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Microcredit and Crime

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Abstract

We document the level, type, and severity of crime in rural Bangladesh. Crime affected 36% of the households. The average cost of crime was worth two weeks' household consumption. We then study how microcredit affects crime. Our theoretical model shows how microcredit may increase cost of crime at the village level while reducing it for borrowers. We estimate a negative household level and a positive village level effect of microcredit on cost of crime, thus providing evidence that observable private protection against crime generates a negative diversion externality of crime towards other households.

JEL Classification: G2, K22, 016

Keywords: borrower, crime, cost of crime, developing country, diversion externality, microcredit, non-borrower, regression discontinuity.

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1 Introduction

The prevailing consensus is that proper institutions are central for growth (e.g. Acemoglu, Johnson and Robinson, 2001). One possible consequence of inefficient institutions is crime. In developing countries, formal institutions seem often powerless to deal with crime and may sometimes be facilitating it, and therefore non-governmental institutions may play a key role in combating it. We study the effect of microcredit on crime at the household (micro) and the village (aggregate) level both by constructing a theoretical model of crime and by using household level survey data from rural Bangladesh to conduct an empirical investigation. As an institution, microcredit is interesting both because it has been shown to have beneficial household and village level effects (e.g. Pitt and Khandker 1998, Karlan and Morduch 2009 and Banerjee and Duflo 2010) and because it seems to fill a relative vacuum when many formal institutions such as police and courts are weak.¹

Microcredit may lead to a lower probability of crime through various mechanisms, including the group incentive schemes for which microcredit is famous.² Besides the group liability mechanism,³ microcredit may affect the level of crime faced by households through other means: Group-based credit organizations teach their members to take responsibility of their group's members. For example, Grameen Bank's social development program recommends that its members should not inflict injustice on anyone, should not allow anyone to do so, and should always be ready to help others. Furthermore, the type of social interaction that program participants undertake via weekly group meetings may also encourage them to deal with criminal gangs more efficiently. Weekly group meetings allow borrowers to obtain more information about different issues relative to the

¹There is a relatively large literature studying the effects of microcredit in Bangladesh. See e.g. Khandker (2005, 2009) and Khandker, Khalily, and Khan (2005) for studies on microcredit performance. McKernan, Pitt and Roskowitz (2004) and Pitt, Khandker and Cartwright (2003) study the effect of gender in the use of the formal and informal financial sectors. Morduch (1998) and Zaman (2000) study whether microcredit helps the poor, and Pitt, Khandker, Chowdury and Millimet (2001) the effect of microcredit on the health status of children. This interest on Bangladeshi microcredit is partly explained by the fact that microcredit originates in Bangladesh (Yunus 2004 tells the story).

² The group liability mechanism makes group members jointly responsible for the default of any member of the group.

³There have been attempts in Bangladesh to transform the microcredit towards individual liability but in practice group lending and liability has continued (see Collins et. al. 2009).

non-borrower households. Additional information helps to alter the social attitudes of program participants (Pitt and Khandker, 1998) and may facilitate a higher ability to deal with criminal gangs. Another reason why microcredit borrowers may face less crime than non-borrowers is that the credit programs protect their members by providing them with legal services in case of victimization.⁴ Furthermore, these credit organizations possess the strongest social networks in Bangladesh, with significant economic and political backing. They have the incentives and the means to force local administration and legal authorities to protect their members. Criminal gangs are presumably aware of the influence of credit organizations and therefore may refrain from harassing their customers.

To analyze the effect of microcredit on crime, we first build a theoretical model: A criminal gang has to decide which households in a village to attack. The size of the booty obtained from a given household is a function of the amount of resources devoted to robbing that household; households, for their part, can invest in protection. At the village level, microcredit has income externalities through the labor market, making non-participating poor households richer through higher wages (they supply labor) and (non-participating) rich households poorer (as they demand labor). Microcredit increases the income of participating households. To capture the effects of microcredit discussed above, we assume that borrowers are partially sheltered from crime through lower marginal cost of protection. Microcredit has then two effects on crime: A diversion effect and a scale effect. The diversion effect is heterogenous both for borrower and non-borrower households. The labor market-based microcredit externality makes poor non-borrower households richer and rich non-borrower households poorer relative to the counterfactual of no microcredit. The former and some rich non-borrowers become more, some rich non-borrowers less attractive targets of crime, but the average effect is ambiguous. For borrowers, the situation is more complicated. The direct income effect is positive, making them more attractive targets; at the same time, the lower cost of protection makes them less attractive targets. The overall effect varies over households. The scale effect means that on the one hand, as microcredit increases aggregate income, the village as a whole becomes a more attractive target for the criminal gang which direct more resources

