) and Chemin (2008), for instance, show that MFI membership can reduce poverty by mitigating the fluctuation of consumption through time. While this study does not examine the impacts of MFI memberships, it is found that the contingent repayment system could work as a safety net during negative shocks compared to the standard system imposing the frequent repayments. This alleviates members temporarily facing further poverty caused by a repayment burden.

Furthermore, the contingent repayments might have the potential to improve the performance of MFIs in different ways as well. For instance, vulnerable households are less likely to join MFIs (Amin et al. 2003), but the introduction of the rescheduling system may improve the outreach of MFIs because it mitigates the risk for them to face a repayment burden.[21] Also, this may, in turn, improve the sustainability of MFI management. A significant amount of arrears caused by excessive rescheduling could obstruct the financial sustainability of MFIs (Norell 2001), but the strictly scheduled standard repayment structure sometimes burdens members' livelihoods and may cause dropout (Hulme 1999). The introduction of the contingent repayments might be able to improve the management of MFIs depending on this tradeoff. However, this study does not tackle these questions because of the limitation of data. More work will be required to examine the issues.

MFIs have undergone dramatic recent changes. However, most previous studies regarding MFIs examine the earlier system. This study's findings suggest the

[21] Pearlman (2007) also reveals a theoretical possibility that the vulnerable choose not to participate in MFIs, and empirically finds a consistent result.

importance of further investigations into new structures of MFIs.

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Appendix

A1: Further Discussion of the Instrumental Variables (Table A1)

Given that the instrumental variable (distance to the meeting) is time-invariant, if the instrument affects the frequency of meals only through the likelihood of rescheduling, it should be uncorrelated to the meal frequency before the rescheduling treatment. Table

A1 reports the household characteristics before the flood relative to the distance to the meeting, and confirms that this condition is satisfied. It also appears that the instrumental variable is uncorrelated to asset holdings. The significant correlations of some characteristics such as the duration of inundation, although the statistical significance is marginal, imply the importance of controlling for them in the covariates.

A2: Sample Selection Bias Caused by the Missing Observations (Table A2)

Since the dataset does not include the data on the number of markets and self-employed shops, I additionally use the variables collected in the IFPRI survey in 1998. While using the IFPRI data addresses the possibility of an omitted variable bias, some observations are dropped because of missing values in the variables. This process might cause a sample selection bias if the estimation omits observations with particular characteristics.

Table A2 compares characteristics of households for which I have data on the two variables to those for which I do not have the data. The table shows that the differences in the instrumental variable, rescheduling, and the frequency of meals are statistically insignificant between the two groups. However, only one variable, distance to rivers, are significantly different.

A3: Robustness Check I: Small Sample Data (Table A3 and A4)

A potential concern regarding this dataset is its small sample size, which is common for uniquely collected datasets. Estimation results of nonlinear specifications such as the Bivariate Probit model using a small-sample data could be unstable. To address this concern, this study takes two approaches. First, I employ the pooled Probit model

rather than the first difference as follows;

$$C_{ijt} = 1\left[R_{it}\alpha + X_{it}\beta_0 + I_{ijt}\beta_1 + u_{ijt} > 0\right] \quad (3)$$

$$R_{it} = 1\left[Z_{it}\gamma_0 + X_{it}\gamma_1 + e_{it} > 0\right] \quad (4)$$

where C_{ijt} takes the value of one if individual *j* in household *i* took meals less than three times a day during the period *t*, and R_{it} takes the value of one if household *i* is allowed to reschedule at least one saving and/or installment during the period *t* and zero otherwise. This specification doubles the number of observations, while it does not control for the time-invariant unobservables.

Table A3 reports similar results to Table 5 and Table 6. The first column of the table shows that the households living far away from the meeting place are more likely to be rescheduled, and rejects the possibility of weak instruments. The second column reports the significant rescheduling impact on ensuring food consumption of flood victims. A difference from the main estimation is that the coefficient of inundation is significant in the first column: the flood affected members were more likely to be rescheduled.

In my second approach to addressing the small sample size, I also attempt the first-difference linear probability model with an endogenous rescheduling treatment. Since the estimation methodology is Linear Two Stage Least Squares rather than the relatively data-hungry Bivariate Probit, this approach addresses the concern of small sample size, while the estimation result is not efficient. Table A4 shows that the result from the first stage estimation is similar to previous estimations. However, while each coefficient of instrument is statistically significant, the joint test of the two coefficients does not reject the null. Also, the predicted probabilities of more than 20% of the observations do not range between zero and one in the second column. As a result of

these issues, the coefficient of rescheduling in the second stage equation is insignificant.

A4: Robustness Check II: The Single Probit Model (Table A5)

Table 6 shows that the correlation of the residuals, rho, is statistically insignificant. Therefore, I also estimate the single Probit model assuming that the correlation is zero, and the result is reported in Table A5. The first column shows the determinants of rescheduling, which is coherent with the result in Table 5. Again, the distance to meeting place has positive and significant impact on rescheduling.

The second column reports that the absolute value of rescheduling effect is smaller than the result from Table 6, and the statistical significance is marginal (the p-value is 0.142). The result is consistent with the discussion in Section 3: the estimated impact of rescheduling in the single Probit model might be affected by endogeneity that poor households were more likely to be rescheduled. Since such households are more likely to skip meals during the flood, this type of endogeneity should cause upward bias in the estimated rescheduling impact. The table indeed shows this expected result. Given that the result of the single Probit model is biased toward the positive, it should be considered as a lower bound of rescheduling impact.

