Evaluation of Flexible Repayment System in Microfinance: A Case Study from a Natural Disaster in Bangladesh[1]

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[1] The author would like to express the gratitude to Hidehiko Ichimura, Amy Ickowitz, and Yasuyuki Sawada for helpful and constructive suggestions. The author is also grateful to financial support from *Foundation for Advanced Studies on International Development* (FASID). Any errors and omissions are the responsibility of the author.

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Abstract

This paper employs a unique dataset to show that a flexible repayment system introduced by Microfinance institutions (MFIs) could result in a greater reduction in poverty than the earlier system which imposed strictly scheduled repayment. A strict repayment system burdens borrowers during natural disasters, when they generally lose income earning opportunities. Some members must borrow from moneylenders to repay installments to MFIs, which adversely affects poverty reduction. To deal with the adverse effect of the earlier system, most MFIs in Bangladesh introduced a flexible repayment system in 2002, which permits members to reschedule installments during disasters.

Although strict repayment during disasters burdens borrowers, arrears deteriorate the sustainable management of MFIs. Some articles describe the importance of rescheduling, but no previous study investigates its impacts based on household data because of a lack of available data. This paper uses a unique dataset based on evidence from a flood in Bangladesh to quantify the impact of rescheduling.

This study finds that the flexible repayment system plays an important role in mitigating MFI members borrowing from moneylenders, which in turn reduces poverty. Also, this study reveals some issues that could be improved upon in the new system.

JEL Codes: O16, G21,

Keywords: Microfinance, Rural Credit Market, Bangladesh

1. Introduction

This paper employs a unique dataset to show that a flexible repayment system used by Microfinance Institutes (MFIs) could play a more important role to reduce poverty than the earlier system of strict repayment. MFIs are considered as effective tool of reducing poverty in developing countries (Pitt and Khandker 1998, Morduch 1999a; 2000, Aghion and Morduch 2005). Their strict repayment system which requires borrowers to repay their loans in tightly structured installments, however, burdens many borrowers. Some members borrow from moneylenders to repay installments to MFIs (Coleman 1999, Jain and Mansuri 2003). Credit from moneylenders is used as a last resort because of high interest rates.

Thus, MFIs may increase the demand for moneylenders, although their aim is to mitigate dependence on them. Dependence on credit from moneylenders can obstruct poverty reduction, since they charge high interest to borrowers (Aleem 1993, Kochar 1995, World Bank 1998; 2001). The demand for credit from moneylenders, particularly, takes off during natural disasters, since the poor lose opportunities to earn income. MFIs need to implement policies to alleviate the adverse effect of strict repayment system.

To overcome the adverse effect, most MFIs in Bangladesh have been introducing a flexible repayment system. The new system permits the poor suffering from disasters to reschedule weekly installments (Meyer 2002). Some articles describe the importance of rescheduling during disasters (Ledgerwood 1998, Norell 2001, Meyer 2002), but no previous study evaluates its impact because of a lack of available data.

This paper uses a unique dataset of a nation wide flood in Bangladesh to quantify the impact of rescheduling on credit from moneylenders. More specifically, this paper examines two questions. First, does rescheduling mitigate informal loans from moneylenders, and if so, by how much? Second, how much does the impact of rescheduling change with the rescheduling amount?

These questions are important to better understand the capacity of MFIs. Although MFIs are believed to be an efficient way to reduce poverty, some studies point out potential problems. First, Coleman (1999) shows that MFI membership does not necessarily improve members' livelihoods. Rather, it increases the demand for moneylenders because of the repayment burden to MFIs, causing further poverty. Second, it is difficult for MFIs to sustainably manage their projects without subsidies (Morduch 1999b). Although strict repayment might deteriorate members' livelihoods, a significant amount of arrears caused by excessive rescheduling could obstruct the sustainable management of MFIs. There seems to exist a tradeoff between these two issues. Hence, the second question of this paper to examine the change in rescheduling effect enables us to discuss the optimal level of intervention. If the marginal effect decreases with the rescheduling amount, this implies the existence of an optimal level of rescheduling.

It is particularly interesting to examine the flexible repayment system in the context of Bangladesh. While MFIs are common in developing countries, they are vulnerable to covariate shocks such as natural disasters (Aghion and Morduch 2005, Khan and Kurosaki 2007). Disasters affect both the livelihoods of borrowers and sustainable management of MFIs. Hence, disaster-prone countries like Bangladesh need to implement a policy to cope with these difficulties.

This paper uses data from a flood in 2004, which affected 39 out of 64 districts, and significantly impacted agricultural and nonagricultural sectors. Most of the MFIs in Bangladesh introduced a flexible repayment structure in 2002 (Dowla and Barua 2006), and the 2004 flood is the biggest natural disaster following this change. This is the only case that most of the MFIs in Bangladesh rescheduled installments at the same time.