⁴See e.g. <http://www.brac.net/content/bangladesh-legal-empowerment>, accessed Jan 11, 2011.

to attack villagers. On the other hand, the increased ability of the (borrower, and thereby also the average) households to protect themselves makes the village less attractive for the gang. We show numerically that even by the diversion effect alone the household level treatment effect of microcredit on crime may be negative (crime is reduced) while the village level effect is positive (crime is increased).

Our study contributes thus also to the research on the externalities and efficiency of private property protection. At the theoretical level several externalities associated with private property protection have been found (Cook 1986). These and their sign depend on the nature of the protection, e.g. on whether protection is observable or unobservable (Shavell 1991, Hotte and Ypersele 2008). Empirical research seems to be very scarce, however. Unobservable protection against crime can have positive externalities, and Ayres and Levitt (1998) find evidence for these. In our case the protection measure, support by a microfinance institution, is publicly known. Thus, in our case one would expect protection to generate negative external effects through diverting crime to other people. We provide evidence on the aggregate strength of this diversion effect. To the best of our knowledge, our paper is the first to do this. There is related empirical research on crime avoidance, i.e., on actions to avoid crime. Among them one can mention the work by Cullen and Levitt (1999, see also Levitt 1999). Closest to ours is the work by Di Tella, Galiani, and Schargrodsky (2006). They focus on the differences in victimization and in crime avoidance measures at different levels of income using cross-sectional survey data from Argentina, but do not measure the spill-overs from avoidance measures by a given group. Studies on the impacts of gun control also exist (see Cook, Ludwig and Samaha 2009 for a survey), but their focus is not on diversion but on other type of externalities, usually the impact of gun control on violent crime.

To be able to study crime empirically, we carried out a household level survey in rural Bangladesh. Given the paucity of micro-level data on crime in developing countries, one contribution of our paper is to document the prevalence and severity of crime. We find that almost 40% of households had suffered crime in the last 12 months. Relative to consumption levels, crime is also severe: The average crime resulted in an economic loss worth two weeks' household consumption. To achieve our objective of identifying the causal effects of microcredit on cost of crime we do the following:

We follow the seminal paper of Pitt and Khandker (1998) and the World Bank administered survey they utilized in data collection. Our questionnaire was otherwise identical to the World Bank survey, but we used updated versions of the income questions and, in particular, we appended questions on crime to the questionnaire. Following Pitt and Khandker, we utilize a landholdings-based discontinuity in the microcredit organizations' decision rule to identify the causal effect of microcredit at the household level. We find evidence that microcredit participation has a negative causal (local average treatment) effect on the cost of crime at the household level. While the existing literature has established that microcredit has a positive impact on different outcomes such as consumption, education, health and empowerment of women, the effect of microcredit on cost of crime has hitherto not been studied.

To study the question at the aggregate level,⁵ we develop a way to estimate externalities from cross-section survey data on microcredit. To the best of our knowledge, our way of identifying aggregate effects (spillovers) is new to the literature.⁶ The idea behind our methodology is to utilize the same discontinuity in the microcredit decision rule at the aggregate level as is used at the household level. We find that microcredit has a positive aggregate effect on crime. That is, crime at the village level is an increasing function of microcredit participation. As the household level effect is negative for participating households, our results indicate that microcredit generates a diversion effect towards non-participating households (and, possibly a scale effect hitting these same households), increasing their cost of crime.

The rest of the paper is organized as follows: In the following Section, we describe crime in rural Bangladesh. Section 3 is devoted to our theoretical model. We discuss NGOs' role in Bangladesh and our data collection in Section 4. We also present our data. The first part of Section 5 is devoted to the household level analysis, the second to the village level analysis. Section 6 provides conclusions.

⁵Durlauf, Navarro and Rivers (2010) offer a fresh discussion of aggregate crime regressions.