A5: Robustness Check III: Specification of the Instrumental Variables (Table A6)

The main estimation employs the distance to the meeting place (km) and its quadratic term as instruments. Although this specification addresses the problem of nonlinearity between the probability of rescheduling and distance to the meeting place, the strong correlation between these two variables can cause the multicolinearity. Therefore, I also attempt another specification of the instrument: log (Distance to the

meeting place (meters) +1). Table A6 shows a robust result that rescheduling plays an important role in ensuring the meal frequency.

A6: Robustness Check IV: Outcomes at the Household Level (Table A7 and A8)

Given that rescheduling is a household-level treatment, I also estimate the impact on two household-level outcomes. The first outcome is a binary variable which takes unity if at least one of household members reduces the meal frequency compared to the pre-flood period. The second outcome variable is the value of monthly food consumption at the household level. Since it is a continuous variable, I estimate the following specification;

$$\Delta F_i = \Delta R_i \alpha + X_i \beta_0 + u_i \tag{5}$$

$$\Delta R_i = 1[Z_i \gamma_0 + X_i \gamma_1 + e_i > 0] \tag{6}$$

where F is the value of monthly food consumption at the household level.

The results from these models are reported at Table A7 and A8. They show similar results to the main specifications in Table 5 and Table 6. The distance to the meeting place is a significant determinant of rescheduling, and rescheduling increases food consumption in terms of both meal frequency and the value of food consumption.

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Table 1: Changes in Income and Consumption during the Flood

	Jan to Jul 2004		Jul to Nov 2004 (Flood period)		Nov to Jul 2005		Jul to Dec 2005	
	Mean	S. D.	Mean	S. D.	Mean	S. D.	Mean	S. D.
Monthly labor income (Tk)	3123	(4779)	2359	(4757)	3044	(4761)	3206	(5522)
Monthly food consumption (Tk)	2583	(1193)	2438	(1184)	2616	(1243)	2804	(1244)
Dummy =1 if rescheduled at least one installment or saving	0.000	(0.000)	0.392	(0.490)	0.020	(0.141)	0.083	(0.277)
N (MFI Households)	148		148		148		148	
Only for rescheduled members								
Amount of rescheduled installments and savings (Tk)	-	-	489.53	(496.78)	311.50	(270.82)	263.00	(180.56)
Duration of rescheduling (week)	-	-	2.72	(1.78)	1.00	(0.00)	1.20	(0.41)
N (Rescheduled MFI Households)	0		57#		2		15	
Individual-level observations								
Dummy =1 if a male aged 18 and over skips meals	0.034	(0.181)	0.184	(0.388)				
N(Adult Males)	207		207					
Dummy =1 if a female aged 18 and over skips meals	0.032	(0.177)	0.230	(0.422)				
N (Adult Females)	217		217					
Dummy =1 if a boy aged 1 to 17 skips meals	0.018	(0.132)	0.140	(0.348)				
N(Boys)	171		171					
Dummy =1 if a girl aged 1 to 17 skips meals	0.028	(0.167)	0.141	(0.349)				
N(Girls)	142		142					

Standard deviations are in parentheses.

#: 58 households were allowed to reschedule during the flood period, but one of them did not remember how long or how much she rescheduled because she did not have her bankbook with her. Therefore, the statistics represent only 57 rescheduled households that remembered the duration and the value of rescheduling.

Table 2: Characteristics of Rescheduled and Non-Rescheduled Households

	During Flood				Mean Difference
	Rescheduled		Non-Rescheduled		
	Mean	S.D.	Mean	S.D.	
Household Characteristics					
Monthly labor income (Tk)	1624	(1642)	2832	(5921)	*
Duration of inundation at home (Days)	2.36	(6.97)	0.50	(3.52)	*
Grain storage (Tk)	643	(1125)	2332	(3692)	***
Owned field (Tk)	72371	(117513)	156603	(312711)	**
Non-land productive assets (Tk)[#]	6091	(8276)	14877	(29896)	***
Distance to rivers (km)	2.48	(2.62)	1.68	(1.66)	**
Distance to paved roads (km)	0.77	(0.78)	0.58	(0.53)	
The number of markets	1.71	(0.83)	1.43	(0.85)	*
The number of self-employed shops	233	(162)	287	(139)	*
Males over 16	1.43	(0.75)	1.74	(1.01)	**
Females over 16	1.55	(0.71)	1.70	(0.88)	
Children under 16	2.05	(1.23)	1.97	(1.52)	
Age of head	46.48	(10.69)	48.92	(12.20)	
Dummy if educated year of head=0	0.64	(0.48)	0.60	(0.49)	
Distance to group meeting (km)	0.23	(0.22)	0.19	(0.21)	
Observations	58		90		
Individual Characteristics					
Dummy=1 if skips meals	0.30	(0.46)	0.11	(0.31)	***
Age	25.23	(17.70)	27.34	(18.82)	
Dummy=1 if female	0.49	(0.50)	0.48	(0.50)	
Educated years	2.66	(3.17)	3.01	(3.41)	
Observations	277		460		

Standard deviations are in parentheses.

*** 1% significant, ** 5% significant, * 10% significant, respectively.

Non-land productive assets include, for example, livestock, rickshaws, sewing machines, and fishing equipment.

