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How Does Contract Design Affect the Uptake of Microcredit among the Ultra-poor?: Experimental Evidence from the River Islands of Northern Bangladesh*

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November 2014

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Abstract:

Despite the professed claims of microcredit alleviating poverty, little is known about what kind of credit contract is suitable for extremely poor households, also called the ultra-poor. To fill this knowledge gap, we initiated a field experiment in the river islands of northern Bangladesh, where a substantial portion of dwellers could be categorized as ultra-poor due to cyclic floods. We randomly offered four types of loans to such dwellers: regular small cash loans with one-year maturity, large cash loans with three-year maturity both with and without a one-year grace period, and in-kind livestock loans with three-year maturity and a one-year grace period. We compared uptake rates as well as the determinants of uptake and found that the uptake rate is the lowest for the regular contract, followed by the in-kind contract. Contrary to prior belief, we also found that the microcredit demand by the ultra-poor is not necessarily small, and in particular the ultra-poor are significantly more likely to join a microcredit program than the moderately poor if a grace period with longer maturity is attached to a large amount of credit, irrespective of whether the credit is provided in cash or in kind. This paper provides evidence that a typical microcredit contract with one-year maturity and without a grace period is not attractive to the ultra-poor. Microfinance institutions may need to design better credit contracts to address the poor's needs.

Keywords: Microcredit, uptake, ultra-poor, program design, Bangladesh
JEL Classification: D12, G21, O12, O16

1. Introduction

It is widely recognized that lack of access to the formal financial market is among the major impediments keeping poor households in developing countries from improving their livelihoods (Kono and Takahashi, 2010). A recent innovation in poverty alleviation has been the emergence of microcredit, which provides collateral-free loans of small value to low-income households that have been deemed unbankable. Based on success in the form of high repayment rates worldwide, microfinance institutions (MFIs) have increased rapidly. As of 2010, they attract more than 205 million clients around the world (Maes and Reed, 2012). In 2006, a microcredit front-runner, the Grameen Bank, and its founder, Professor Yunus, were awarded the Nobel Peace Prize for their contribution to poverty reduction.

Despite growing enthusiasm regarding its potential, however, recent rigorous empirical studies have shown that microcredit is not a silver bullet for poverty reduction (Karlan and Zinman, 2011; Banerjee et al., 2013; Creon et al., 2013; Roodman and Morduch, 2014). In particular, many existing studies note that the poorest of the poor, or the ultra-poor, have been excluded from microcredit services (Morduch, 1999; Navajas et al., 2000; Duong and Izumida, 2002; Copestake et al., 2005; Cuong, 2008). For example, Copestake et al. (2005) find that microcredit programs in Zambia are not reaching the extremely poor, but are mainly targeting households at the upper margins of poverty, some even targeting those above the poverty line. Similarly, Navajas et al. (2000) show that five MFIs in Bolivia work with households just above and below the poverty line, but not with the extremely poor, and Lonborg and Rasmussen (2014) conclude that microfinance in nothern Malawi adopts regressive targeting.

There seem to be both demand- and supply-side constraints on the provision of microcredit to the ultra-poor. On the one hand, MFIs may hesitate to lend money to the ultra-poor due to fear of their high default risk. It is widely believed that the ultra-poor demand cash more for meeting daily ends rather than for productive investment to expand a business, even though MFIs often require clients to use their loans only for business purposes (see e.g., Karlan and Zinman, 2012). Ghana's case shows that returns to credit to the poor are significantly higher when credit is provided in kind rather than in cash presumably because the credit is partly used outside of microenterprises (Fafchamps et al., 2014). The existence of this so-called flypaper effect, whereby "capital coming directly into the business sticks there, but cash does not" (Fafchamps et al., 2014), is likely to increase the probability of default. Moral hazard may also be more severe for the ultra-poor if they are more mobile than the moderately poor and non-poor because of their lack of immobile assets.

On the other hand, the expected returns to credit may not be sufficiently high for the ultra-poor, thereby inducing them to exclude themselves. Indeed, while existing studies show high average returns to capital in self-employed- or micro-enterprises on which most microcredit is placed (Udry and Anagol, 2006; de Mel et al., 2008; Fafchamps et al., 2014), evidence has accumulated that not every client can benefit from microcredit: Banerjee et al. (2014) show that impacts on income are positive only for households with an existing business or those who manage to start a business, while de Mel et al. (2008) find that returns to credit significantly differ with clients' entrepreneurial ability and household wealth. These findings imply that the expected returns to credit could be low for the ultra-poor, who are characterized by less experience or willingness to participate in self-employed activities due to risk aversion as well as a lack of entrepreneurial ability. Exclusively targeting the ultra-poor in India, Morduch et al. (2013) provide supporting evidence that microcredit programs for the ultra-poor result in neither significantly greater total income nor asset accumulation by its clients.

Irrespective of whether these possible supply- and demand-side constraints actually bind, the ultra-poor have long been excluded from microcredit services despite the professed goal of microcredit to improve the welfare of the poor. Yet, assumptions that the ultra-poor have a smaller demand for microcredit and/or that expected returns on ultra-poor lending are lower than on moderately poor lending have not been adequately validated. If these assumptions are incorrect, they would adversely affect not only efficiency but also equality. To prove the bankability of the ultra-poor, therefore, rigorous analysis is clearly required. Although prior studies have explored heterogeneous returns to microcredit (de Mel et al., 2008; Banerjee et al., 2014), little work has examined heterogeneous demands for microcredit across wealth classes. Also, while some studies have examined how microcredit contract designs affect repalyment rates and returns to credit (de Mel et al., 2008; Field and Pande, 2008; McKenzie and Woodruff, 2008; Fischer and Ghatak, 2010; Field et al., 2013; Fafchamps et al., 2014; Gine and Karlan, 2014; Shonchoy and Kurosaki, 2014), few have explored what microcredit designs suit the poor’s needs. According to Field et al. (2013), more risk-averse clients generally benefit more if a grace period is provided in the repayment schedule. Hulme (1999) discusses that poorer clients are more likely to drop out from microcredit sevices if a high-value loans are offered. Do these observations imply that a microcredit contract with a smaller value and/or with a grace period induces a higher probability of participation among the extremely poor? Alternatively, do the ultra-poor demand loans of large amounts from the beginning if there is non-convexity in technology and they need a lumpy investment at the beginning of the project to move them out of poverty traps (Banerjee and Newman, 1993; Galor and Zeira, 1993; Lybbert and Barrett, 2010)?

To fill this knowledge gap, this study sheds light on differential uptake rates across microcredit designs between the ultra-poor and moderately poor. Our sample comprises households that expressed interest in microcredit. We then randomly offer a particular type of microcredit product to these households. Between notification of random assignment and actual loan distribution, we ask their willingness to join the microcredit program. This survey structure permits us to effectively exclude the possiblity that those who drop out from our program at the second participation decision are the ones who fail to repay loans and are thereby forced to leave or the ones who graduate from microcredit with success. Thus, unlike previous studies, which do not clearly distinguish dropouts from defaulters and graduates (Hulme, 1999; Siliki, 2012), our survey provides a unique opportunity to determine the pure preferences of the poor regarding loan contract types. To explore this issue in detail, this study employs microdata generated from our randomized controlled trial in the river island areas in northern Bangladesh, where periodic floods and land erosion severely affect the livelihoods of its dwellers, making the majority of the population vulnerable and poor.

More specifically, we introduced the following four treatment arms. The first treatment arm is a regular microcredit program with a small loan amount, which requires clients to start repayment two weeks after receiving the loan, with one-year maturity. The second treatment arm provides a loan that is three times larger than the regular program, with three-year maturity. The third treatment arm adjusts the second one, giving borrowers a one-year grace period before they start repaying but offers the same three-year maturity (effectively repaying in two years). The last treatment arm is the in-kind loan with necessary services to implement a microenterprise project using the loan as an investment. This arm has the same features as the third arm except for the fact that the loan is provided in kind. The designated in-kind investment is a cow, as suggested by numerous NGOs and other community-based organizations in the study site as the most popular and plausibly the only viable investment option for microfinance program borrowers. In comparison to smaller livestock such as goats, cows are more versatile in flood-prone areas, while they require the maximum of one year to start giving milk, which corresponds to the grace period length provided under the third and fourth treatment arms. Additional services to assist dairy production, such as animal fodder, veterinary services, training programs, and marketing consultancy services were also provided. It is expected that the in-kind credit (or a lease) program thus designed would overcome the problem of lack of entrepreneurial experience and ability of the ultra-poor.

Our results show that, among both the moderately poor and ultra-poor, the uptake rate is lowest for the regular contract, followed by the rate for the in-kind contract. It is also found that the ultra-poor's microcredit demand is not necessarily small, and in particular, the ultra-poor are significantly more likely to join the program than the moderately poor if a grace period with longer maturity is attached to large-scale loans, irrespective of whether the credit is provided in cash or in kind.

The rest of the paper is organized as follows. Section 2 explains the study site, sampling framework, and detailed designs of the randomized microcredit contract experiment. Section 3 discusses summary statistics of the sample households. Section 4 outlines the estimation strategy, followed by a discussion of the estimation results in

Section 5. Section 6 concludes the paper.