⁶The use of aggregate data to identify spillovers is not new, see e.g. Levy and Terleckyj (1983) who estimate the effects of R&D subsidies on R&D investment. Our solution to the endogeneity problem is new to our knowledge.

2 Crime and corruption in Bangladesh

2.1 Crime

It is well known that reliable data on crime is hard to come by, especially in developing countries.⁷ This notwithstanding, the consensus (see e.g. the UN report on Crime and Development in Africa 2005) seems to be that the levels of crime in developing countries is high, and hinders development. In our survey (details of which are reported in section 4 and Aktaruzzaman 2009), we therefore collected detailed information on the level and type of crime. These we report here.

In Bangladesh, most crime is perpetrated by local gangs. Most gangs are local, and concentrate on extracting a living out of one or a few villages. Gangs have a lot of influence: For example, Cameron (2009) reports that NGOs wishing to operate in the slums of Bangladesh cities “have to gain the permission of “mastaans” - leaders with links to criminal gangs, the police, and local political parties”.

Incidence of crime.⁸ In Table 1 we report the incidence of different types of crime, also conditioning on being a (non-)borrower. We asked each respondent whether his/her household had been subject to crime of different types during the previous 12 months. 36% of households were subject to at least one type of crime; non-borrowers were affected significantly more often (42% versus 23%). While most households that were victims of crime had experienced a single type of crime, one third of those facing crime suffered at least two types of crime. It is more common for non-borrowers to have suffered two or more types of crime (36% versus 21%). The most common crime was the loss of household property (27%), followed by theft/extortion of money (13%) and physical assault (6%). 4% of households lost some income due to having been assaulted by a criminal gang. Non-borrowers suffered each type of crime more often, apart from loss of household property. Looking at the frequency of crime, we find that, conditional on being a subject of crime at least once, households were subject to crime on average 1.4 times a year. Non-borrowers fare worse than borrowers in every respect.

⁷Bangladesh joined the UN Crime Trends Survey as late as 2009.

⁸The statistics reported here are based on program villages where at least one microcredit organization is present. Statistics using also non-program villages are very similar. We use weights that take our survey design into account.

[Table 1 here]

Cost of crime. All these crimes had monetary consequences. For each type of crime, we asked questions designed to measure the monetary consequences (see section 4.3 for more detail). To put these costs into perspective, we divide them by the daily consumption (also measured in the survey).⁹ In the first row of panel A of Table 2 we report the cost of crime, summing over all different types of crime suffered by the household, and averaging over all households. The figures in panel A can therefore be interpreted as the expected costs of crime over a year. The total cost of crime is high, equalling on average 5 days' household consumption. Non-borrowers experience higher costs of crime than borrowers: The average total cost of crime for borrowers and non-borrowers are worth almost 2 and almost 8 days' consumption, with the difference being statistically significant. These figures however do not take into account that not every household suffers crime so we report figures that condition on being a victim of crime in panel B. The total cost of crime equals almost 15 days' consumption, conditional on being a victim of crime. The figure is 8 days' consumption for borrowers and 16 days' for non-borrowers. Finally, note that the variation (over households) is high for essentially all measures of crime.

Looking at the composition of this, the Table shows that the expected medication costs are relatively low compared to the expected costs of other types of crime. The crime having the highest expected cost is the loss of household property, worth more than 4 days' consumption. Looking at panel B, we find that a similar pattern emerges when looking at costs conditional on being a crime victim. Those losing household property suffer a loss worth more than 2 weeks' household average consumption. While the means are higher for non-borrowers than borrowers, the differences aren't statistically significant, but for wage loss and total cost of crime.

⁹We measure consumption as the sum of expenditure on food, clothes and textiles, furniture, cosmetics, repair, public transport, medical costs, recreation, gifts, dowry and legal expenses.

Our cost of crime may be underestimated because during the survey period it was realized that the perception about crime is such that the villagers do not define an act as a criminal act if its severity is minimal. For example, the following may not have been reported as crimes: Extortion for 50 taka, stealing chicken, fearing to go outside at night. Households define an incidence as a criminal act only when its severity is "large". However, in such cases households' fear of the criminal gang prevents them from reporting the crimes. Therefore, we had to spend a lot of time to get familiar with the interviewee before obtaining the information. It is thus possible that our measure of the cost of crime is downward biased.