Table 3: Flood Damages Based on Open-Response Question (Multiple answers)

	MFI members		Non members	
	Frequency	Fraction	Frequency	Fraction
Income	137	77.0%	130	63.7%
House/utensil	4	2.2%	5	2.5%
Other assets	7	3.9%	12	5.9%
Death of household member	0	0.0%	1	0.5%
Injury/sickness of member	0	0.0%	1	0.5%
No damage	30	16.9%	55	27.0%
Total	178	100.0%	204	100.0%

Table 4: Distance to Group Meeting and MFI Characteristics

Whether member of major MFIs (Grameen Bank, ASA, BRAC)			
Major MFIs	Local MFIs	Mean Difference	p-value
0.220 (0.219)	0.189 (0.207)	0.030	0.144
Whether the number of MFI group member is 10 and larger			
Large Group	Small Group	Mean Difference	p-value
0.212 (0.231)	0.213 (0.211)	-0.001	0.960

Standard deviations are in parentheses.

Table 5: Determinants of Rescheduling [Equation (2)]

	Coef.	S.E.	Marginal Effect
Instrumental Variables			
Distance to group meeting (km)	3.65**	1.57	116%
Quadratic term	-3.89*	2.09	-124%
Flood Damage and Assets			
Duration of inundation (days)	0.01	0.02	0.18%
Grain (Tk $x10^3$)	-0.49***	0.18	-15.50%
Owned field (Tk $x10^6$)	1.50*	0.87	47.77%
Non-land productive assets (Tk $x10^3$)	-0.002	0.005	-0.07%
Geographic Variables			
Distance to rivers (km)	0.04	0.10	1.27%
Distance to paved roads (km)	0.48**	0.19	15.44%
The number of markets	0.64***	0.21	20.29%
The number of self-employed shops	0.002	0.002	0.07%
Demographics			
Males over 16	0.12	0.17	3.85%
Females over 16	-0.21	0.17	-6.60%
Children under 16	-0.18	0.11	-5.74%
Log (age of head)	-0.17	0.77	-5.54%
Dummy if educated year of head=0	-0.07	0.30	-2.29%
District Fixed Effects			
Chandpur	1.42***	0.54	47.98%
Magura	-1.00	0.66	-28.00%
Constant	-1.04	2.82	
Observations	629		
H_0: Coefficients of IVs are zero	5.85*		

Dependent variable takes unity if the household rescheduled during the flood.
Cluster-adjusted robust standard errors and marginal effects at the mean are reported.
*** 1% significant, ** 5% significant, * 10% significant, respectively

Table 6: Rescheduling Effect on Individual Consumption [Equation (1)]

	All			Landless		
	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Marginal Effect
Dummy=1 if rescheduled[#]	-1.11*	0.65	-5.06%	-1.48***	0.50	-23.00%
Flood Damage and Assets						
Duration of inundation (days)	0.04***	0.01	0.18%	0.04	0.03	0.71%
Grain (Tk x10^3)	-0.23**	0.11	-1.11%	-0.34***	0.10	-5.85%
Owned field (Tk x10^6)	-0.28	0.76	-1.39%	-	-	-
Non-land productive assets (Tk x10^3)	-0.05***	0.02	-0.25%	-0.02	0.02	-0.39%
Geographic Variables						
Distance to rivers (km)	0.03	0.05	0.16%	0.04	0.07	0.72%
Distance to paved roads (km)	0.32*	0.18	1.55%	0.29	0.21	4.92%
The number of markets	-0.11	0.25	-0.56%	0.06	0.30	0.94%
The number of self-employed shops	-0.006*	0.003	-0.03%	-0.003	0.004	-0.06%
Demographics						
Males over 16	0.15	0.12	0.72%	0.08	0.20	1.41%
Females over 16	-0.29**	0.13	-1.43%	-0.24	0.22	-4.15%
Children under 16	-0.16	0.12	-0.78%	-0.16	0.13	-2.78%
Log (age of head)	-0.31	0.64	-1.53%	-0.84	0.90	-14.24%
Dummy if educated year of head=0	0.74***	0.26	3.50%	0.59	0.40	8.94%
District Fixed Effects						
Chandpur	0.98	0.67	7.13%	1.74*	1.01	32.46%
Magura	0.85	0.80	5.91%	1.11	0.97	24.12%
Individual Characteristics						
Female dummy	0.16	0.13	0.77%	0.18	0.14	3.14%
Log (age)	0.71***	0.15	3.49%	0.69**	0.34	11.73%
Educated year	0.05*	0.02	0.23%	0.05	0.04	0.86%
Constant	-0.69	2.36		0.43	2.75	
Observations	629			322		
Rho	0.42	0.35		0.87	0.27	
H_0: Coefficients of IVs are zero	5.85*			5.52*		

Dependent variable takes unity if the individual took meals less than three times a day during the flood, while he/she could take three meals during the pre-flood period.
#: Endogenous variable
Cluster-adjusted robust standard errors and marginal effects at the mean are reported.
*** 1% significant, ** 5% significant, * 10% significant, respectively