Empirical analyses show that MFI members borrow from moneylenders to repay a fraction of installments during natural disasters. This paper also reveals that the flexible repayment system plays an important role to mitigate this behavior, which in turn reduces poverty. If rescheduled members were not rescheduled, they would borrow 140% more from moneylenders. This paper, however, finds some remaining problems in the current MFI repayment system. At least 2 weeks of rescheduling is required during the flood to see a statistically significant rescheduling effect. However, 32% of rescheduling did not satisfy the required level in the 2004 flood. Also, although the poor and flood-affected are likely to be rescheduled on average, the duration of rescheduling does not necessarily reflect the difference in demand for rescheduling.

This paper is organized as follows. The first part of section 2 describes features of Bangladeshi floods, MFIs, and the rescheduling. The second part describes the dataset and provides summary statistics. In Section 3, this paper investigates the impact of rescheduling. Section 4 examines the change in the rescheduling effect with the rescheduling duration. Finally, Section 5 concludes.

2. Floods in Bangladesh, Rescheduling of Installment, and Data

2.1 The 2004 flood and Rescheduling of Installment in MFIs

MFIs are one of the most common poverty reduction tools used in Bangladesh (Pitt and Khandker 1998, Morduch 1999a; 2000, Aghion and Morduch 2005). They provide the poor with opportunities for investment loans with low interest and without collateral. This program was originally established by Grameen Bank and the Bangladesh Rural Advancement Committee (BRAC) to prevent the poor from dependency on credit from informal moneylenders with high interest.

MFIs achieve high repayment rates thanks to their unique repayment structure. Once an MFI member borrows from her MFI, the amount to be repaid, including original principal and interest, is divided into 40 to 50 installments. She is required to pay tightly scheduled installments, beginning soon after loan disbursement, to inculcate the idea of making regular repayments. Even if she does not borrow money, all of the MFI members are required to accumulate deposits every week. Also, borrowers who default are excluded from future access to credit, which provides a dynamic incentive. These structures are considered to be efficient in alleviating the moral hazard problem that is a well known feature of credit market (Chowdhury 2005, Tedeschi 2006, Gine, Jakiela, Karlan, and Morduch 2006)[3].

These structures, however, make MFI members borrow from moneylenders more than non-members to repay installments to MFIs (Coleman 1999, Jain and Mansuri 2003). Credit from moneylenders with high interest rates burden people (Aleem 1993, Kochar 1995, World Bank 1998; 2001). The demand for credit from moneylenders, in particular, increases during natural disasters as a last resort, since people lose opportunities to earn income on a regular basis.

Bangladesh is one of the most disaster-prone countries in the world. Floods are the most frequent events because of three major rivers running into Bengal Bay through Bangladesh. People benefit from normal floods, since they make soils fertile. However, when the peak times of rainfall come at the same time in the upstream of major rivers, the level of flood water increases, causing severe damage for many households. To make matters worse, it is hard to predict the level of floods beforehand, since it depends on the timing and the amount of rainfall. The timing of floods is, therefore, considered exogenous.

The flood in July 2004 affected 39 out of 64 districts in Bangladesh, damaging agricultural and non-agricultural sectors. Since the flood started during the planting period of the rainy season, it affected the harvest expected in December, even though the flood waters receded by the end of September.

[3] In addition to the frequent repayment and dynamic incentive structure, many studies examine the mechanism of high repayment in MFIs based on joint liability (Besley and Coate 1995, Ghatak and Guinnane 1999, Ghatak 1999, Van Tassel 1999, Aghion and Gollier 2000). However, most MFIs in Bangladesh shifted from group lending to individual lending in 2002 (Dowla and Barua 2006).

To mitigate the repayment burden of MFI members, MFIs introduced a flexible repayment system in 2002. The new repayment system allows rescheduling of weekly installments and saving during disasters without charging additional interest. Rescheduling alleviates the binding liquidity constraint. It, however, causes the delay of the next loan disbursement, because borrowers are not allowed to apply for new credit, until they pay off the current debt. MFIs also benefit from rescheduling, since it prevents members, who can not repay temporarily, from dropping out of MFI membership. The significant amount of arrears, however, obstructs the self-sufficiency management of MFIs. Both MFIs and members, therefore, face benefits and costs from rescheduling.

MFIs choose beneficiaries of rescheduling from their poor and flood-affected members. They do not, however, use concrete targeting criteria such as land holding. Once a flood starts, head offices of MFIs pick out the affected districts as the first step. In the second step, local MFI officers at selected branches choose the beneficiaries of the rescheduling treatment. Officers know the members well from group meetings before the disaster, and determine for whom and for how long the MFIs will reschedule installments based on severity of damage and poverty level. In the 2004 flood, the rescheduling mostly started in the middle of July.

2.2 Data Issues and Summary Statistics

This study uses a unique dataset based on interviews with 326 households. A key feature of the data is the availability of the amount and duration of rescheduling. The survey team collected the data in December 2005. The data set consists of both MFI members and non-members.