[Table 2 here]

Variation over villages. The level of crime varies considerably over villages. In Table 3 we report village-level descriptive statistics on different types of crime. The means differ from those in Table 1 as we here use weights that take village size into account. Panel A reports the incidence, and panel B the cost of crime. The main interest is in between-village variation. The standard deviation over villages of being the victim of at least one type of crime is 17% with a mean of 38%, yielding a coefficient of variation of 0.43; the standard deviation of wage loss is 5% (mean 2.7%), that of medical expenses 5.6% (4%), that of lost property 11.4% (17.5%), and that of theft 5% (mean 9%). Looking at the severity of crime conditional on being a victim, we find larger variation. Relative to daily household consumption, the standard deviation over villages' cost of crime from wage loss is 1.5 (mean 2.1), medical expenses 2.4 (1.2), value of lost property 19 (17) and the sum that was extorted 3.9 (2.3).

[Table 3 here]

Summary. Taken together, these statistics show that crime is wide-spread in (rural) Bangladesh, affecting a large proportion of households. Those households that are directly affected suffer costs that are large relative to consumption, but even the expected costs are high. Finally, there is large variation both within and across villages both in the prevalence as well as the severity of crime

2.2 Corruption

Transparency International (TI) ranks Bangladesh 139th out of 180 countries (in 2009) using its Corruption Perception Index. Transparency International Bangladesh (2005) reports that the law enforcement agencies are the most corrupted sector in Bangladesh. According to the report, that 92% of households who lodged a First Information Report (FIR) to the police station had to

pay 2430 taka¹⁰ and 91% of households who registered at a General Dairy (GD) had to pay a bribe worth 939 taka on average. 80% households who needed a clearance certificate from the police and 71% of those accused of a crime had to pay a bribes of 881 and 57 000 taka on average. Transparency International (2010) places Bangladesh on the shared 7th place in the world in terms of corruption of the police in its Global Corruption Barometer.¹¹ The Bangladeshi newspaper The Daily Star reports (based on TI 2010) that in addition to police (79%), civil servants (68%), political parties (58%) and the judiciary (43%) are seen as the most corrupt sectors of the society.

There is also a huge police shortage in Bangladesh. Government data shows that there are 0.87 police per 1000 people – less than half compared with neighboring Sri Lanka.¹² Partly as a result of this, the police was not able to execute more than 71% of the warrants in 2000 (UNDP, Human Security in Bangladesh). Furthermore, the lower judicial sector in Bangladesh is as corrupt as the Bangladesh police. For example, TIB (2005) finds that magistrates, attorneys, and court officials demand bribes from defendants in more than 66% of the cases filed under the Speedy Trial Act (STA).

The above evidence of corruption and inefficiencies in the law enforcing agencies suggest that property rights are relatively weak in Bangladesh, and poorly protected by official institutions. Weakly enforced property rights provoke local criminal gangs to operate with the help of village leaders (matobbers) and local political leaders (The Bangladesh Observer 2004). One of the main activities of gangs is household extortion. Any failure to pay leads to mental and physical assaults, confiscation of goods, and/or kidnapping of children. The victims of these criminal gangs have to surrender to the gang's demands because the victims know not only that the law enforcing institutions are not helpful, but also that the gangs are well connected with the village leaders. Weak property rights such as those in Bangladesh lead to increased transaction costs, decreased commercial certainty, and lower incentives for efficiency, and thereby decrease the welfare of households.

¹⁰One year 2009 U.S. dollar is worth 86 year 2006 taka using World Development Indicator data for Bangladeshi inflation and the dollar-taka exchange rate. In 2005, the average monthly household income was 2560 taka in Bangladesh (TIB, Household survey, 2005).

¹¹Pakistan and 5 African countries have a higher score than Bangladesh.

¹²Sources: <http://www.police.gov.bd/index5.php?category=18> (accessed October 8th 2010) and Seventh United Nations Survey of Crime Trends and Operations of Criminal Justice Systems, covering the period 1998 - 2000 (United Nations Office on Drugs and Crime, Centre for International Crime Prevention); International Centre for Prison Studies; Mr Lennox-Boyd's reports to the House of Commons.