2. Study Settings

2.1. Study Area

The study was conducted in the river island areas, known as *Chars* in Bengali, of northern Bangladesh in Gaibandha and Kurigram districts. *Chars* are formed by sediments and silt depositions, and are prone to cyclical river erosion and floods. *Chars* are, by nature, not stable in size and even in existence, and episodes of their partial or complete erosion or sub-merging are quite common. *Chars* accommodate ultra-poor inhabitants who are forced, as a desperate attempt for survival, to relocate across islands due to river erosion and floods (Barkat et al., 2007; Shonchoy, 2014). Seasonal floods periodically occur during the wet seasons as monsoon precipitation swells the river together with glacial melting of the Himalayas, causing heavy downstream inflows of water that pass through the rivers of Bangladesh to reach the Bay of Bengal.

Boats are the major mode of transportation in *Char* areas. The majority of boat services are run by the informal sector, and the services are vulnerable to bad weather conditions and are infrequent. Due to the poor transportation infrastructure, few governmental services, like health and education, are available (Marks and Vignon, 2008). *Char* dwellers have extremely limited access to regular markets. Provision of national grid electricity is rare, and hardly any *Chars* have been properly electrified by the Rural Electrification Board of Bangladesh. Even microfinance services are scarce on *Chars* despite widespread networks of MFIs in northern Bangladesh (Khandker, 2005).

2.2. Sampling Strategy

The sampling of our survey involves multiple stages, or a double-stratified two-stage clustered sampling; in the first stage, we selected *Chars* (villages, as the primary survey unit: PSU), and in the second stage, we selected households (as the secondary survey unit: SSU). In both stages, we stratified PSU and SSU. Our sample frame is poor residents of island *Chars* without MFI activities in Gaibandha and Kurigram districts. We describe the detailed procedures of the sampling strategy below.

***Char* selection:** *Chars* could be categorized as islands, peninsulas, or bridged *Chars* based on the existing connection with river banks. The present study mainly concentrated on island *Chars*, which are completely detached from river banks.[1] We initially used Landsat images to identify sample *Chars*. Given that *Chars* are unstable, we needed to use the most recent images (April, 2012) before the time of the baseline survey (September–October, 2012). By visual inspection, we counted the number of *Chars* throughout the image and inspected all *Chars* by field visits. Figure 1 shows the number of points on the Landsat image where GPS coordinates were measured to determine the rough location information of each *Char*. Upon a field visit, the local area staff of our counterpart NGO, Gana Unnayan Kendra (GUK)[2] identified the name of each *Char* and verified the existence of inhabitants on the *Char*. GUK provided us with a list of all the villages over the points shown in the image (Figure 1).

Once we identified *Chars*, we collected detailed information on existing program coverage or development assistance run by different NGOs or humanitarian

[1] Peninsula *Chars* are divided by small, perennial streams or sometimes even merely connected to river banks when the water level is low. Bridged *Chars* are a type of island *Chars* lying next to a river bank and are connected by an earthen passage.

[2] GUK is an NGO with 28 years of experience conducting development and microfinance activities in northern Bangladesh and one of the very few NGOs that works directly with *Char* dwellers.

agencies in different villages on these *Chars*. Our aim was to select only those villages without pre-existing microcredit activities by other MFIs. We did not find it difficult to locate *Chars* without microfinance services, as most MFIs in northern Bangladesh target clients predominantly from the mainland areas. We found a few *Char* villages having some NGO coverage, with these NGOs mainly conducting non-financial activities, such as education or health provision, or disaster-related relief and support activities. We took particular care not to select any village under the existing coverage of the Chars Livelihoods Program (CLP), which makes attempts similar to our interventions.[3] Through these procedures, we collected information on 128 *Chars* that fulfilled our selection criteria, and out of this list, we randomly selected 80 *Chars*, stratified based on the distance to nearby boat stations.

Household selection: Household selection within each village was conducted in two steps. In the first step, employing the participatory rural appraisal (PRA) method with the help of local elites, religious leaders, and GUK staff members, we listed all the households in each village and ranked them according to their wealth categorization (non-poor, moderately poor, or ultra-poor) based on GUK's wealth gradation criterion.[4]

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[3] The Chars Livelihoods Program (CLP) is jointly funded by the UK and Australia through the Department for International Development and the Australian Agency for International Development (AusAID), respectively, to move extremely poor households living on *Chars* in northwestern Bangladesh out of poverty. CLP has designed a packaged grant intervention that consists of an asset purchasing fund, stipends, and other social interventions, given to beneficiaries selected through eligibility criteria.

[4] The eligibility criteria used by GUK to identify an ultra-poor household are households: a) without any source of regular income and/or totally dependent on other people; b) exposed to chronic food insecurity, i.e., members of the households often skip meals due to food insufficiency; c) with gross monthly per capita income below Tk. 800; d) without any land or shelter on embankment or other place; e) with at least one family member suffering from malnutrition; f) with at least one family member with disability and/or chronic illness; g) without any livestock or productive assets that generate income. The criteria to

Then, GUK officials randomly visited the listed ultra-poor households to verify whether the categorization was carried out accurately and truthfully, following which the list was sent to the research team. Typically, it took three working days to complete all the required tasks for one village.

Once we received the list of all the households that reside in a village on a particular *Char*, we separately listed a group of ultra-poor households (UP) and a group of moderately poor households (MP) households. Then, in each group, we randomly re-arranged the order of households. These two sequences of household names,[5] which were randomly ordered in a mutually exclusive way, were sent back to GUK to select 14 UP and 6 MP from each village on the *Char*. We included both UP and MP households to determine the differential demands for our planned interventions. A larger weight was given to UP than MP households, in a 7 to 3 ratio, since the majority of *Char* dwellers belong to the UP category. The group size for each village was kept at 20 to follow the GUK's typical microcredit group size, where loans are distributed with individual liability, but a group is formulated for the purpose of peer monitoring.

Using the above-mentioned random sequences, GUK was instructed to give an offer of microcredit group membership to households such that there would be four different credit products assigned randomly at the group level, but the group members at the time of registration did not know which one of the four they would be assigned. Residents were also notified that the treatment status will be randomized among each group, so there is a chance of being in the control group. If the household accepts the

distinguish a moderately poor household from the non-poor are similar, only with higher thresholds than the above.

[5] By *name*, we mean the eligible female member/s of the household as GUK's microcredit program is given only to women.

condition, it is offered formal microcredit group membership; if it rejects the offer, another household is drawn from the randomly ordered list to be offered a membership. This process is repeated until the target group size of 20 households per village is secured, with 14 UP and 6 MP members. Following this process, we created 80 groups of 20 potential clients each, with one group per *Char* village.

After the group formation, a detailed survey (baseline survey) was administered to understand the socioeconomic conditions of *Char* dwellers. The survey included questions on household and personal characteristics; details of land holding and leasing; durable and non-durable asset information; and debt, savings, and credit information. The detailed timeline of our survey and sampling steps are given in Figure 2.

2.3. Experimental Design

Once our baseline survey was completed, we implemented the randomized credit offer in two levels: *Char* and household levels. First, we randomly allocated 80 groups of *Char* villages into one of the following four treatment arms (clustered randomization). Second, within each *Char*, the credit was given only to 10 (i.e., 7 UP and 3 MP) randomly selected households (hereafter, treated households) in the initial phase, and other members (hereafter, control households) would need to wait at least for a year to receive credit. On the whole, we had 800 treatment and 800 control households with village-level clustered randomization across four treatment arms as follows:

Regular microcredit (RC): The design of this treatment arm is similar to that of the flagship Grameen-style microcredit lending, which is widespread in Bangladesh. Under this treatment arm, members of the group will receive 5,600 taka credit, with loan repayment to begin two weeks after disbursement. The amount is approximately 8% of the average annual household income according to our baseline survey. Members will repay under a weekly repayment scheme and will be required to attend weekly meetings as well as to regularly save an amount decided jointly by the group members. The contract maturity of this loan is one year, and if borrowers successfully repay the due amount following the repayment discipline, they are eligible for another two loan contracts of equivalent amounts over the next consecutive years. The required regular weekly repayment for this group is 125 taka, payable in 50 weekly installments.

Large credit, without a grace period (LC): Under this treatment arm, group members will receive 16,800 taka credit with a longer period of loan maturity, where loan repayments begin two weeks after disbursement The loan repayment discipline is the same as in the RC groups. The contract maturity period of this loan is three years. The required weekly repayment for this group is 125 taka payable in 150 weekly installments (for three years).

Large credit, with a one-year grace period (LC + GP): Under this treatment arm, group members will receive 16,800 taka credit with loan repayments to begin one year after disbursement. The loan repayment discipline is the same as in the RC groups. However, during the first year grace period, members are required to meet weekly and follow group activities such as compulsory savings. The contract maturity of this loan is three years. The required weekly repayment for this group is 190 taka payable in 100 weekly installments, starting after one year.