The sample is based on surveys in 1998, 1999, and 2004 by the International Food Policy Research Institute (IFPRI) (Ninno, Dorosh, Smith, and Roy 2001). The survey team in this study interviewed a part of IFPRI survey households. IFPRI used a stratified random sample of 757 households from 7 districts in Bangladesh. In the first stage of sampling, IFPRI selected seven districts based on flood severity, poverty level, and past research experience: Chadpur, Manikganj, Magura, Barisal, Sunamganj, Narsingdi, and Madaripur. In the second stage, IFPRI chose one Thana from each district, and it chose three unions from each Thana randomly[4]. From each union, IFPRI randomly selected six villages and two clusters from each of the villages. Finally, three households were selected from each cluster.

The data in this paper were collected from three out of the seven districts based on the flood severity, poverty level, geographical properties, and MFIs' diffusion: Chadpur, Manikganj and Magura. Chadpur lies downstream from the rivers and the flood affected this area the most severely of the three. Manikganj is adjacent to the major rivers, therefore damage in this area was also severe. More than 60% of households register MFIs in the district. Magura is relatively poor compared to the other study areas. However, the damage from the flood was moderate since it is far from the major rivers. While IFPRI interviewed 335 households in these three districts, this survey succeeded in interviewing 326 out of them[5]. The survey was designed to collect data on: flood damage, basic demographic information, labor and non-labor income, asset holding, saving, MFI membership, rescheduling, and food consumption. The survey period covers 2 years ranging from January 2004 until December 2005[6].

This study divides the whole survey period into four sub-periods to obtain 1304 observations from 326 households: mid January to mid July 2004, mid July to mid November 2004 (During Flood), mid November 2004 to mid July 2005, and mid July to December 2005. The rescheduling mainly started in the beginning of the second period. Each period corresponds to the agricultural

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4 Thana and union are administrative units of Bangladesh. Each union consists of multiple villages, and each Thana includes multiple unions.

5 The attrition is 2.7% mainly because of migration.

6 There is potentially a concern of the measurement error in the data due to recall bias, since the interviewers asked the livelihood for two years at one time. Yet, the survey used bankbooks of MFIs to alleviate recall bias regarding the record of rescheduling treatment. They describe in detail the records of installment payment, amount of loan, and rescheduling treatment.

calendar in rural Bangladesh. This paper uses only 642 observations for households which include MFI member(s), since it aims to compare outcomes for MFI members with rescheduling to those without rescheduling. Each period includes 141, 148, 174, and 179 observations, respectively.

Table 1 illustrates the change in livelihood through the survey periods. The table shows that income and food consumption declined during the flood. Food consumption was relatively smoothed through periods when compared to income fluctuation. To help members cope with the decline in income, MFIs permitted poor and flood-affected members to reschedule installments. 39% of MFI members received the treatment of rescheduling in the 2004 flood. Also, the average duration and amount of rescheduling were 2.72 weeks and 122Tk per month, respectively[7].

It is noteworthy that people borrowed from moneylenders during the flood more than the other seasons[8]. Quasi credit was not used during the flood, since the flood was a form of covariate shock. It is also noteworthy that loans from banks and MFIs increased after the flood. This might be because they provide loans for investment rather than for consumption. Demand for investment loans increased after the flood to recover from the damage.

Table 2 summarizes the differences in the household characteristics by MFI membership and rescheduling treatment. Note that non-rescheduled members borrow from moneylenders more than non-members. This is consistent with the findings in a series of previous studies, which find that MFI members use moneylenders to repay installments to MFIs. Rescheduled members borrow from moneylenders less than other groups. This paper finds no statistically significant difference between

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[7] 122Tk is equal to 1.4 days of food consumption.

[8] This paper defines credit from moneylenders and quasi credit as credit from non-institutional sources with and without interest, respectively. This is because the term *Mohajon*, which means professional moneylenders in Bengali, also means informal credit contract with interest. According to the classification, minimum interest rate of loan from moneylenders is 10% per year, and average rate is 71.2%.

the rescheduling treatments in terms of the access to other sources of credit.

Also, this table shows the necessity of an econometric methodology to measure the rescheduling effect. The first to fourth rows indicate that the rescheduled group is the poorest and most affected of the three groups[9]. The differences between the rescheduled and non-rescheduled groups are statistically significant.

3 Impact of Rescheduling on Informal Loan with Interest

3.1 Matching Estimation

This section quantifies the effect of rescheduling on credit from moneylenders. The summary statistics reject the random treatment of rescheduling. Neither a regression model with an endogenous dummy variable nor a switching regression model is adequate for this dataset, since the outcome variable, credit from moneylenders, is censored at zero (Wooldridge 2001). Hence, this paper employs the propensity score matching estimator to control for the endogenous rescheduling treatment (Rosenbaum and Rubin 1983, Heckman, Ichimura, and Todd 1998). Matching estimation quantifies how much more the rescheduled member would borrow from moneylenders, if they were not rescheduled. This approach compares the credit from moneylenders for each rescheduled member with members who have similar characteristics to the rescheduled member but did not reschedule installments. The propensity score matching estimation employs only one characteristic: the probability of being rescheduled, given various household characteristics.