3 A model of microcredit and crime in a village economy

This section provides a simple model of the impact of microcredit on crime. After presenting the model we simulate it to show the possibility of simultaneous negative effects (decreasing cost of crime) at the household level and positive effects (increasing cost of crime) at the village level. The core elements of the model are a) household decision on how to allocate labor between home activities and laboring in other farms, b) household decision on how much resources to use to combat crime, c) the gang decision on how to allocate criminal activities between households. The first feature is needed to model the impacts of microcredit on household behavior and the externalities (positive or negative depending on the household type) associated with microcredit. The second feature is needed to understand how microcredit affects both the safeguard activities at the household level and the externalities this creates for other households. Cook (1986), Shavell (1991), de Meza and Gould (1992) and Hotte and Ypersele (2008) argue that the improved safeguards used by one household have a negative externality on other households as they become relatively easier targets for criminals. As Shavell (1991) and Hotte and Ypersele (2008) show, this depends on private property protection actions being publicly observable. Here this is the case, as the presence of microcredit institution, its support to its clients and the clients identity are observable. The third feature is needed to study both this externality and the overall impact of microcredit both at the household and the village level. We focus on the behavior of a single gang, but our framework can easily be generalized to a setting where several gangs exist. Our model is closest to Hotte and Ypersele (2008). We differ from them by studying the simultaneous effects of two types of externalities: Those created by the microcredit program and those created by private protection against crime. We study explicitly the allocation of criminal activity across households to understand the diversion effect. We also distinguish theoretically between the pure diversion effect, (i.e., the effect at given aggregate level of effort by the criminals) and the scale effect (i.e., the level of criminal activity and its allocation when criminals reallocate the activities between different communities), and focus on the implications of the pure diversion effect, as it is theoretically more interesting.¹³

¹³Microcredit increases the incomes of the poor households and reduces incomes of the richer households. Both effects (see below) make the village more attractive to gangs to attack the village inducing it to spend more resources

We simplify the analysis by studying the actions of only one criminal gang. This should not be crucial for our results as Hotte and Ypersele show that with a large number of gangs the negative diversion externality from private property protection dominates the impacts of crime on aggregate costs of crime on victims.

The diversion effect can in itself imply that at the village level cost of crime increases if microcredit induces a diversion of criminal effort towards richer households.¹⁴ This requires that there is some non-monotonicity in the rewards that the gang obtains from different households. This holds in our model: Richest households protect themselves so well that the potential income from households has an inverted U-shape when plotted against the household landholdings. In our model microcredit is, in line with microcredit organizations' own rules, directed only to those households having small landholdings (below 0.5 acres). It has a negative externality on rich households through the local labor market: Microcredit reduces the supply of labor to these markets increasing local wage. Poor households, being net suppliers to this market, benefit while richer households, being net demanders of labor, lose.¹⁵

We proceed by first modeling crime in the absence of microcredit, and then add microcredit to the model. In doing this, we assume that microcredit creates an externality that is non-monotonic in the land holdings of a household and model this externality in reduced form. We provide a model for this externality in Appendix A. Finally, we show using numerical simulations that it is possible that the effect of microcredit on the cost of crime is negative at the household level (i.e., a household obtaining microcredit has a lower cost of crime than it would had it not obtained credit), while the effect at the village level is positive (i.e., the cost of crime increases at the aggregate level).

on it. This just strengthens our case.

¹⁴In this section, by "rich" ("poor") households we mean households with large (small) landholdings, i.e., not their incomes. Richest (poorest) households are those with the largest (smallest) landholdings.

¹⁵ There exists evidence that microcredit generates consumption and income externalities at the village level. Perhaps the most convincing evidence is presented in Khandker (2005) using panel data collected in Bangladesh. Khandker does not present any evidence on the mechanisms creating the externalities. The village level aggregate externality is positive, consistent with our model.

3.1 Crime without microcredit

We analyze a two-stage game where households invest in protection from crime, and the criminal gang decides how to allocate its effort among heterogeneous households. In the first stage the households invest in protection. This makes a proportion of their income unavailable to the gang. In the second stage, the gang attacks the households. These attacks are costly to the gang.