Table 7: Heterogeneous Rescheduling Effect across Gender

	Males			Females		
	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Marginal Effect
Dummy=1 if rescheduled[#]	-1.18*	0.63	-3.47%	-1.18**	0.60	-5.46%
Flood Damage and Assets						
Duration of inundation (days)	0.05***	0.01	0.16%	0.02	0.02	0.11%
Grain (Tk x10^3)	-0.24**	0.10	-0.76%	-0.27**	0.13	-1.34%
Owned field (Tk x10^6)	-1.63	1.04	-5.11%	0.31	0.82	1.52%
Non-land productive assets (Tk x10^3)	-0.05**	0.02	-0.16%	-0.06***	0.02	-0.28%
Geographic Variables						
Distance to rivers (km)	0.07	0.06	0.22%	-0.002	0.048	-0.01%
Distance to paved roads (km)	0.37*	0.21	1.16%	0.27	0.18	1.34%
The number of markets	-0.01	0.25	-0.03%	-0.09	0.29	-0.42%
The number of self-employed shops	-0.004	0.003	-0.01%	-0.007*	0.004	-0.04%
Demographics						
Males over 16	0.21	0.13	0.66%	0.12	0.15	0.58%
Females over 16	-0.28*	0.16	-0.88%	-0.38**	0.15	-1.84%
Children under 16	-0.24*	0.14	-0.76%	-0.08	0.13	-0.41%
Log (age of head)	-0.77	0.64	-2.42%	0.32	0.76	1.57%
Dummy if educated year of head=0	0.87**	0.37	2.62%	0.63**	0.29	3.01%
District Fixed Effects						
Chandpur	0.75	0.73	3.42%	1.14	0.70	8.66%
Magura	0.21	0.80	0.70%	1.50	0.94	14.41%
Individual Characteristics						
Log (age)	0.60***	0.19	1.90%	0.95***	0.22	4.66%
Educated year	0.02	0.04	0.06%	0.09***	0.04	0.46%
Constant	1.08	2.59		-3.37	2.56	
Observations	318			311		
Rho	0.48	0.31		0.56	0.39	
H_0: Coefficients of IVs are zero	4.7*			8.08**		

Dependent variable takes unity if the individual took meals less than three times a day during the flood, while he/she could take three meals during the pre-flood period.
#: Endogenous variable
Cluster-adjusted robust standard errors and marginal effects at the mean are reported.
*** 1% significant, ** 5% significant, * 10% significant, respectively

Table A1: Household Characteristics by Distance to the Member Meeting

	Distance>=0.2km		Distance<0.2km		Mean
	Mean	S.D.	Mean	S.D.	Diff.
Pre-Flood Period					
Dummy =1 If anybody in the household skips meals	0.03	0.16	0.06	0.24	
Labor income (Tk/month)	3068	2184	3185	6626	
Grain	2710	4428	1879	4348	
Owned field	119725	231343	128384	285886	
Non-land productive assets	10638	13149	10880	31913	
Males over 16	1.71	0.96	1.52	0.88	
Females over 16	1.70	0.82	1.58	0.81	
Children under 16	2.19	1.41	1.78	1.40	*
Log (age of head)	3.86	0.24	3.82	0.26	
Dummy if educated year of head=0	0.57	0.50	0.67	0.47	
Distance to river (km)	1.80	2.15	2.21	2.08	
Distance to paved road (km)	0.58	0.52	0.75	0.76	
The number of markets	1.35	0.84	1.73	0.83	**
The number of self-employed shops	280.00	151.06	249.00	150.15	
Flood Period					
Dummy =1 If anybody in the household skips meals	0.24	0.43	0.35	0.48	
Labor income (Tk/month)	1757	2888	3048	6200	*
Dummy=1 if rescheduled	0.42	0.50	0.36	0.48	
Duration of inundation (Days)	1.92	6.87	0.43	1.85	*
Observations	79		69		

Standard deviations are in parentheses.
*** 1% significant, ** 5% significant, * 10% significant, respectively.

Table A2: Sample Selection by Missing Values of IFPRI data

	Observed		Missing		Mean Diff.
	Mean	S.D.	Mean	S.D.	
Pre-Flood Period					
dummy =1 if anybody in the household skips meals	0.05	0.21	0.00	0.00	
Flood Period					
dummy =1 if anybody in the household skips meals	0.29	0.46	0.15	0.37	
Dummy=1 if rescheduled	0.37	0.49	0.35	0.49	
Labor income (Tk/month)	2486.4	5062.9	1543.3	1709.1	
Duration of inundation (Days)	1.34	5.53	0.50	2.24	
Grain	1522.6	2935.0	2616.0	3779.7	
Owned field	11224.6	25020.9	12773.0	18671.0	
Non-land productive assets	120916.4	270734.4	140725.0	149560.7	
Males over 16	1.63	0.90	1.55	1.15	
Females over 16	1.67	0.78	1.45	1.00	
Children under 16	2.04	1.42	1.75	1.37	
Log (age of head)	3.83	0.25	3.89	0.24	
Dummy if educated year of head=0	0.59	0.49	0.75	0.44	
Distance to rivers (km)	2.13	2.22	1.06	0.79	**
Distance to paved roads (km)	0.63	0.65	0.85	0.59	
Distance to meeting place (km)	0.19	0.22	0.24	0.19	
Observations	128		20		

Standard deviations are in parentheses.
*** 1% significant, ** 5% significant, * 10% significant, respectively.