The goal of this section is to estimate the average treatment effect to the treated (ATT) defined as

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[9] Income damage is defined as the gap between average monthly income and monthly income. This is considered the approximation of transitory income. Paxson (1992) and Jacoby and Skoufias (1998) utilize the exogenous and unpredictable rainfall information to decompose income into the anticipated and unanticipated parts. This study, however, does not employ this methodology because of data availability.

$E(Y_1 - Y_0 \mid D = 1)$, where D_i takes unity if an observation i is rescheduled, and zero otherwise, and Y_j denotes credit from moneylenders for each rescheduling regime $j=0, 1$. Since $E(Y_0 \mid D = 1)$ is not observable, this paper assumes selection on observables, $Y_0 \perp D \mid X$, where X denotes the set of observable determinants of rescheduling treatment. The assumption means that the non-rescheduled outcome Y_0 is independent of rescheduling treatment D conditional on X. Given this assumption, the following rearrangement is obtained (Rosenbaum and Rubin 1983):

$$\begin{aligned} E\{Y_1 - Y_0 \mid D = 1\} &= E\{E(Y_1 - Y_0 | D = 1, \Pr(D = 1 \mid X)) \mid D = 1\} \\ &= E\{E(Y_1 | D = 1, \Pr(D = 1 \mid X)) - E(Y_0 | D = 0, \Pr(D = 1 \mid X)) \mid D = 1\} \end{aligned} \quad (1)$$

This study estimates the propensity score using a pooled Probit model with the following covariates: damage to income, land holding, liquid assets, household size, ratio of male members over 16 years old to total household size, head of household's years of education, sex, age, religion, the number of MFI he/she attends, and group size of MFI meeting[10]. The first three variables indicate economic status. The next six variables approximate the accumulation of human and social capital, and preference. The last two covariates control for the heterogeneity of MFI characteristics.

Table 3 shows the estimation of the propensity score; 1000Tk of income damage increased the probability of being rescheduled by 2.9% on average; 1000Tk of liquid asset holding reduced the probability by 0.5%. These results indicate that poor and flood-affected members are more likely to be rescheduled. As for demographic variables, households with fewer working age males tend to be rescheduled, while characteristics of the head of the household did not statistically affect the rescheduling decision. In this sample, the more a household participated in MFIs' programs, the less

[10] This paper uses the values in the beginning of each period to alleviate the specification error caused by the simultaneous behavior.

it is likely to be rescheduled.

It is straightforward to verify the validity of the estimated propensity score using the balancing score test (Rosenbaum and Rubin 1983, Dehejia and Wahba 1999; 2002). Conditional on the propensity score, the covariates are independent of assignment of treatment. Figure 1 displays the estimated propensity score and its histogram. It does not reject the null that the means of covariates are the same across groups for any bundle of propensity scores. This implies the validity of selection on observables assumption. Also, this figure shows that there is a positive probability of either being rescheduled or not for any strata of the propensity score; the common support condition, $0 < \Pr(D = 1 \mid X) < 1$, is satisfied in this specification.

The bottom row of Table 3 shows that the estimated rescheduling impact is -42.478 and is significant at the 5% level[11]. It indicates that if the rescheduled members were not rescheduled, they would borrow 42.478Tk per month more from moneylenders; this is about 40% of the average rescheduled amount[12]. This also implies that they would borrow 140% more from moneylenders[13]. This shows that MFI members borrow from moneylenders to repay a fraction of their MFI installments during natural disasters. It also shows that the rescheduling plays a role in reducing credit from moneylenders, which in turn could reduce poverty.

More matching specifications are reported to verify the robustness of the findings. The first specification attempts Difference-in-Differences matching estimation to control for unobservable and time-invariant factors (Heckman, Ichimura, and Todd 1997; 1998). This specification takes first differences between the first and second period, and third and fourth period, since rescheduling is

[11] This study uses radius matching estimation with the radius 0.0025. Also, independent outcomes across units are assumed to derive the standard error.

[12] As is shown at Table 2, the average monthly rescheduled value is 105.98Tk.

[13] The average amount of credit from moneylenders for the rescheduled group is 30.7Tk per month, while the estimated counterfactual amount is 73.2Tk.

rarely observed in dry seasons. The second specification adds district-season dummies in the Probit model to control for time-region heterogeneity. The third specification uses a more strict definition of rescheduling. Specifications 4 and 5 address the possibility of recall bias and contaminated data because of the persistent treatment effect, by dropping the observations in the first period and third period, respectively. Finally, specification 6 adds income damage in the previous period as well as the current period to address persistent flood damage. The results are qualitatively consistent with the benchmark specification.

3.2 Regression Approach

This subsection discusses the robustness of the findings by comparing the results from the matching estimator with maximum likelihood estimation in order to address the consistency-efficiency tradeoff. Matching estimation is considered a data-hungry methodology, but it has the advantage of not assuming a functional form. By contrast, parametric approaches generally require fewer observations, but have a possibility of bias caused by misspecifications.