We assume that the distribution of land in the village is given by the cdf $F(a)$, with a denoting the farm acreage. Let the income generated by a farm be $y(a)$, with $y'(a) > 0$, $y''(a) \leq 0$. Household land and $y(a)$ are common knowledge. The total amount of effort (or the number of gang members) the gang devotes to the village is D . The gang decides on how to allocate this effort between the households.

To solve for the subgame perfect Nash equilibrium, we start from the second stage, where the gang decides on how to allocate its effort between households. Let $d(a)$ denote the share of income the gang steals from households owning a units of land. The decision problem of the gang is

$$\begin{aligned} \max \int_0^{a^{\max}} d(a) (1 - s(a)) y(a) dF(a) \\ \text{s.t.} \\ \int_0^{a^{\max}} \frac{c}{2} d(a)^2 dF(a) = D. \end{aligned}$$

$s(a)$ denotes the share of income that is protected (through household investment) from the gang's attack. This has been decided in the first stage of the game. We assume that there is a household specific cost to the gang from investing criminal effort on the household. The cost is assumed to be quadratic and hence convex.

The problem is isoperimetric giving

$$(1 - s(a)) y(a) - \lambda c d(a) = 0$$

as the first order condition where λ = the shadow price of gang's resources. This yields

$$d(a) = \frac{(1 - s(a)) y(a)}{\lambda c}. \quad (1)$$

The shadow price is given by

$$\lambda^2 = \frac{\int_0^{a^{\max}} [(1 - s(a)) y(a)]^2 dF(a)}{2cD}. \quad (2)$$

With the given specification of the cost function, the gang attacks all households, but the intensity varies across households.

Next we turn to the households' problem, i.e., the first stage of the game. When analyzing the household optimization problem we assume that the households are "small", i.e., they take the shadow price of the gang as given and do not think they can alone have an effect on it. In more concrete language, the households take the village level threat of the gang as given. Instead the households understand that they can have an effect on how the gang allocates its resources within the village. Assume that household welfare if it chooses to protect share s of its income is

$$[(1 - d(a))(1 - s) + s] y(a) - \frac{v}{2} s^2$$

where $\frac{v}{2} s^2$ = cost of protection to the household. The household maximizes this subject to (1).

The optimal level of protective effort is given by

$$s(a) = \frac{2y(a)^2}{\lambda vc + 2y(a)^2}. \quad (3)$$

Obviously $s'(a) > 0$. Also since

$$1 - s(a) = \frac{\lambda vc}{\lambda vc + 2y(a)^2},$$

(note that this is increasing in λ) we get

$$[1 - s(a)] y(a) = \frac{\lambda v c y(a)}{\lambda v c + 2y(a)^2}. \quad (4)$$

Equation (4) gives the attractiveness of the household to the gang (the L.H.S.). This also determines how much effort the gang invests in attacking the household. We differentiate (4) with respect to income to get

$$\begin{aligned} \frac{\partial [1 - s(a)] y(a)}{\partial y(a)} &\geq 0 \Leftrightarrow \\ y(a) &\leq \left(\frac{\lambda v c}{2} \right)^{\frac{1}{2}}. \end{aligned} \quad (5)$$

Thus, the relationship between household income and its attractiveness as a target to the gang is non-monotonic: The richest households protect their incomes so efficiently that the gang spends effort on them by the same amount as on some relatively poorer households. The "middle-class" faces the most serious threat of crime, even though the poorer a family, the less it protects itself. The reason for this is that the value of a given amount of criminal effort directed towards a poorer family is lower, than its value when directed towards a richer family.

In this framework the theoretical equivalent to the concept of "cost of crime" used in the empirical work is the following:

$$cc(a) = d(a) [1 - s(a)] y(a) + \frac{v}{2} s^2 \quad (6)$$

Using (3) and (4) this becomes

$$cc(a) = \left[\frac{\lambda v c y(a)}{\lambda v c + 2y(a)^2} + \frac{v}{2} \left(\frac{2y(a)^2}{\lambda v c + 2y(a)^2} \right)^2 \right] \frac{v y(a)}{[\lambda v c + 2y(a)^2] \lambda c}. \quad (7)$$

The (subgame perfect equilibrium) solution for the village level threat λ is the solution to (obtained

by inserting (4) into (2)):

$$\lambda^2 = \frac{\int_0^{a^{\max}} \left[\frac{\lambda v c y(a)}{\lambda v c + 2y(a)^2} \right]^2 dF(a)}{2cD} \quad (8)$$

Because the L.H.S. is a convex function of λ with derivative 0 at 0 and the R.H.S. is a concave function of λ with positive derivative at 0, there exists a unique solution to the equation. For empirics (8) implies that the village level of threat depends on land distribution and distribution of income.