In-kind credit, with a one-year grace period (IK + GP): Under this treatment arm, group members will be eligible to receive in-kind credit in the form of a cow, within the price range of 16,000 taka with loan repayment to begin one year after disbursement. In addition, the members will receive fodder, training on cow rearing, regular VET and vaccination services, and marketing consultancy services from the GUK authority, worth 800 taka for the entire service given over three years. The loan repayment discipline and contract maturity of this in-kind loan are the same as the LC + GP groups. The required weekly repayment for this group is 190 taka payable in 100 weekly installments, starting after one year. Detailed designs of our randomization protocol and treatment arms are given in Figure 3.

After the clustered randomization for different treatment arms at the village level, we randomly selected 7 UP and 3 MP households from each group for the initial loan distribution. We kept the rest as waiting members who need to wait for at least a year to become eligible to borrow, but still need to attend weekly meetings. It was also explained that the type of credit to be offered to the control households would be the same as that offered to the treatment households within the same group.[6]

Once this two-level randomization was completed, we announced the randomization results to our group members and explained that they would need to decide whether or not to accept the offer before the actual loan disbursement. It is important to note that the initial registration was made before the specifics of the arms were revealed, and all the subjects in our sample agreed to participate at that time. So no selection had occurred by the time of compliance according to the specific contents of each arm, except for the fact that they selected themselves into an unknown microfinance program. This gives us an opportunity to study the clients' response to various types of microcredit contracts, which has not been clearly addressed in the

[6] The objective to have control households is to create exogenous variations within the group to identify the impact of credit, which will be examined in detail in future research.

previous literature.

3. Summary Statistics

3.1.Household Characteristics and Balance Test

Table 1 presents selected demographic and wealth information for the sample households, collected before announcement of the treatment arms and credit eligibility. To examine whether the clustered randomization functions as expected, the means in differences between the RC group (the reference group) and each of the other three groups are also compared at the household as well as the group level, where the group-level mean differences are computed by setting the group as the unit of observation.

The annual total household income is, on average, 73 thousand taka (equivalent to USD903).[7] Approximately 55% of sample households are classified as poor if we set a daily per capita income of 49.56 taka as a poverty line, following the Bangladesh Bureau of Statistics' computation of regional poverty lines used in Household Income and Expenditure Survey in 2010. The majority of *Char* dwellers are actively engaged in wage employment, including temporary migration (Shonchoy and Kurosaki, 2014). Indeed, the predominant source of income for our sample households is wage employment, followed by non-farm enterprises. The role of agriculture is minor partly because less than 1% of the sample households report owning agricultural land and partly because productivity and cropping intensity are substantially low due to the infertility of the sandy soil and periodic flooding. Livestock and poultry provide supplementary income to sample households; 48% of the households had, at least once,

[7] 1 USD is equivalent to 97 BDT as of September 2012.

raised livestock, especially small animals like goats or cows through an informal leasing contract, locally known as *Adhi*. At the same time, as the average number of current cattle holdings, including cows, oxen, and calves, is small (less than one, as shown in the table), the percentage contribution of livestock to total household income is small.

The average household size is slightly more than four, with the dependency ratio (number of household members below 15 and above 65 years relative to the number of household members between 15 and 64 years) equal to approximately 0.9. The average age of the household head is 39 years, and about 91% of them are male. Many household heads have never received formal education, with the average years of completed education well below one year. The sample households have lived in the current location for 5 years, with approximately 70% of them being in the Gaibandha district.

As far as balance tests are concerned, overall balance seems to be achieved, but some variables are significantly different across treatment arms. For example, the average years of education for household heads are highest within the IK + GP group, followed by those in the LC group, both of which are statistically significantly longer than in the RC group. It is also revealed that years in current location are significantly longer among the LC group than in the RC group. Given that our randomization was at the village level and we have only 80 sample villages, such imbalances may be unavoidable. Since the treatment arms are randomized, however, covariate imbalance will not result in inconsistent estimates. Yet, to control for finite sample biases caused by imbalances in baseline characteristics, we will include them as control variables in our regression analysis.

3.2. Uptake of the Microcredit Program

Table 2 reports group- and household-level uptake status by treatment arms and rejection types. In Table 2A, the top panel shows the total number, while the middle and bottom panels show the number within the treated households that are eligible to receive credit immediately and control households that should wait for more than a year to become clients, respectively. We presume that the reasons for rejecting the offer will differ between treated and control households. Namely, the treated households may reject the offer if the offered credit design does not suit their needs while the control households may reject it if they do not want to wait for a long period, during which they have to attend weekly meetings; this could be an additional reason to the mismatch of the offered credit design with their needs.

Out of these 80 groups, 4 groups were not able to join the program because they were affected by erosion and forced to relocate after early November 2012. Because each erosion-affected household had to find a new location geographically scattered over *Chars*, transaction costs to trace them became prohibitively high. As a result, we were not able to continue their involvement in the microcredit program. As this appears to be a purely exogenous event, we exclude them from the subsequent discussion.

Out of the remaining 76 groups, 7 groups voluntarily quit the program after learning the random credit product assigned to the group. We call the event a *Group rejection*. The remaining 69 groups, which remained in the program, had 1,380 initial members. Out of these, 169 individuals voluntarily quit the program after learning the random credit product assignment to the group and the random assignment of the treatment status (immediate credit or waiting) to the individual. We call these events

Individual rejections. This implies that, on average, 2.4 individuals out of 20 members rejected the program when the group as a whole accepted the program.

As can be seen, the uptake rate is lowest in the RC group. Among 360 households in this arm who were not affected by erosion, only 226 (62.8%) households remained in the group after the randomization was announced. Group rejection is more prevalent. The rates for individual rejection do not differ greatly between the treated and control households within the RC arm.

Interestingly, the second lowest uptake rate observed is among clients of the IK + GP group (with an uptake rate of only 80%). This is surprising, as our *a priori* conjecture was that given limited investment choices in the study area, in-kind livestock credit should be no less attractive than cash credit. In fact, we obtained the impression from our counterpart NGO that the IK + GP arm might be even more attractive because it can reduce transaction costs to buy livestock animals in the market and can provide an opportunity to join training to enhance clients' livestock-rearing skills. However, as apparent from Table 2A, the uptake rate in the IK + GP group is much lower than that in the LC and LC + GP groups, and the detailed analysis shows that these differences are statistically significant. By contrast, the difference in uptake between the LC and LC + GP groups seems to be statistically negligible.

Table 2B shows the pattern of individual-level rejection within a group. Out of the 69 groups that did not reject the program as a group, 29 groups had no individual-level rejection, 13 groups had only one rejection, 15 groups had 2 to 5 rejections, 7 groups had 6 to 9 rejections, and 5 groups had 10 or more rejections. The percentage of complete acceptance (no occurrence of individual-level rejection) was higher among the LC and LC + GP arms.

In sum, in the bivariate analysis, we found that the uptake rate of the IK + GP arm was greater than the RC arm but significantly smaller than both the LC and LC + GP arms.

4. Estimation Strategy

4.1. Conceptual Framework

To derive an empirical strategy to estimate uptake decisions, let us discuss a simple framework. We observe uptake result j for individual i belonging to group g, which is offered credit product type k and treatment status t. We denote the uptake result by a dummy variable Y_{igkt}^{j}, where $j =$ 1 (Accept), 2 (Individual rejection), and 3 (Group rejection); $i = 1,2,...,20$; $g = 1,2,...,76$; k = 0 (RC: traditional), 1 (LC: large credit without grace period), 2 (LC + GP: large credit with grace period), and 3 (IK + GP: in-kind credit with grace period); and t = 0 (Control: asked to wait for a year) and 1 (Treatment: offered the credit immediately). We estimate a regression model where Y_{igkt}^{j} is used as the left-hand-side variable while other observables are employed as right-hand-side (R.H.S.) variables. Because the three uptake results are mutually exclusive, $\sum_j Y_{igkt}^{j} = 1$.

Let us also define the group-level uptake decision dummy, Y_{gk}, which takes the value of 0 if group rejection occurred and 1 if group rejection did not occur. In other words, if $Y_{igkt}^{3} = 1$, then $Y_{gk} = 0$ (remember that if $Y_{igkt}^{3} = 1$, then $Y_{i'gkt}^{3} = 1 \quad \forall i' \in g$); if $Y_{igkt}^{1} = 1$ for some i in g, then $Y_{gk} = 1$.

As a benchmark to understand uptake decision-making at the group level, we assume a simple model of majority voting without member interactions. Individual members have an unobservable, latent variable V_{igkt}, which is defined as the net benefit for individual member i in group g from continuing as a member in the program, where the group is randomly assigned to product k, and the member is randomly assigned to treatment t. A critical assumption is that V_{igkt} does not depend on other members' net benefit $V_{i'gkt}$ or group-level decision-making. This is what we mean by *without member interactions*.