A Bivariate Probit model is used, where the dependent dummy variables are credit from moneylenders and rescheduling of installments. This specification does not use the information on the amount of credit from lenders, but can reduce the possibility of misspecification.

This estimation employs two variables representing the characteristics of MFIs as instrumental variables: the size of the MFI group and the number of MFIs in which the individual is a member. Since some rescheduling treatments were based on meeting-group-wise decision, the livelihoods of the other meeting members within the same group affect the rescheduling treatment in such cases[14]. They are, however, exogenous for each member. MFI membership and group size can affect access

[14] In some cases, officers rescheduled installments of whole group members, so that officers did not have to organize group meetings.

to treatment. They, however, do not change the demand for moneylenders directly.

Table 4 summarizes the results of the Bivariate Probit model. The estimated coefficient of rescheduling in the first column is negative and significant. Rescheduling reduces the probability of borrowing from moneylenders by 14.4% on average. Also, the table shows that damage to income increases the credit from moneylenders and poor people tend to borrow from them. Although poor and disaster-affected people are likely to borrow from moneylenders, MFIs choose such members as treatment beneficiaries, which decreases the credit borrowed from moneylenders.

4 Change in Rescheduling Effect by Rescheduling Level

This section reveals the change in rescheduling effect with the rescheduling level. To address the issue, this paper employs propensity score matching with multiple treatments (Imbens 2000). Define R_i as the level of rescheduling for observation *i*. If observation *i* is not rescheduled, R_i takes zero. Instead of $\Pr(D=1 \mid X)$, this approach uses a conditional probability of belonging to the rescheduling level *r*, given a treatment level of *r* or zero: $P^{r|r0}(X) \equiv \Pr(R=r|X) / \{\Pr(R=r|X) + \Pr(R=0|X)\}$. The modified version of Equation (1) is

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\begin{aligned}
E\{Y_r - Y_0 \mid R=r\} &= E\{E(Y_r - Y_0 | R=r, \Pr^{r|r0}(X)) \mid R=r\} \\
&= E\{E(Y_r | R=r, \Pr^{r|r0}(X)) - E(Y_0 | R=0, \Pr^{r|r0}(X)) \mid R=r\}
\end{aligned}
\tag{2}
$$

Results from Table 5 are used to estimate propensity scores for each rescheduling level. The table divides the rescheduled group into three levels based on the rescheduled duration to estimate a Multinomial Logit model. In the 2004 flood, the treatments of rescheduling ranged from 1 to 8 installments. The boundaries of these rescheduling levels are based on the percentiles of rescheduling duration. The table shows similar results as were seen in the previous section. The probability of being rescheduled increases with income damage. Also, households with less liquid assets are more likely to be rescheduled. Although the coefficients of these variables are insignificant in the second columns, the signs are consistent with the other columns.

The bottom of Table 5 shows the rescheduling impact by different duration of rescheduling. First, there is no rescheduling effect at the lowest rescheduling level; at least 2 weeks of rescheduling is required during the flood. However, 32% of rescheduling was less than the required amount in the 2004 flood. Second, the gap of rescheduling effect between the medium level and the highest level is smaller than that between the lowest and medium levels. These gaps, however, do not necessarily indicate that the marginal rescheduling effect declines with the rescheduling level. This is because the difference in the estimated parameters can be rewritten as follow;

$$\begin{aligned} E(Y_{r+1} - Y_0 | R = r+1) - E\left(Y_r - Y_0 | R = r\right) &= E\left(Y_{r+1} - Y_r | R = r\right) \\ &+ E\left(Y_{r+1} - Y_0 | R = r+1\right) - E\left(Y_{r+1} - Y_0 | R = r\right) \end{aligned} . \tag{3}$$

The second and third terms on the right hand side indicate the sample selection bias which results from the endogeneity of the rescheduling level, while the first term represents the actual change in rescheduling effect[15].

If MFIs choose the duration and the amount of rescheduling based on members' poverty and damage level, the sample selection terms are expected to be negative. This causes the estimated gaps to overestimate the actual absolute value change in rescheduling effect. It is, therefore, straightforward to discuss the severity of the sample selection bias across rescheduling duration.

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[15] It might be straightforward to directly examine $E\left(Y_{r+1} - Y_r \mid R = r\right)$ using the conditional probability of belonging to the rescheduling level *r+1*, given a treatment level of *r+1* or *r*, so as to estimate the marginal treatment effect. Unfortunately it is, however, impossible because of the small sample size.

Table 5 shows that the specifications based on the Multinomial Logit model estimations do not reject the null that all coefficients of covariates are jointly the same across the rescheduling levels (Chi^2 is 20.49). The result does not change qualitatively even when looking at the coefficients of each variable separately[16]. Only the coefficient of land holding is significantly different across the rescheduling level. Rich members could reschedule installments only for a short duration at best.