Table A3: Bivariate Probit Model with the Pooled Data [Equation (3) and (4)]

Dependent Variables	Rescheduling			Meal Frequency		
	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Marginal Effect
Dummy=1 if rescheduled#				-1.04***	0.17	-4.84%
Instrumental Variables						
Distance to group meeting (km)	2.74***	0.96	47.14%			
Quadratic term	-3.07**	1.34	-52.92%			
Flood Damage and Assets						
Duration of inundation (days)	0.05***	0.01	0.88%	0.06***	0.01	0.42%
Grain (Tk $x10^3$)	-0.29***	0.08	-4.99%	-0.22***	0.05	-1.61%
Owned field (Tk $x10^6$)	0.65	0.46	11.14%	-0.69	0.65	-5.16%
Non-land productive assets (Tk $x10^3$)	-0.002	0.003	-0.03%	-0.05***	0.01	-0.40%
Geographic Variables						
Distance to rivers (km)	0.004	0.049	0.07%	0.08**	0.04	0.56%
Distance to paved roads (km)	0.41***	0.10	7.01%	0.08	0.11	0.58%
The number of markets	0.46***	0.14	7.98%	-0.14	0.15	-1.02%
The number of self-employed shops	0.002	0.002	0.04%	-0.001	0.002	-0.01%
Demographics						
Males over 16	0.08	0.11	1.42%	0.07	0.12	0.54%
Females over 16	-0.20*	0.10	-3.43%	-0.10	0.11	-0.76%
Children under 16	-0.09	0.07	-1.51%	-0.16**	0.07	-1.16%
Log (age of head)	-0.11	0.47	-1.93%	0.01	0.40	0.10%
Dummy if educated year of head=0	-0.10	0.19	-1.65%	0.34*	0.20	2.47%
District Fixed Effects						
Chandpur	0.68***	0.40	13.46%	0.68*	0.35	6.33%
Magura	-1.10**	0.48	-15.76%	0.05	0.46	0.40%
Individual Characteristics						
Female dummy				0.04	0.07	0.33%
Log (age)				0.30***	0.09	2.27%
Educated year				0.003	0.012	0.03%
Constant	-1.45	1.76		-1.19	1.52	
Rho	0.95***	0.06				
Observations	1235					
H_0: Coefficients of IVs are zero	9.22***					

#: Endogenous variable
Cluster-adjusted robust standard errors and marginal effects at the mean are reported.
*** 1% significant, ** 5% significant, * 10% significant, respectively

Table A4: First-Differenced Linear Probability Model [Equation (1) and (2)]

	All			
	Rescheduling		Meal Frequency	
	Coef.	S.E.	Coef.	S.E.
Dummy=1 if rescheduled[#]			-0.101	0.231
Instrumental Variables				
Distance to group meeting (km)	0.854**	0.403		
Quadratic term	-0.974**	0.489		
Flood Damage and Assets				
Duration of inundation (days)	0.006	0.006	0.013***	0.003
Grain (Tk $x10^3$)	-0.036***	0.013	-0.012	0.010
Owned field (Tk $x10^6$)	0.122	0.130	0.024	0.067
Non-land productive assets (Tk $x10^3$)	-0.001	0.001	-0.0007	0.0005
Geographic Variables				
Distance to rivers (km)	0.004	0.021	0.004	0.010
Distance to paved roads (km)	0.151***	0.051	0.063*	0.038
The number of markets	0.151***	0.055	0.002	0.040
The number of self-employed shops	0.001	0.001	-0.0004	0.0004
Demographics				
Males over 16	-0.008	0.043	0.006	0.020
Females over 16	-0.075*	0.039	-0.041	0.025
Children under 16	-0.039	0.026	-0.011	0.017
Log (age of head)	0.129	0.208	0.021	0.106
Dummy if educated year of head=0	0.033	0.077	0.068*	0.036
District Fixed Effects				
Chandpur	0.394***	0.151	0.206	0.158
Magura	-0.180	0.173	0.029	0.098
Individual Characteristics				
Female dummy			0.017	0.021
Log (age)			0.088***	0.019
Educated year			0.0004	0.0041
Constant	-0.426	0.777	-0.118	0.397
Observations	629			
H_0: Coefficients of IVs are zero	2.30			
Observations with the predicted probability between 0 and 1	581		490	

#: Endogenous variable

Cluster-adjusted robust standard errors are reported.

*** 1% significant, ** 5% significant, * 10% significant, respectively

Table A5: The Single Probit Models [Equation (1) and (2)]

Dependent Variables	Rescheduling			Meal Frequency		
	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Marginal Effect
Dummy=1 if rescheduled				-0.45	0.30	-1.91%
Instrumental Variables						
Distance to group meeting (km)	3.67**	1.57	119%			
Quadratic term	-3.93*	2.10	-127%			
Flood Damage and Assets						
Duration of inundation (days)	0.01	0.02	0.18%	0.03***	0.01	0.16%
Grain (Tk $x10^3$)	-0.46***	0.17	-14.99%	-0.16	0.10	-0.74%
Owned field (Tk $x10^6$)	1.40*	0.81	45.45%	-0.44	0.80	-2.01%
Non-land productive assets (Tk $x10^3$)	-0.002	0.005	-0.08%	-0.05***	0.02	-0.22%
Geographic Variables						
Distance to rivers (km)	0.04	0.10	1.14%	0.03	0.04	0.13%
Distance to paved roads (km)	0.48**	0.19	15.55%	0.24	0.17	1.10%
The number of markets	0.62***	0.21	20.14%	-0.23	0.22	-1.08%
The number of self-employed shops	0.002	0.002	0.07%	-0.006**	0.003	-0.03%
Demographics						
Males over 16	0.11	0.17	3.56%	0.15	0.13	0.68%
Females over 16	-0.22	0.17	-7.24%	-0.25*	0.13	-1.13%
Children under 16	-0.18	0.12	-5.76%	-0.14	0.12	-0.65%
Log (age of head)	-0.13	0.75	-4.07%	-0.42	0.62	-1.95%
Dummy if educated year of head=0	-0.04	0.28	-1.33%	0.76***	0.26	3.40%
District Fixed Effects						
Chandpur	1.41***	0.52	48.25%	0.74	0.61	4.59%
Magura	-0.96	0.66	-27.55%	1.07	0.73	7.75%
Individual Characteristics						
Female dummy				0.17	0.14	0.81%
Log (age)				0.75***	0.14	3.43%
Educated year				0.05*	0.03	0.22%
Constant	-1.16	2.78		-0.53	2.28	
Observations	629			629		
Pseudo-R^2	0.3745			0.4222		