We can further assume that V_{igkt} comprises a part determined by a function of observables and an additional component of zero-mean, i.i.d., unobservable factor, e_{igkt}:

$$V_{igkt} = f(X_{ig}, X_g, D_{gk}, D_{igt}) + e_{igkt}, \tag{1}$$

where $f(.)$ is an unknown function, X_{ig} is individual characteristics of member i in group g, X_g is group characteristics for group g, D_{gk} is a dummy variable for group g randomly assigned credit offer k, and D_{igt} is a dummy variable for individual i in group g randomly assigned to treatment status t.

The twenty members in group g then vote for group-level acceptance or rejection based only on their own net benefit. Each member casts his or her vote in favor of acceptance if $V_{igkt} \geq 0$ or in favor of rejection if $V_{igkt} < 0$ (assuming a continuous function for V_{igkt}, it is irrelevant whether the strict inequality is in acceptance or rejection).

The group leader simply counts the number of votes in favor of rejection. If the number favoring rejection (i.e., the number of members whose $V_{igkt} < 0$) is above the threshold value (under the simple majority rule, the threshold is 10; under the two-third majority rule, it is 13), then group rejection occurs. For simplicity, we assume for the moment that the threshold is the same for all groups.[8]

If the group jointly decides to reject the program, we observe $Y_{igkt}^{1} = Y_{igkt}^{2} = 0$ and $Y_{igkt}^{3} = 1$ for all i belonging to group g.

If the group jointly decides to accept the program, each of the twenty members decides whether or not to remain in the program purely considering his or her own payoff. In other words, we observe $Y_{igkt}^{1} = 1$ if the group accepts the program and $V_{igkt} \geq 0$, and we observe $Y_{igkt}^{2} = 1$ if the group accepts the program and $V_{igkt} < 0$.

Given this structure, the key variable is π_{igkt}, which is the probability that $V_{igkt} \geq 0$ holds. Based on equation (1),

$$\pi_{igkt} = \mathrm{P}(-e_{igkt} \leq f(X_{ig}, X_{g}, D_{gk}, D_{igt})), \tag{2}$$

where P(.) denotes the probability.

This expression shows that π_{igkt} is a function of observable variables X_{ig}, X_{g}, D_{gk}, and D_{igt}.

Another key variable is π_{gk}, which is the probability that group g does not

[8] As there are 5 groups with 10 or more individual-level rejections (see Table 2B), one of which had as high as 17 rejections, the homogeneous and simple majority may not necessarily be valid for our sample.

reject the program as a group. Using the majority cut-off threshold of 10, π_{gk} is the sum of probabilities that 10 to 20 members have $-e_{igkt} \leq f(X_{ig}, X_g, D_{gk}, D_{igt})$ while 10 to zero members have $-e_{igkt} > f(X_{ig}, X_g, D_{gk}, D_{igt})$. Although well-defined as a binomial distribution, it is not possible to express this probability in a neat form. Nevertheless, it is clear that π_{gk} is a function of observable variables. In other words,

$$\pi_{gk} = h(X_{g,i\in g}, X_g, D_{gk}, D_{gt,i\in g}), \tag{3}$$

where $X_{g,i\in g}$ is a group-level vector of X_{ig}, $D_{gt,i\in g}$ is defined from D_{igt} in a way similar to $X_{g,i\in g}$, and $h(.)$ is a function dependent on the functional form of $f(.)$ and implicitly operates the group decision-making rule as mentioned above.

Equation (3), when interpreted as an expression with unknown function $h(.)$, can correspond to other decision-making rules for a group as well. Under the simple model of majority voting without member interactions, the variable X_g enters equation (3) only by its effect on π_{igkt}. In more general cases (for example, group-level decision-making reflects unequal bargaining power within a group[9] or a preference for equality), variable X_g enters equation (3) directly as well as indirectly through its effect on π_{igkt}.

As a special case for the simple model of majority voting without member

[9] In our data, we came across one group that did not reject the program as a group, with as many as 17 members who rejected the program individually. Although it is likely that this is an exceptional case, this suggests a possibility that some members can have a strong say in group-level decision-making.

interactions, we can consider the case where no heterogeneity exists within a group in the sense that $X_{ig} = X_{g,\bar{i}}$, where $X_{g,\bar{i}}$ is the group-aggregated variables (mean, standard deviation, etc.) of X_{ig}, and the treatment status does not affect the payoff for all i in group g. Then we have

$$\pi_{igkt} = \mathrm{P}(-e_{igk} \leq f(X_{g,\bar{i}}, X_g, D_{gk})) \equiv p_{gk}, \tag{4}$$

and

$$\pi_{gk} = \sum_{m=10}^{20} \binom{20}{m} (p_{gk})^m (1-p_{gk})^{(20-m)} I_{\{0,1,\ldots,20\}}(m), \tag{5}$$

which is the closed-form expression for a standard binomial distribution (Mood et al. 1974).

An information problem, however, exists in that we do not have binary information on V_{igkt} if group rejection occurs. By construction, $V_{igkt} \geq 0$ if $Y_{igkt}^1 = 1$, and $V_{igkt} < 0$ if $Y_{igkt}^2 = 1$. On the other hand, we cannot know whether $V_{igkt} \geq 0$ or $V_{igkt} < 0$ if $Y_{igkt}^3 = 1$. In addition, as each group is offered one of the four credit products, for each group Y_{igkt}^j, we can observe for that specific k only. By using the strategic method popular in behavioral economics, we could have obtained Y_{igkt}^j for all k. Considering the context of microcredit, however, the application of the strategic method in our context was unfortunately infeasible.

4.2.Estimation Strategy

Given the information constraint, how can we implement a structural estimation corresponding to the simple theoretical model? Let us assume a linear function form for $f(.)$ and the standard normal distribution for e_{igkt} in equation (1).[10] Then equation (2) is specified as

$$\pi_{igkt} = \Phi(X_{ig}\theta_1 + X_g\theta_2 + D_{gk}\theta_3 + D_{igt}\theta_4) = \Phi(Z_{igkt}\theta), \tag{6}$$

where $\Phi(.)$ denotes the standard normal cumulative distribution function, Z_{igkt} combines four vectors of explanatory variables to save notation, and θ are vectors of parameters characterizing function $f(.)$. Then $\pi_{gk} = h(X_{g,i\in g}, X_g, D_{gk}, D_{gt,i\in g} \mid \theta)$, for which we do not have a neat expression. As before, we denote $X_{g,i\in g}, X_g, D_{gk}, D_{gt,i\in g}$ by Z_{gt} to save notation. Then the density of Y^j_{igkt} given $X_{ig}, X_g, X_{g,i\in g}, D_{gk}, D_{igt}$ is expressed as

$$\mathrm{P}(Y^1_{igkt} = 1 \mid Z_{igkt}, Z_{gk}) = \Phi(Z_{igkt}\theta)\pi_{gk}(Z_{gk} \mid \theta),$$

$$\mathrm{P}(Y^2_{igkt} = 1 \mid Z_{igkt}, Z_{gk}) = (1-\Phi(Z_{igkt}\theta))\pi_{gk}(Z_{gk} \mid \theta),$$

$$\mathrm{P}(Y^3_{igkt} = 1 \mid Z_{igkt}, Z_{gk}) = 1-\pi_{gk}(Z_{gk} \mid \theta). \tag{7}$$

Theoretically, a likelihood function exists that corresponds to the system of equations (7). However, computationally, it appears unrealistic to estimate parameters θ by the maximum likelihood method as the function π_{gk} does not have a compact expression. When individual members are heterogeneous within a group, there are $2^{20} = 1{,}048{,}576$ combinations of binomial outcomes generated simply by whether or

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[10] The assumption of linearity is not as restrictive as it appears; we can include interaction terms and higher-order polynomials in an additively separable way. Such addition does not change the discussion below.

not $V_{igkt} \geq 0$ for the 20 members. About a half of these combinations are associated with group-level rejection.[11]

Furthermore, in our dataset, group rejection actually occurred for only 7 groups (140 individuals). Even if we can write a likelihood function, it is doubtful that we would have sufficient degrees of freedom.

For these reasons, we should abandon the idea of estimating θ simultaneously with group-level decision-making, as in the system of equations (7). Moreover, if our main interests are in θ, marginal impacts of observable variables on the individual's benefit from the program, we do not need the system of equations (7). We can simply estimate the probit model of equation (6) using the subsample belonging to 69 groups that did not reject the program as a group. Using 1,380 observations comprising 1,211 members who remained in the program ($Y^1_{igkt} = 1$) and 169 members who individually rejected the program ($Y^2_{igkt} = 1$), we can estimate a standard probit model. Regarding the impact of the microcredit product types, we can enrich the model by estimating the probit model separately for each credit product. These separate regressions could encounter the classical selection problem if the households self-select themselves into each treatment arm. However, because of the experimental setup, treatment allocation was exogenously determined by the research team. Therefore, these sets of treatment-specific separate regressions should yield consistent estimates without

[11] Here comes the cost of the information constraint mentioned above. If we had known if $V_{igkt} \geq 0$ or $V_{igkt} < 0$ for the individuals with $Y^3_{igkt} = 1$, the likelihood to be calculated would have been only for that exact combination (1 combination) instead of about a half million combinations.

worrying about the need for selection correction.