This paper assumes that the sample selection bias across rescheduling levels among the rescheduled members is not severe. Figure 2 plots the results from Table 5. This illustrates that the marginal effect of rescheduling declines with the treatment level. This result holds as long as the sample selection term in Equation (3) is negative. This implies the existence of an optimal level of rescheduling, given the costs of treatments.

The decline of the marginal effect might be because of the effect of a binding credit constraint. The rescheduling affects households' saving and consumption level more significantly when they face a credit constraint. However, once this constraint is no longer binding, the impact of rescheduling could be small.

5 Conclusion

This study evaluates the effect of a newly introduced flexible repayment system in MFIs, using unique data from a sample of Bangladeshi households. MFIs aim to help the poor grow out of poverty, and to lessen dependence on moneylenders in rural credit markets. The strictly scheduled repayment system, however, increases the demand for moneylenders during natural disasters as a last resort to repay installment. MFIs are required to cope with the adverse effect of an early repayment system.

This paper shows that the newly introduced flexible repayment structure could play an

[16] The results are not reported in the table.

important role in mitigating members borrowing from moneylenders, which in turn may reduce poverty. However, this paper also reveals some remaining problems in the new repayment system. Although at least 2 weeks of rescheduling is required for a significant impact, 32% of those who received rescheduling did not receive the required level in the 2004 flood. Also, the duration of treatment did not necessarily reflect households' poverty and damage levels, although the poor were more likely to be rescheduled at least.

MFI members borrow from moneylenders to repay a fraction of their installments during natural disasters. This study recommends that the MFIs promote a flexible repayment system particularly in disaster-prone countries. However, MFIs have to be careful in choosing the beneficiaries and the duration of treatment. This paper shows that at least 2 weeks of rescheduling was required, while the marginal rescheduling effect declines with the rescheduling level.

Although MFIs are thought to be an efficient instrument in reducing poverty, they can, under certain circumstances, result in increased poverty and can face problems of sustainable financed management. A significant amount of arrears caused by excessive rescheduling would affect sustainable management, while strict repayment burdens members during disasters. This study uses evidence to examine the tradeoff between these two issues. Further studies are expected to clarify the optimal level of rescheduling, given impacts of rescheduling on the management of MFIs. Unfortunately, this data set does not enable us to discuss these issues, since it has little information on the cost of rescheduling for MFIs.

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Table 1: Summary Statistics of MFI members by Period

	Jan. 15 to Jul. 14 2004		Jul. 15 to Nov. 14 2004 (Flood Season)		Nov. 15 to Jul. 14 2005		Jul. 15 to Dec. 2005	
Variables	[1] Mean	[2] S.D.	[3] Mean	[4] S.D.	[5] Mean	[6] S.D.	[7] Mean	[8] S.D.
(1) Income ($x10^3$ Tk/month)	3.26	4.86	2.57	4.68	3.18	4.51	3.19	6.14
(2) Income Damage ($x10^3$ Tk/month)	-0.16	1.68	0.45	2.05	-0.11	1.32	-0.19	1.90
(3) Land Holding ($x10^6$ Tk)	0.12	0.26	0.12	0.26	0.13	0.29	0.13	0.29
(4) Liquid Asset ($x10^3$ Tk)	14.97	21.70	12.35	19.04	12.02	19.54	12.90	21.59
(5) Food Consumption ($x10^3$ Tk/month)	2.61	1.21	2.44	1.18	2.66	1.27	2.87	1.26
(6) Loan from Bank (Tk/month)	0.00	0.00	0.00	0.00	42.39	266.27	32.40	254.53
(7) Quasi Credit (Tk/month)	0.00	0.00	25.68	221.96	64.59	616.45	100.89	583.44
(8) Loan from Moneylenders (Tk/month)	4.73	44.29	108.11	845.74	105.03	443.44	84.92	304.92
(9) Loan from MFIs (Tk/month)	385.34	662.83	336.15	684.94	641.52	829.59	1041.79	1741.36
(10) Installment to MFIs (Tk/month)	108.50	232.23	54.38	145.77	232.60	394.55	285.71	526.87
(11) Dummy=1 if Rescheduled	0.00	0.00	0.39	0.49	0.02	0.15	0.09	0.29
N	141		148		174		179	
Only for Rescheduled Members (Total observation: 79)								
(12) Rescheduled Duration (weeks)	-	-	2.72	1.78	1.00	0.00	1.20	0.41
(13) Amount of Rescheduling (Tk/month)	-	-	122.38	124.19	38.94	33.85	52.60	36.11
N	0		57		2		15	