Cluster-adjusted robust standard errors are reported.

*** 1% significant, ** 5% significant, * 10% significant, respectively

Table A6: A Different Specification of the Instrument [Equation (1) and (2)]

Dependent Variables	Rescheduling			Meal Frequency		
	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Marginal Effect
Dummy=1 if rescheduled[#]				-1.19*	0.72	-5.64%
Instrumental Variables						
Log (Distance (meters) +1)	0.13**	0.06	4.00%			
Flood Damage and Assets						
Duration of inundation (days)	-0.004	0.022	-0.12%	0.04***	0.01	0.18%
Grain (Tk $x10^3$)	-0.53***	0.19	-16.68%	-0.24**	0.11	-1.20%
Owned field (Tk $x10^6$)	1.78*	0.92	56.04%	-0.27	0.75	-1.39%
Non-land productive assets (Tk $x10^3$)	-0.002	0.005	-0.06%	-0.05***	0.02	-0.25%
Geographic Variables						
Distance to rivers (km)	0.05	0.10	1.47%	0.04	0.05	0.18%
Distance to paved roads (km)	0.48**	0.19	15.27%	0.32*	0.18	1.62%
The number of markets	0.60***	0.21	18.95%	-0.11	0.26	-0.55%
The number of self-employed shops	0.002	0.002	0.06%	-0.005*	0.003	-0.03%
Demographics						
Males over 16	0.08	0.17	2.57%	0.15	0.12	0.75%
Females over 16	-0.18	0.17	-5.68%	-0.29**	0.13	-1.48%
Children under 16	-0.19	0.12	-5.87%	-0.16	0.12	-0.81%
Log (age of head)	-0.27	0.77	-8.60%	-0.30	0.63	-1.54%
Dummy if educated year of head=0	-0.13	0.29	-4.06%	0.72***	0.27	3.55%
District Fixed Effects						
Chandpur	1.36**	0.56	45.79%	0.98	0.68	7.44%
Magura	-0.98	0.66	-27.01%	0.83	0.82	5.85%
Individual Characteristics						
Female dummy				0.16	0.13	0.81%
Log (age)				0.70***	0.15	3.57%
Educated year				0.05*	0.02	0.24%
Constant	-0.53	2.80		-0.65	2.37	
Rho	0.47	0.40				
Observations	629					
H_0: Coefficients of IVs are zero	5.27**					

#: Endogenous variable

Cluster-adjusted robust standard errors and marginal effects at the mean are reported.

*** 1% significant, ** 5% significant, * 10% significant, respectively

Table A7: Household Level Outcomes

Methods	Bivariate Probit						Regression with Endogenous Dummy			
Dependent Variables	Rescheduling			Meal Frequency			Rescheduling		Food Consumption	
	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Coef.	S.E.
Dummy=1 if rescheduled[#]				-1.54***	0.30	-23.80%			298.63***	107.87
Instrumental Variables										
Distance to group meeting (km)	2.64	1.63	87.56%				2.70*	1.50		
Quadratic term	-2.23	2.10	-73.96%				-2.00	1.66		
Flood Damage and Assets										
Duration of inundation (days)	-0.002	0.024	-0.08%	0.10*	0.06	1.71%	-0.003	0.021	0.14	3.28
Grain (Tk $x10^3$)	-0.55***	0.16	-18.11%	-0.29***	0.11	-4.99%	-0.39**	0.18	13.24	19.06
Owned field (Tk $x10^6$)	1.83**	0.82	60.73%	-0.08	0.78	-1.39%	1.07	1.36	247.97	245.94
Non-land productive assets (Tk $x10^3$)	-0.005	0.012	-0.16%	-0.07**	0.03	-1.21%	-0.03*	0.02	1.32	0.96
Geographic Variables										
Distance to rivers (km)	0.07	0.07	2.30%	-0.03	0.08	-0.60%	0.02	0.07	-2.88	8.85
Distance to paved roads (km)	0.40*	0.23	13.26%	0.51**	0.24	8.82%	0.54***	0.20	30.98	37.99
The number of markets	0.54***	0.20	17.94%	0.01	0.21	0.09%	0.58***	0.20	25.56	45.35
The number of self-employed shops	0.002	0.003	0.06%	-0.006	0.004	-0.10%	0.001	0.003	-0.04	0.65
Demographics										
Males over 16	0.10	0.19	3.41%	0.16	0.28	2.79%	0.02	0.24	25.21	46.21
Females over 16	0.12	0.21	4.01%	-0.29	0.28	-4.96%	0.23	0.21	-74.99*	40.58
Children under 16	-0.14	0.12	-4.64%	-0.28	0.17	-4.81%	-0.14	0.12	16.50	19.02
Log (age of head)	-0.95	0.71	-31.61%	0.42	0.89	7.35%	-0.62	0.81	-74.35	146.43
Dummy if educated year of head=0	-0.23	0.32	-7.56%	0.72*	0.40	11.81%	-0.23	0.30	-103.68*	59.40
District Fixed Effects										
Chandpur	1.51**	0.60	52.21%	1.90***	0.72	46.64%	1.41***	0.52	-204.36**	101.77
Magura	-0.66	0.65	-20.14%	1.38	0.93	31.56%	-0.34	1.03	-35.46	180.66
Constant	1.51	2.73		-0.64	3.04		0.42	2.80	83.84	495.27
Rho	1.00***	1.83E-11					-0.77***	0.14		
Observations	119						117			
H_0: Coefficients of IVs are zero	4.31						5.65*			