If the actual group-level decision-making is reasonably close to the one shown in the simple model of majority voting without member interactions, the probit estimation provides us with estimates for marginal impacts of observable variables on the individual's benefit from the program, which are independent of group-level decision-making. In other words, the estimates are valid for the entire sample, including the group-rejection individuals ($Y_{igkt}^{3} = 1$). On the other hand, if the actual group decisions are not as modeled here, the estimates are still valid as estimates for marginal impacts of observable variables on the individual's benefit from the program, conditional on the group favoring group-level participation. The estimates are valid only for the subsample (but the majority) with $Y_{igkt}^{3} = 0$. Even with this reservation, we believe that the estimates are useful.

The whole section of this analysis is therefore implemented with the probit model. The control variable includes: (1) a dummy equal to one if the household is specified as being ultra-poor; (2) a dummy equal to one if the household is in the treatment group (the reference is the control group); (3) years in the current location; (4) a dummy equal to one if the household has ever raised any livestock; (5) the number of owned cattle; (6) the value of assets; (7) the household size and the dependency ratio; (8) a set of household head characteristics, such as gender, age, and years of education; and (9) a district dummy for Gaibandha (the reference is Kurigram district). Clustered standard errors at the *Char* level are employed for all regressions to derive statistical inference.

Let us briefly discuss the expected impacts of control variables on the uptake.

Regarding D_{gk} (dummy variables for randomly-assigned credit product), with the reference category ($k = 0$) to be the RC group, we expect $\partial f/\partial D_{g1} > 0$ as large credit can be divided and used in smaller amounts but the opposite is not possible. Between credit type 1 (LC) and 2 (LC+GP), under the assumption of rational consumers, we expect $\partial f/\partial D_{g2} > \partial f/\partial D_{g1}$ as the grace period provides more flexibility to borrowers. Therefore, we expect $\partial f/\partial D_{g2} > \partial f/\partial D_{g1} > 0$.

Regarding the attractiveness of credit type 3 (IK+GP) against credit type 2 (LC+GP), we do not have *a priori* reason to expect which of $\partial f/\partial D_{g2}$ and $\partial f/\partial D_{g3}$ is larger. The money credit is more flexible, favoring credit type 2, wheares in-kind provision is more convenient and associated with low transaction costs, favoring credit type 3.

Regarding D_{igt} (a dummy variable for randomly-assigned treatment), we expect $\partial f/\partial D_{ig1} > 0$ because receiving the credit immediately is better than waiting for a year to receive the credit.

Among X_{ig} (individual characteristics), X_{ig}^{a}, which is associated with higher entrepreneurship ability may have $\partial f/\partial X_{ig}^{a} > 0$ for all k (i.e., additional credit is more attractive for those with better ability to use the money productively). This implies that those who have more experience of livestock rearing will be more eager to join our project.

5. Estimation Results

5.1.Factors Associated with Individual Rejection

Estimated results for individual rejections are presented in Table 3. To interpret the results in a straightforward way, the dependent variable takes 1 if respondents accept the offer. The observations for this analysis are restricted to those who do not jointly reject the offer as a group. Column (1) uses all observations conditional on group acceptance. Columns (2) through (5) present the results of the separate regressions for each treatment arm.

The values reflect the marginal effect with respect to a unit change in the regressor for continuous variables and to a discrete change from zero to one for dummy variables.

One of the most important results obtained is that, holding other variables constant, the probability of program participation is statistically significantly higher for non-regular designs than the RC design, by 13 percentage points for the LC group and 9 percentage points for the LC + GP group, but not for the IK + GP group (Column 1). The results generally suggest that the demand for credit by poor households is not necessarily small, contrary to the standard presumption in the existing literature (Hulme, 1999). Our present study does not reveal anything about how large-scale credit induces higher default rates. Yet the result at least suggests that if MFIs agree to provide the poor with larger loans from the beginning, they will attract more clients from poorer segments of the society, which can potentially contribute to reducing extreme poverty. Potentially, this particular finding could reflect the technological characteristics pervasive in our study area: Smaller livestock animals such as goats are riskier due to high morbidity/mortality, while larger livestock animals such as cows have more stable returns, a view widely held by farmers and NGO practitioners.

This finding raises another question of why the in-kind credit design (i.e., IK + GP) is not preferred over cash. In all likelihood, the great advantage of a cash loan compared to an in-kind loan is the former's fungibility. On the other hand, in-kind credit is attractive to those who have too little entrepreneurial capacity to select where to invest. In the end, as the number of the second type of household becomes greater than the number of the first type of household, the cow provision is highly attractive at the group level. In our settings, a non-negligible number of households may prefer the fungibility of credit because it may be more useful in coping with climate shocks, but they do not necessarily lead to group rejections, which are found to be infrequent among the in-kind contracts in our sample.

We have previously discussed, based on popular belief, that being in a control group may create an additional reason to reject the offer (dissatisfaction with being forced to wait for a long period). The regression results, however, suggest otherwise. The probability of individual rejection is significantly higher for persons allocated to a treatment group (Columns 1–3).[12] Another popular belief, namely that the ultra-poor may have lower demand for microcredit, is also not supported by our data. Individual rejection rates are significantly reduced among the ultra-poor relative to the moderately poor (Columns 1, 4, and 5). This finding also hints that our overall program designs may fit well with their demand.

It is also important to note that the ultra-poor tend to accept the offer if there is

[12] One possible interpretation of this puzzling result is that initial participation decision (to be in our experiment) that had been expressed before the second participation decision (after learning about the arms and treatment assignments) may be upwardly biased or overly optimistic, and only those who have made their decisions seriously from the onset remained in the program. The plausibility of this interpretation and the potential effect of self-selection on the repayment rate will be examined in future research.

a grace period in the repayment schedules. Indeed, the acceptance rates among the ultra-poor are significantly higher than the moderately poor under the LC + GP and IK + GP arms (Columns 4 and 5). Combined with the earlier findings that overall uptake is higher for the ultra-poor than the moderately poor, the results imply that the ultra-poor are attracted more if they do not have to repay loans immediately after they receive them. Provided that the ultra-poor tend to be more cautious in taking risks, our results are consistent with Field et al. (2013) who find that more risk-averse clients benefit more if a grace period is offered in the repayment schedule. Alternatively, our results are consistent with the interpretation that the ultra-poor want to have a time buffer before having to deal with the challenges generated by the loans.

Judging from variables of head's age and its square, middle-aged (i.e., not too young and not too old) household heads are more likely to accept our offer and borrow credit, especially in the RC and LC + GP groups (Columns 1, 2, and 4). Years of head's education are generally positively correlated with uptake, even though they are not statistically significant. Experience of livestock rearing induces participation especially in the LC + GP groups (Column 4) probably because those who have experienced livestock production have more concrete projects in which to invest, such as a cow, and/or have better know-how regarding management. Against our expectation, the probability of acceptance in the IK + GP design does not significantly differ between those who have experience of livestock production and those who do not. This result is not robust, however, as shown below. Also, the number of current cattle holdings does not systematically affect the probability of accepting one of the large credit treatment arms, i.e., the LC, LC + GP and IK + GP groups.

5.2.Heterogeneity Analysis

Our analysis thus far includes both the treated and control households. As repeatedly argued, it is likely that that the reasons for rejection differ between the two. As members assigned to the control group had additional reasons to reject program participation and the strength of the main reason (dissatisfaction of staying in the group without obtaining the credit for a year or so) may differ across treatment arms and household characteristics, regressions using only treatment households could offer a clearer picture of the attractiveness of different credit types. In other words, it is possible that the response of treatment households with respect to rejection or acceptance could highly differ from those of control households, differences which may not be captured by the dummy variable for the treatment household adopted in Tables 3. To address this possibility, Table 4 shows the estimation results of probit models for only treatment households. Since the treatment status is randomly assigned to each household within the group, our estimation here does not suffer from a selection problem.

While most results are similar to the previous ones, several notable changes are observed. First, the IK + GP arm turns out to be positively, though not significantly, related to individual acceptance (Column 1). Second, among the treated households, male-headed households are more likely to accept the offer individually (Column 1). Third, if the households have prior experience of livestock rearing, they are more likely to accept the offer (Columns 1, 4, and 5). These three findings seem to reflect behavioral consequences when a large amount with a grace period is offered. As can be seen in Columns (4) and (5) in Table 4, the coefficients on male-headed dummy and experience dummy turn out to be positive and significant in the LC + GP and IK + GP arms. In other words, households headed by males and with previous livestock-rearing experiences are more likely to accept if the large loans with grace periods are offered, irrespective of whether they are in kind or in cash. Since raising livestock requires physical strength, it seems natural that male-headed households prefer this form of credit. Female-headed households may also have constraints on market and business linkages to gain from large loans. Also, without prior experience of livestock production, livestock credit may be burdensome. These results together suggest that the in-kind livestock credit requires better targeting. Also, the differences between the overall sample and only the treated households reflect the possibility that the latter take the decision more seriously because they could actually borrow credit once they agree.