Table 2: Summary Statistics by MFIs Membership and Rescheduling Treatment

Variables	Not MFI Members		Rescheduled Members		Members without Rescheduling		Mean Difference [3]-[5]
	[1] Mean	[2] S.D.	[3] Mean	[4] S.D.	[5] Mean	[6] S.D.	[7]
(1) Income ($x10^3$ Tk/month)	2.61	4.06	1.77	1.46	3.24	5.42	-1.47***
(2) Income Damage ($x10^3$ Tk/month)	0.05	1.53	0.31	0.81	-0.06	1.86	0.37***
(3) Land Holding ($x10^6$ Tk)	0.22	0.39	0.08	0.15	0.13	0.29	-0.05***
(4) Liquid Asset ($x10^3$ Tk)	19.74	38.48	5.91	6.57	13.98	21.56	-8.07***
(5) Food Consumption ($x10^3$ Tk/month)	2.78	1.75	2.20	0.71	2.72	1.29	-0.53***
(6) Household Size	6.51	2.88	5.67	1.72	6.26	2.39	-0.59***
(7) Ratio of Male Over 16	0.33	0.16	0.30	0.15	0.33	0.16	-0.04**
(8) Educated Year of Head	4.03	4.29	2.14	3.28	2.50	3.45	-0.37
(9) Female Head Dummy	0.12	0.32	0.10	0.30	0.09	0.29	0.01
(10) Age of Head	52.48	13.75	46.46	10.28	48.14	11.95	-1.69
(11) Hindu Dummy	0.10	0.29	0.08	0.27	0.10	0.31	-0.03
(12) Loan from Bank (Tk/month)	35.23	335.18	41.14	263.82	17.63	181.73	23.51
(13) Quasi Credit (Tk/month)	213.26	1114.79	25.93	115.27	55.15	487.24	-29.22
(14) Loan from Moneylenders (Tk/month)	56.51	453.96	30.70	168.37	84.75	524.49	-54.06*
(15) Loan from MFIs (Tk/month)	-		495.89	927.69	644.78	1172.20	-148.90
(16) Installment to MFIs (Tk/month)	-		110.14	282.34	188.74	390.98	-78.60**
(17) # of MFIs Membership	-		1.14	0.38	1.25	0.51	-0.11**
(18) Group Size of MFIs	-		12.43	12.36	10.76	11.81	1.67
(19) Rescheduled Duration (weeks)	-		2.36	1.70	-		-
(20) Amount of Rescheduling (Tk/month)	-		105.98	114.09	-		-
N	662		79		563		

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

Table 3: Propensity Score Matching with Probit Model

	Dummy = 1 if rescheduled	
Variable	Coef.	Marginal Effect
Income Damage	0.172*** (0.058)	0.029
Land Holding	-0.141 (0.400)	-0.024
Liquid Asset	-0.029*** (0.009)	-0.005
Household Size	-0.037 (0.035)	-0.006
Ratio of Male Over 16	-0.876* (0.533)	-0.147
Education	0.012 (0.023)	0.002
Female Head Dummy	-0.035 (0.227)	-0.006
Age	0.005 (0.007)	0.001
Hindu	0.157 (0.268)	0.029
# Membership	-0.278* (0.165)	-0.047
Groups Size	0.002 (0.005)	0.0003
N	636	
Rescheduling Effect		
Benchmark Estimation	-42.478** (19.212)	
DID Matching#	-139.368** (55.726)	
District-Season Fixed Effect#	-55.933** (27.815)	
Strict Definition of Rescheduling#	-40.494** (19.903)	
Recall Bias	-57.645** (23.977)	
Persistent Rescheduling Effect	-40.630* (21.619)	
Persistent Flood Damage#	-192.177*** (56.265)	

Standard errors are in parentheses.
*** 1% significant, ** 5% significant, * 10% significant, respectively
# The other propensity scores are estimated by Probit models, but they are not reported since they give qualitatively similar results to the benchmark estimation.

Table 4: Rescheduling Effect with Bivariate Probit Model

	Credit from Moneylenders		Rescheduling Dummy	
	Coef.	Marginal Effect	Coef.	Marginal Effect
Rescheduling Dummy	-1.538*** (0.228)	-0.144	-	-
Income Damage	0.097** (0.048)	0.018	0.163*** (0.051)	0.028
Land Holding	0.340 (0.313)	0.063	0.152 (0.371)	0.027
Liquid Asset	-0.012* (0.007)	-0.002	-0.028*** (0.008)	-0.005
Household Size	-0.019 (0.033)	-0.003	-0.045 (0.035)	-0.008
Ratio of Male Over 16	-0.427 (0.494)	-0.080	-0.720 (0.523)	-0.125
Education	-0.029 (0.025)	-0.005	0.012 (0.022)	0.002
Female Head Dummy	-0.048 (0.213)	-0.009	-0.051 (0.221)	-0.009
Age	0.000 (0.007)	0.000	0.003 (0.007)	0.001
Hindu	-0.287 (0.334)	-0.046	0.049 (0.266)	0.009
# Membership	-	-	-0.251* (0.138)	-0.044
Groups Size	-	-	-0.003 (0.004)	-0.001
N	636			