#: Endogenous variable. Robust standard errors and marginal effects at the mean are reported. *** 1% significant, ** 5% significant, * 10% significant, respectively

Table A8: Household Level Outcomes: [Instrument = Log (Distance)]

	Bivariate Probit						Regression with Endogenous Dummy			
	Rescheduling			Meal Frequency			Rescheduling		Food Consumption	
	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Coef.	S.E.
Dummy=1 if rescheduled[#]				-1.47***	0.32	-22.28%			284.02***	110.09
Instrumental Variables										
Log (Distance (meters) +1)	0.13**	0.05	4.39%				0.13**	0.05		
Flood Damage and Assets										
Duration of inundation (days)	-0.01	0.02	-0.22%	0.09*	0.06	1.59%	-0.004	0.021	0.20	3.27
Grain (Tk x10^3)	-0.58***	0.17	-19.24%	-0.28**	0.12	-4.75%	-0.41**	0.20	12.69	19.21
Owned field (Tk x10^6)	2.03**	0.84	67.08%	-0.04	0.79	-0.63%	1.37	1.37	248.79	245.67
Non-land productive assets (Tk x10^3)	-0.004	0.013	-0.14%	-0.07**	0.03	-1.26%	-0.03**	0.01	1.30	0.96
Geographic Variables										
Distance to rivers (km)	0.08	0.08	2.53%	-0.03	0.07	-0.58%	0.02	0.08	-2.78	8.67
Distance to paved roads (km)	0.41*	0.23	13.43%	0.51**	0.24	8.75%	0.59***	0.21	32.77	38.28
The number of markets	0.54***	0.20	17.96%	0.01	0.22	0.09%	0.58***	0.20	27.52	46.06
The number of self-employed shops	0.001	0.003	0.03%	-0.005	0.004	-0.09%	0.0004	0.0033	-0.02	0.64
Demographics										
Males over 16	0.09	0.19	2.88%	0.18	0.27	3.06%	0.01	0.23	25.50	45.75
Females over 16	0.18	0.21	5.94%	-0.31	0.27	-5.22%	0.24	0.21	-74.92*	40.17
Children under 16	-0.19	0.13	-6.17%	-0.23	0.17	-3.95%	-0.16	0.12	16.33	18.90
Log (age of head)	-1.14	0.75	-37.73%	0.47	1.09	7.97%	-0.79	0.82	-75.24	144.59
Dummy if educated year of head=0	-0.25	0.29	-8.22%	0.72*	0.41	11.62%	-0.24	0.30	-103.90*	59.00
District Fixed Effects										
Chandpur	1.40**	0.63	48.65%	1.91***	0.74	46.57%	1.39***	0.49	-197.71*	101.31
Magura	-0.51	0.65	-15.73%	1.29	0.92	28.63%	-0.32	1.05	-39.37	178.29
Constant	2.30	2.98		-1.01	4.08		1.01	2.84	85.15	487.32
Rho	1.00***	3.03E-09					-0.75***	0.16		
Observations	119						117			
H_0: Coefficients of IVs are zero	6.04**						5.35**			

#: Endogenous variable. Robust standard errors and marginal effects at the mean are reported. *** 1% significant, ** 5% significant, * 10% significant, respectively