5.3. Factors associated with group rejection

Are the above findings valid for the entire population under study or only for the subsample who jointly accepted our offer as a group? To obtain insights into this question, we turn to examine group-level decisions. Theoretically, the group-level uptake decision is a function of $X_{g,i\in g}$, X_g, D_{gk}, and $D_{gt,i\in g}$. However, the number of observations is only 76, out of which 69 accepted while 7 rejected. Thus, incorporating all of them into explanatory variables is not feasible due to the degrees of freedom problem. In addition, since a unit of observation between the group-level selection (first stage) and the individual decision (second stage) is different, standard Heckman selection-type estimation is not applicable.

To check for any systematic difference between accepted and rejected groups, therefore, we simply test the mean differences beween those two groups.[13] The results provided in Table 5 show that only the average years of household head's education is weakly statistically significantly different at the 10% level. Although we do not strongly claim that these two groups are the same, we may safely say that they are sufficiently similar. Given this similarity, the probit estimation results shown in Tables 3–4 could be interpreted as correlates of individual-level acceptance, valid for the entire sample including individuals belonging to groups that rejected uptake of the credit scheme.

6. Conclusion

Given the ultra-poor's limited access to credit and the paucity of economic research on the contract form most suitable for such households in developing countries, we know little about what types of credit designs are effective for expanding the outreach of microcredit to the ultra-poor. To shed light on this issue, we initiated a field experiment in the river islands of northern Bangladesh, where a substantial portion of dwellers can be categorized as the ultra-poor due to periodic floods. We randomly offered four types of loans to such dwellers to establish a causal inference: regular small loans in cash, large cash loans with immediate repayment, large cash loans with a one-year grace period, and in-kind livestock loans with a one-year grace period. Using microdata obtained from this experiment, we compared the uptake rates of each loan and investigated the correlates of the uptake rates.

The regression results showed that the uptake rate is significantly lower in the regular contract than the other three arms. Contrary to popular belief, we found that

[13] We have also conducted a single regression analysis with probit by replacing one explanatory variable with another, and again found that only the average years of household head's education is statistically significant.

large-scale loans are preferred even by the ultra-poor, who are usually believed to be risk-averse and who demand small-scale loans. Although the overall uptake of in-kind credit is significantly lower than equivalently-valued cash credit, the ultra-poor are more likely to accept the in-kind offer than the moderately poor. Indeed, a key to attracting the ultra-poor is to provide a grace period in the repayment schedule, irrespective of whether credit is provided in cash or in kind. It is also found that when offered, in-kind (cow) credit was more likely to be accepted if a potential borrower had previous experience of livestock rearing, indicating the necessity of supplementary training for the ultra-poor. This paper provides evidence that a typical microcredit offer with a one-year maturity period without a grace period is less attractive for the ultra-poor. Our results suggest the possibility that microfinance institutions can expand their outreach to the ultra-poor by offering them longer maturity loans with convenient grace periods, without compromising loan repayment schedules.

As a thorough study of the suitability of long maturity loans with a grace period for the ultra-poor in developing countries, this paper lacks an analysis of the impact of contract designs on borrower repayment behavior and their welfare indicators. While our field observations indicate that repayment rates have not substantially differed across the treatment arms, and some clients with a grace period contract have even voluntarily started saving to smooth future repayments, we cannot judge at this moment whether the large loans with a grace period benefit both MFIs and their clients. As the data collection remains on-going in the field, these issues will be analyzed in more detail after appropriate data becomes available. Another remaining issue is understanding within-group dynamics of members that led to group rejection. The results shown in this paper are reduced-form, with little insight into this issue. Modeling interactions among members, and theoretically and empirically analyzing the case in northern Bangladesh also remain for future studies.

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Figure 1: Satellite Image of *Chars* located in Northern Bangladesh

(Note: *Blue dots indicate the points where GPS coordinates were measured*)

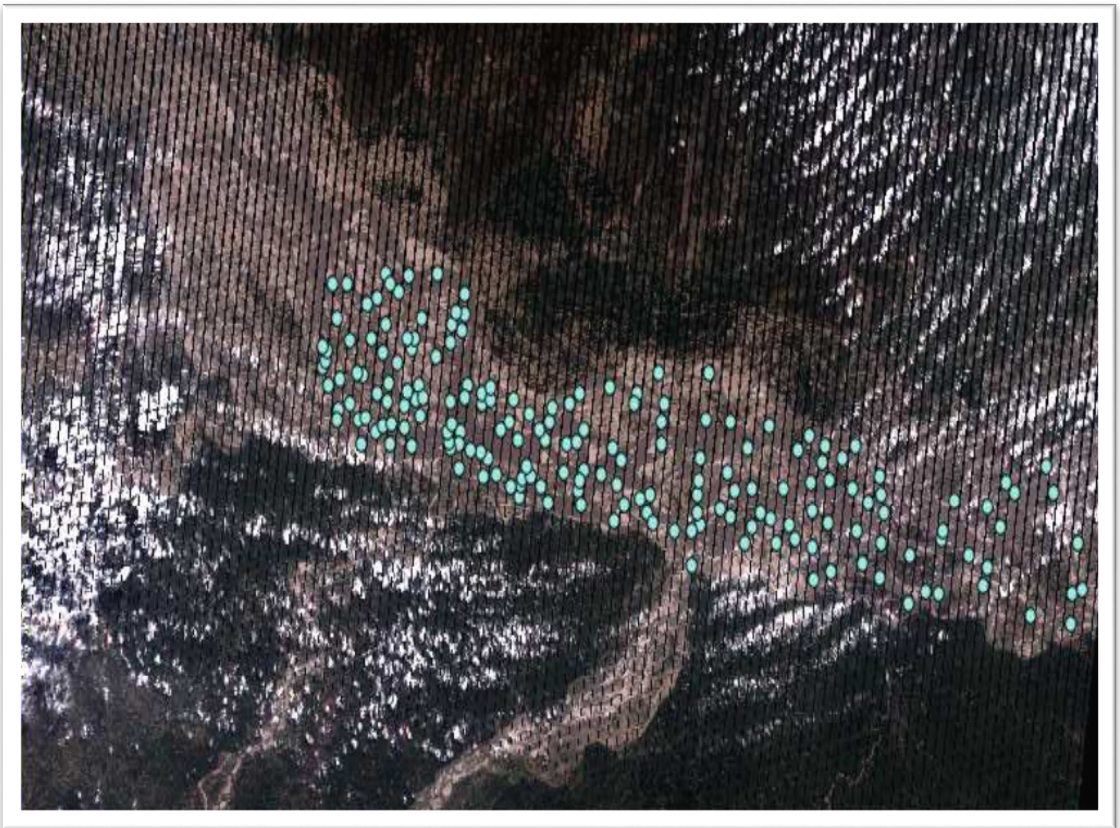
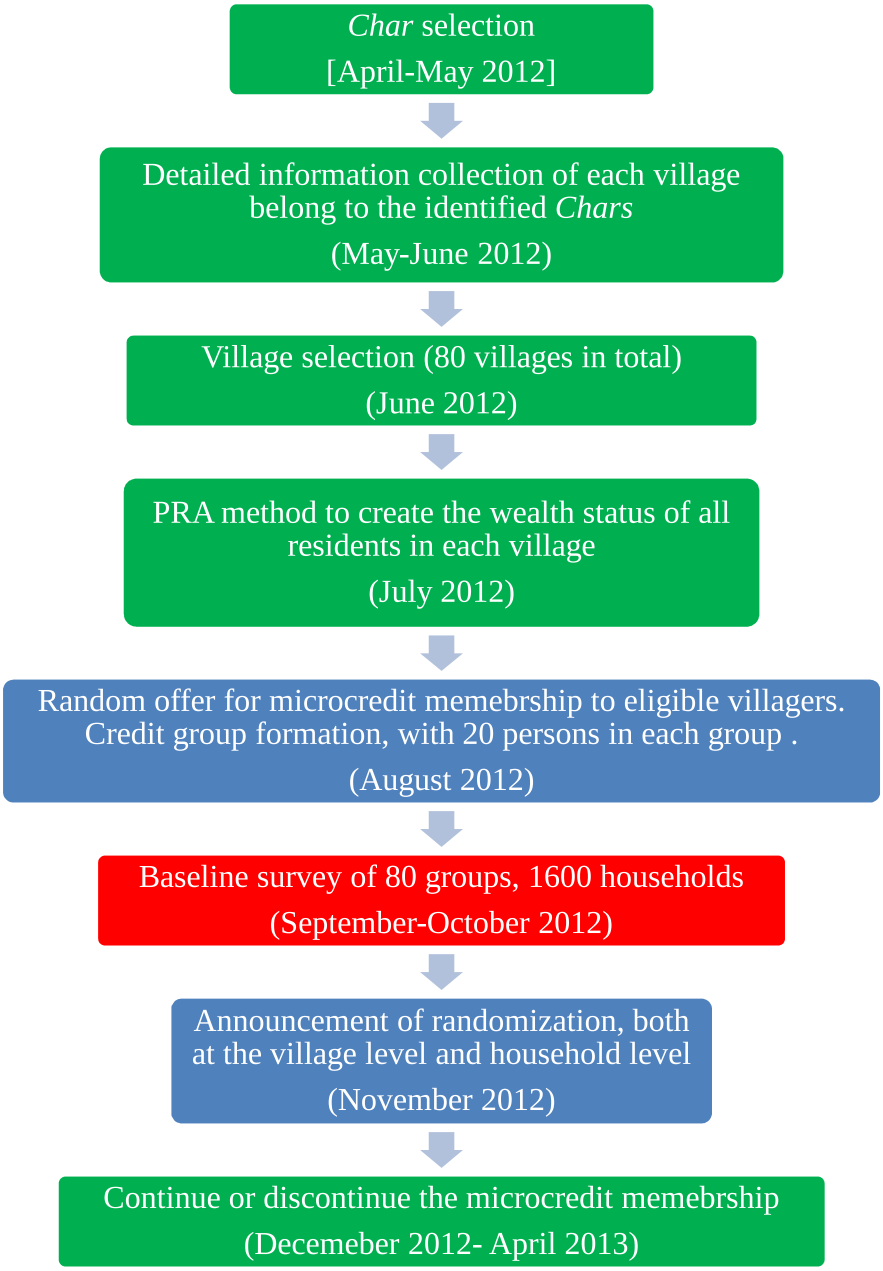