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

Table 5: Change in Rescheduling Effect with Rescheduling Level

Dependent Variable	Rescheduling Level		
Duration of Rescheduling	1 week	2 weeks	More than 2 weeks
Income Damage	0.271*	0.229	0.601***
	(0.142)	(0.182)	(0.207)
Land Holding	0.132	0.831	-8.110*
	(1.296)	(0.991)	(4.136)
Liquid Asset	-0.054*	-0.042	-0.065**
	(0.031)	(0.027)	(0.032)
Household Size	-0.110	-0.167	0.088
	(0.108)	(0.118)	(0.113)
Ratio of Male Over 16	0.055	-4.292**	-0.729
	(1.588)	(1.747)	(1.735)
Education	-0.011	-0.049	0.061
	(0.073)	(0.076)	(0.079)
Female Head Dummy	-1.195	0.154	0.721
	(1.041)	(0.613)	(0.702)
Age	0.004	0.027	-0.006
	(0.020)	(0.021)	(0.025)
Hindu	-0.729	1.411**	0.000
	(1.079)	(0.689)	(1.117)
# Membership	0.016	-0.396	-1.809*
	(0.436)	(0.541)	(1.031)
Groups Size	-0.019	0.022	0.016
	(0.021)	(0.014)	(0.015)
N		631	
H_0: 3 coefficients are the same in each covariate, Chi^2		20.49	
H_0: All coefficients are zero, Chi^2		56.81***	
Rescheduling Effect (ATT)	-42.682	-68.452***	-96.622***
	(47.521)	(17.535)	(23.794)

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

Figure 1: Estimated Propensity Score

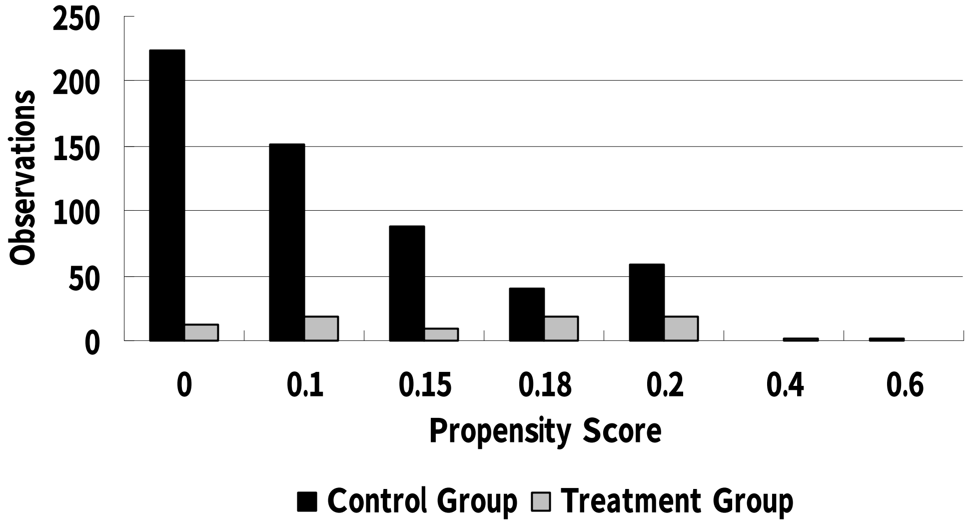
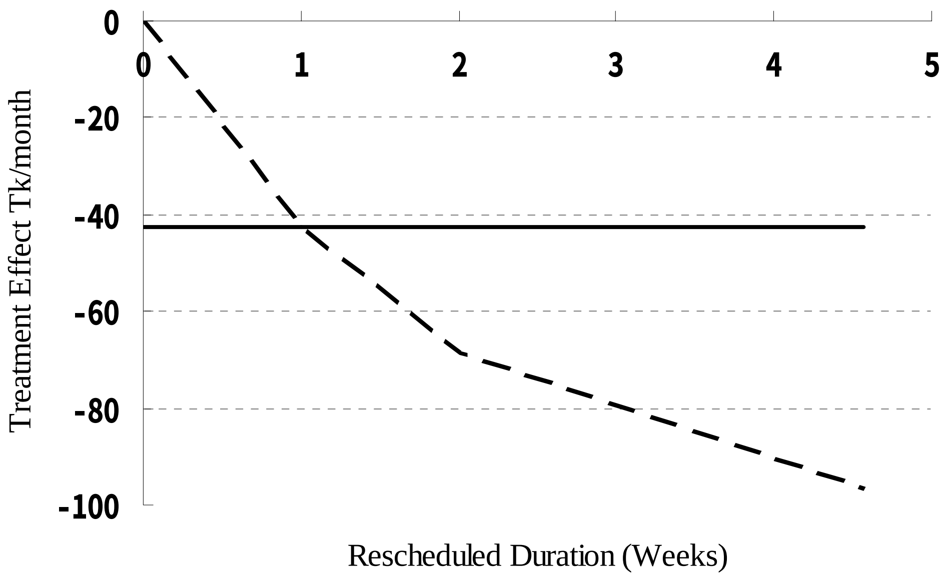


Figure 2: Change in Rescheduling Impact by Duration of Rescheduling



Auxiliary line indicates the average treatment effect (-42.5Tk/month)