Table A9: Determinants of Rescheduling: Sub-Sample Estimations

	Landless			Males			Females		
	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Marginal Effect	Coef.	S.E.	Marginal Effect
Instrumental Variables									
Distance to group meeting (km)	4.77**	2.39	159%	3.26*	1.67	103%	4.47***	1.58	142%
Quadratic term	-3.80	2.73	-127%	-3.12	2.16	-99%	-5.40**	2.16	-171%
Flood Damage and Assets									
Duration of inundation (days)	-0.02	0.03	-0.72%	-0.01	0.02	-0.18%	0.03	0.02	0.84%
Grain (Tk $x10^3$)	-0.37**	0.18	-12.37%	-0.51***	0.18	-15.98%	-0.50***	0.18	-15.88%
Owned field (Tk $x10^6$)				1.50*	0.81	47.23%	1.60*	0.94	50.83%
Non-land productive assets (Tk $x10^3$)	0.003	0.006	0.09%	-0.001	0.005	-0.04%	-0.003	0.005	-0.10%
Geographic Variables									
Distance to rivers (km)	-0.09	0.09	-3.12%	0.08	0.09	2.62%	0.002	0.100	0.06%
Distance to paved roads (km)	0.95***	0.29	31.79%	0.41*	0.22	13.06%	0.57***	0.19	17.94%
The number of markets	0.53*	0.29	17.80%	0.63***	0.22	20.02%	0.66***	0.22	21.00%
The number of self-employed shops	-0.004	0.006	-0.13%	0.002	0.002	0.07%	0.002	0.003	0.06%
Demographics									
Males over 16	0.33	0.24	10.92%	0.15	0.17	4.64%	0.13	0.17	4.02%
Females over 16	-0.86***	0.32	-28.66%	-0.24	0.17	-7.57%	-0.20	0.17	-6.47%
Children under 16	-0.10	0.15	-3.39%	-0.15	0.11	-4.71%	-0.21*	0.12	-6.52%
Log (age of head)	-0.55	0.91	-18.52%	-0.12	0.77	-3.86%	-0.24	0.80	-7.67%
Dummy if educated year of head=0	-0.40	0.48	-13.79%	0.03	0.31	0.79%	-0.20	0.30	-6.33%
District Fixed Effects									
Chandpur	1.99*	1.18	60.75%	1.35**	0.56	45.91%	1.49***	0.56	49.67%
Magura	1.25	1.45	43.92%	-1.15*	0.68	-31.48%	-0.94	0.69	-25.99%
Constant	1.33	3.31		-1.36	2.92		-0.74	2.86	
Observations	322			318			311		
H_0: Coefficients of IVs are zero	5.52*			4.7*			8.08**		

Dependent variable takes unity if the household rescheduled.
Cluster-adjusted robust standard errors and marginal effects at the mean are reported.
*** 1% significant, ** 5% significant, * 10% significant, respectively

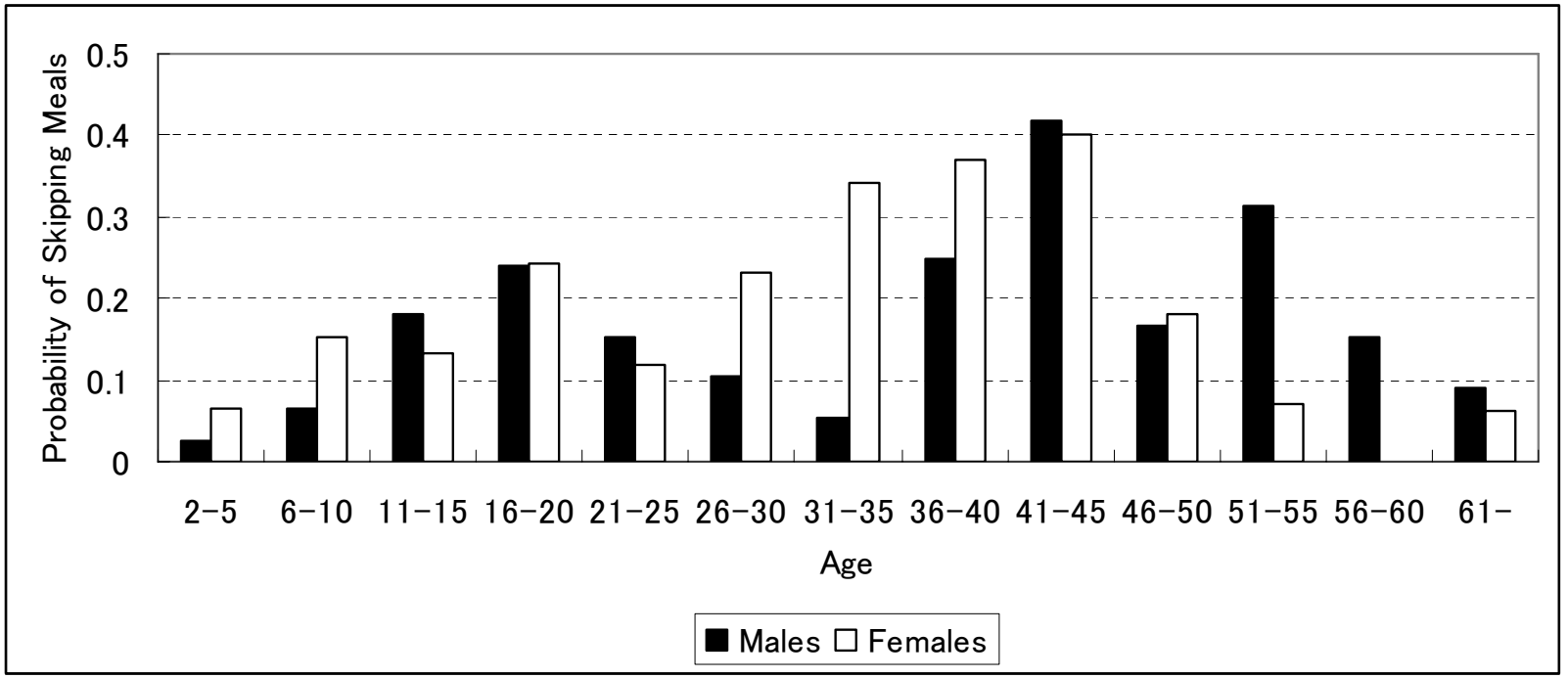

Figure 1: Probability of Skipping Meals during the 2004 Flood by Age