Figure 2: Timeline of Interventions and Surveys



Source: *Prepared by the authors. The blue panels show events regarding interventions, red panels show events regarding surveys and the green panels show events regarding sample selection .*

Figure 3: Randomization design

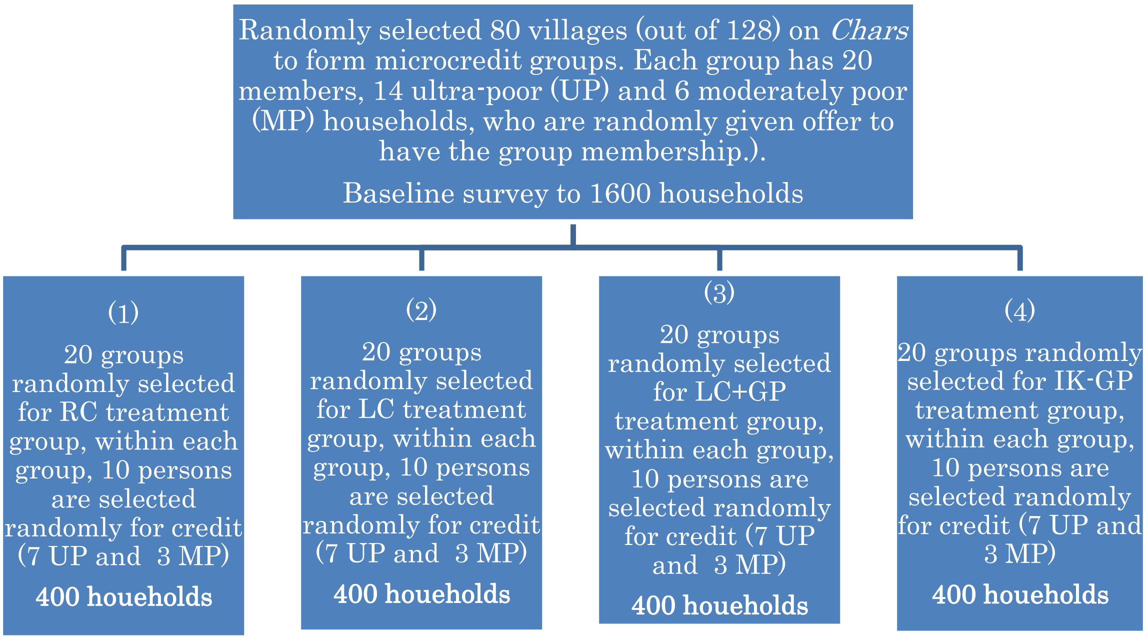


Table 1. Characteristics of sample households and balance test

	Sample mean					Difference in mean at the household level			Difference in aggregate mean at the group level		
	Total	RC (1)	LC (2)	LC+GP (3)	IK+GP (4)	(1)-(2)	(1)-(3)	(1)-(4)	(1)-(2)	(1)-(3)	(1)-(4)
Treatment (=1)	0.500	0.500	0.500	0.500	0.500	0.000	0.000	0.000			
	(0.500)	(0.501)	(0.501)	(0.501)	(0.501)	(0.035)	(0.035)	(0.035)			
Ultrapoor (=1)	0.700	0.700	0.700	0.700	0.700	0.000	0.000	0.000			
	(0.458)	(0.459)	(0.459)	(0.459)	(0.459)	(0.032)	(0.032)	(0.032)			
Total HH income ('0000taka)	7.289	7.003	7.355	7.824	6.975	-0.353	-0.821**	0.028	-0.353	-0.821	0.028
	(3.760)	(3.307)	(3.173)	(4.754)	(3.544)	(0.229)	(0.290)	(0.242)	(0.415)	(0.610)	(0.353)
Agricultural income ('0000taka)	0.018	-0.008	0.047	0.001	0.033	-0.054*	-0.008	-0.041	-0.054	-0.008	-0.041
	(0.376)	(0.239)	(0.481)	(0.033)	(0.523)	(0.027)	(0.012)	(0.029)	(0.030)	(0.012)	(0.026)
Livestock and poultry income ('0000taka)	0.169	0.132	0.192	0.166	0.184	-0.060	-0.035	-0.052	-0.060	-0.035	-0.052
	(0.488)	(0.355)	(0.544)	(0.498)	(0.532)	(0.032)	(0.031)	(0.032)	(0.053)	(0.053)	(0.060)
Non-farm enterprise ('0000taka)	0.306	0.264	0.149	0.449	0.361	0.115	-0.185	-0.098	0.115	-0.185	-0.097
	(1.405)	(1.207)	(0.848)	(1.883)	(1.464)	(0.074)	(0.112)	(0.095)	(0.085)	(0.140)	(0.107)
Wage income ('0000taka)	6.759	6.577	6.932	7.173	6.356	-0.355	-0.596*	0.220	-0.355	-0.596	0.220
	(3.870)	(3.444)	(3.308)	(4.911)	(3.562)	(0.239)	(0.300)	(0.248)	(0.429)	(0.646)	(0.357)
Non-income ('0000taka)	0.037	0.038	0.036	0.035	0.040	0.002	0.003	-0.002	0.002	0.003	-0.002
	(0.133)	(0.102)	(0.124)	(0.167)	(0.132)	(0.008)	(0.010)	(0.008)	(0.011)	(0.012)	(0.013)
Poverty (=1)	0.558	0.547	0.530	0.555	0.598	0.018	-0.008	-0.050	0.018	-0.007	-0.050
	(0.497)	(0.498)	(0.500)	(0.498)	(0.491)	(0.035)	(0.035)	(0.035)	(0.057)	(0.062)	(0.054)
Experience of livestock production (=1)	0.476	0.435	0.525	0.482	0.460	-0.090*	-0.048	-0.025	-0.090	-0.048	-0.025
	(0.500)	(0.496)	(0.500)	(0.500)	(0.499)	(0.035)	(0.035)	(0.035)	(0.059)	(0.066)	(0.058)
# cattle owned	0.456	0.422	0.448	0.568	0.385	-0.025	-0.145*	0.037	-0.025	-0.145	0.038
	(0.950)	(0.906)	(0.967)	(1.072)	(0.833)	(0.066)	(0.070)	(0.062)	(0.131)	(0.124)	(0.123)
Value of assets ('0000taka)	0.221	0.196	0.209	0.273	0.204	-0.012	-0.077*	-0.008	-0.012	-0.077	-0.008
	(0.441)	(0.274)	(0.262)	(0.722)	(0.331)	(0.019)	(0.039)	(0.022)	(0.033)	(0.044)	(0.042)

Table 1. (cont'd) Characteristics of sample households and balance test

Household size	4.206	4.080	4.235	4.282	4.225	-0.155	-0.202	-0.145	-0.155	-0.202	-0.145
	(1.483)	(1.490)	(1.523)	(1.479)	(1.435)	(0.107)	(0.105)	(0.103)	(0.163)	(0.172)	(0.153)
Dependency ratio	0.862	0.815	0.861	0.862	0.909	-0.045	-0.046	-0.094*	-0.045	-0.046	-0.094
	(0.616)	(0.603)	(0.635)	(0.598)	(0.625)	(0.044)	(0.042)	(0.043)	(0.049)	(0.058)	(0.058)
Head's age	38.583	38.925	38.042	38.672	38.690	0.883	0.252	0.235	0.883	0.253	0.235
	(10.528)	(10.529)	(10.533)	(9.878)	(11.153)	(0.745)	(0.722)	(0.767)	(0.989)	(1.121)	(1.167)
Head is male (=1)	0.899	0.907	0.902	0.897	0.890	0.005	0.010	0.018	0.005	0.010	0.018
	(0.301)	(0.290)	(0.297)	(0.304)	(0.313)	(0.021)	(0.021)	(0.021)	(0.035)	(0.031)	(0.027)
Head's years of schooling	0.748	0.498	0.877	0.660	0.958	-0.380**	-0.163	-0.460**	-0.380*	-0.163	-0.460*
	(2.150)	(1.816)	(2.248)	(2.015)	(2.445)	(0.145)	(0.136)	(0.152)	(0.181)	(0.189)	(0.216)
Years of current location	5.090	4.185	8.482	3.277	4.415	-4.298***	0.907	-0.230	-4.297*	0.908	-0.230
	(8.654)	(8.214)	(10.244)	(7.369)	(7.568)	(0.657)	(0.552)	(0.558)	(1.755)	(1.188)	(1.338)
Gaibandha (=1)	0.750	0.700	0.850	0.700	0.750	-0.150***	0.000	-0.050	-0.150	0.000	-0.050
	(0.433)	(0.459)	(0.358)	(0.459)	(0.434)	(0.029)	(0.032)	(0.032)	(0.133)	(0.149)	(0.145)
N	1600	400	400	400	400	800	800	800	40	40	40

Note: The difference is statistically significant at the 1% ***, 5% **, and 10% * level.

Source: Compiled from the microdata in the baseline survey (same as the following tables).

Table 2A. Household-level uptake status by treatment arms and type of rejection

	# of respondents				
	Uptake	Individual rejection	Group rejection	Erosion and relocation	Total
RC (traditional)	226	54	80	40	400
LC (large w/o grace period)	347	13	40		400
LC+GP (large w grace period)	337	23	20	20	400
IK+GP (inkind)	301	79		20	400
Total	1211	169	140	80	1600
if treated					
RC	107	33	40	20	200
LC	170	10	20		200
LC+GP	166	14	10	10	200
IK+GP	149	41		10	200
if control					
RC	119	21	40	20	200
LC	177	3	20		200
LC+GP	171	9	10	10	200
IK+GP	152	38		10	200

Table 2B. Group-level uptake status by treatment arms and type of rejection

	# of groups														
	Group-level uptake, distinguished by the number of members within each group who rejected individually												Group rejection	Erosion and relocation	Total
	0	1	2	3	4	5	6	7	8	9	10 and more	Sub-total			
RC	5		1	1	2	1	1			1	2	14	4	2	20
LC	10	5	1	2								18	2	0	20
LC+GP	12	1	2	1	1						1	18	1	1	20
IK+GP	2	7	1	1	1		2	2		1	2	19	0	1	20
Total	29	13	5	5	4	1	3	2	0	2	5	69	7	4	80

Table 3. Correlates of individual-level uptake decisions (including control households)

	Dep.var = Uptake dummy				
	Full sample	RC	LC	LC+GP	IK+GP
	(1)	(2)	(3)	(4)	(5)
LC [a]	0.126***				
	(0.030)				
LC+GP [a]	0.089***				
	(0.034)				
IK+GP [a]	-0.005				
	(0.043)				
Treatment (=1)	-0.036**	-0.105*	-0.029*	-0.014	-0.001
	(0.016)	(0.056)	(0.016)	(0.024)	(0.033)
Ultra-poor (=1)	0.044**	0.028	0.004	0.041*	0.110**
	(0.018)	(0.053)	(0.016)	(0.021)	(0.051)
HH size	0.007	0.036	0.002	-0.008	0.033*
	(0.009)	(0.026)	(0.006)	(0.011)	(0.020)
Dependency ratio	-0.011	-0.034	-0.003	-0.001	-0.059
	(0.014)	(0.049)	(0.011)	(0.018)	(0.048)
Head's age	0.012**	0.037**	0.001	0.016*	0.002
	(0.006)	(0.019)	(0.002)	(0.008)	(0.011)
Its squared/1000	-0.138**	-0.461**	-0.020	-0.183*	-0.014
	(0.062)	(0.219)	(0.028)	(0.093)	(0.136)
Head is male (=1)	0.032	-0.146***	-0.010	0.128	0.074
	(0.036)	(0.051)	(0.016)	(0.088)	(0.066)
Head's years of schooling	0.006	0.006	0.003	-0.002	0.017
	(0.004)	(0.010)	(0.005)	(0.004)	(0.012)
Years of current location	-0.002	0.000	0.000	-0.002	-0.007
	(0.001)	(0.003)	(0.001)	(0.002)	(0.005)
Experience of livestock production (=1)	0.011	-0.014	0.013	0.029*	-0.029
	(0.018)	(0.075)	(0.014)	(0.016)	(0.037)
# cattle owned	0.016	0.091*	0.017	-0.002	-0.010
	(0.010)	(0.051)	(0.010)	(0.006)	(0.028)
Value of assets (10 thousands taka)	-0.004	-0.039	0.055	-0.016	-0.022
	(0.019)	(0.062)	(0.038)	(0.014)	(0.049)
Gaibandha (=1)	-0.016	0.110	-0.001	-0.031	-0.048
	(0.032)	(0.129)	(0.015)	(0.035)	(0.073)
	1,380	280	360	360	380

Notes: Estimated by probit, using the subsample of members whose groups accepted the credit scheme. The parameter estimate is significantly different from zero at the 1% ***, 5% **, and 10% * level, using Char-level clustered standard error. [a] The omitted category is the regular microcredit (RC).

Table 4. Correlates of individual-level uptake decisions (using treatment households only)

	Dep.var = Uptake dummy				
	All treated	RC	LC	LC+GP	IK+GP
	(1)	(2)	(3)	(4)	(5)
LC [a]	0.137***				
	(0.036)				
LC+GP [a]	0.118***				
	(0.037)				
IK+GP [a]	0.018				
	(0.048)				
Ultra-poor (=1)	0.063**	-0.010	0.028	0.067*	0.119*
	(0.027)	(0.070)	(0.027)	(0.036)	(0.064)
HH size	-0.009	0.011	-0.002	-0.012	-0.013
	(0.012)	(0.040)	(0.006)	(0.009)	(0.031)
Dependency ratio	0.015	0.089	0.000	0.018	-0.023
	(0.022)	(0.086)	(0.017)	(0.021)	(0.070)
Head's age	0.020**	0.041	0.003	0.020**	0.011
	(0.008)	(0.031)	(0.004)	(0.008)	(0.013)
Its squared/1000	-0.233**	-0.477	-0.053	-0.221**	-0.119
	(0.095)	(0.389)	(0.047)	(0.092)	(0.147)
Head is male (=1)	0.117*	-0.210***	-0.002	0.223*	0.272**
	(0.068)	(0.069)	(0.025)	(0.131)	(0.131)
Head's years of schooling	0.009	0.005	0.003	-0.000	0.035*
	(0.007)	(0.015)	(0.006)	(0.004)	(0.019)
Years of current location	-0.002	-0.002	0.001	-0.002	-0.009
	(0.002)	(0.004)	(0.001)	(0.001)	(0.006)
Experience of livestock production (=1)	0.061***	0.068	0.023	0.051**	0.073**
	(0.022)	(0.086)	(0.026)	(0.025)	(0.036)
# cattle owned	0.010	0.086*	0.019	-0.014	-0.046
	(0.015)	(0.048)	(0.013)	(0.010)	(0.037)
Value of assets (10 thousands taka)	-0.012	-0.020	0.105	-0.021**	-0.078
	(0.032)	(0.110)	(0.067)	(0.008)	(0.130)
Gaibandha (=1)	-0.011	0.141	-0.022	0.014	-0.081
	(0.039)	(0.155)	(0.018)	(0.036)	(0.076)
	690	140	180	180	190

Notes: See Table 3.

Table 5. Comparison of group characteristics

	Mean (Std.Dev.) of group-level statistics		
	accept	reject	difference
Group mean			
HH size	4.207	4.114	-0.092
	(0.474)	(0.411)	(0.186)
Head's age	38.591	37.993	-0.598
	(3.538)	(2.692)	(1.379)
Head is male (=1)	0.896	0.929	0.032
	(0.102)	(0.086)	(0.040)
Head's years of schooling	0.798	0.243	-0.555*
	(0.655)	(0.276)	(0.251)
Years of current location	4.949	7.414	2.465
	(4.821)	(9.203)	(2.107)
Experience of livestock production (=1)	0.480	0.400	-0.080
	(0.202)	(0.147)	(0.079)
# cattle owned	0.446	0.329	-0.117
	(0.392)	(0.283)	(0.152)
Value of assets (10 thousands taka)	0.212	0.215	0.003
	(0.126)	(0.075)	(0.049)
Gaibandha (=1)	0.754	0.714	-0.039
	(0.434)	(0.488)	(0.174)
Head's Characteristics			
GHead' age	31.188	31.000	-0.188
	(6.811)	(6.733)	(2.699)
Ghead's years of schooling	2.261	2.143	-0.118
	(3.151)	(3.078)	(1.248)
Ghead' is in treated group (=1)	0.710	0.429	-0.282
	(0.457)	(0.535)	(0.184)
N	79	7	

Note: The difference is statistically significant at the 1% ***, 5% **, and 10% * level.