3.2 Crime with microcredit

Assume now that among poor households who are eligible for credit (those with less than half an acre of land, $a < \frac{1}{2}$), a share $m(a)$ receive microcredit. We assume that having microcredit reduces the marginal cost of protection:

$$v_{mcB} < v.$$

We also assume that microcredit has a direct effect on those households receiving the credit (note that the effect is conditional on household land):

$$y(a, mcB) \geq y(a).$$

We also assume microcredit to have an externality on other households. To motivate both the direct effect of microcredit on a household and the externality, we provide in Appendix A a model of household production and village-internal labor markets. In that model, poor households (those with small land-holdings) are supplying labor whereas rich households (with large landholdings) are on the demand side. We show that introducing microcredit which is allocated to some proportion of poor households increases the equilibrium wage, benefiting poor households, but imposing a cost

on rich households. Here, we model the externality in reduced form:

$$y(a, mcNB) \geq y(a).$$

Again in line with the labor market model, we assume that

$$y(a, mcB) \geq y(a, mcNB). \quad (9)$$

Even with this formulation, the maximization problem of the gangs is isoperimetric and the Lagrangian (Hamiltonian) of the gang is

$$\begin{aligned} H = & \int_0^{\frac{1}{2}} \left[d_{mcB}(a) (1 - s_{mcB}(a)) y(a, mcB) + \lambda \left(D - \frac{c}{2} d(a)^2 dF(a) \right) \right] m(a) dF(a) + \\ & \int_0^{\frac{1}{2}} \left[d(a) (1 - s(a)) y(a, mcNB) + \lambda \left(D - \frac{c}{2} d(a)^2 dF(a) \right) \right] (1 - m(a)) dF(a) + \\ & \int_{\frac{1}{2}}^{a^{\max}} \left[d(a) (1 - s(a)) y(a, mcNB) + \lambda \left(D - \frac{c}{2} d(a)^2 dF(a) \right) \right] dF(a). \end{aligned}$$

We take into account that the gang allocates a different amount of effort (d_{mcB}) to households who have microcredit and that these households invest a different amount in protection (s_{mcB}). For each group of households, the solution is of the same type as above, (1).

The household decisions also have the same form as above in (3). For households receiving microcredit the solution is

$$s_{mcB}(a) = \frac{2y(a, mcB)^2}{\lambda v_{mcB} c + 2y(a, mcB)^2}.$$

Thus, microcredit improves the security of borrowers through two direct channels, by reducing the costs of protection and by increasing their incomes.

What counts for the gang is the income available for robbing. For borrowers this is given by (analogously to (4)):

$$[1 - s_{mcB}(a)] y(a, mcB) = \frac{\lambda v_{mcB} c y(a, mcB)}{\lambda v_{mcB} c + 2y(a, mcB)^2}$$

To understand the effect that microcredit has on the cost of crime of different households, it is useful to start from non-borrowing households. The richest households will experience a decrease in their income through the negative microcredit-induced (wage) externality. They hence become less attractive targets for the gang, even after taking into account the reduction in their crime-prevention effort. The poorest non-borrower households, on the other hand, experience an increase in their income through the positive microcredit-induced (wage) externality, and become more attractive targets for the gang. Hence, for the richest (poorest) non-borrower households, the introduction of microcredit leads a decrease (increase) in the cost of crime. For the middle-income non-borrower households, the net effect depends, and can go either way.

Moving then to borrowers, who all are poor given our assumption on how microcredit is allocated, the following holds: On the one hand, microcredit makes the poorest borrowing households more attractive targets both through the direct as well as the externality-induced income effect. On the other hand, microcredit reduces their cost of preventing crime. The total effect hence depends, and can go either way. For the (less) poor borrower households, the relative increase in income is smaller (as they sell less of their labor) and hence for them, the cost-reduction effect of microcredit may dominate. Hence, for the least poor borrower households, the effect is unambiguous: The introduction of microcredit leads to a reduction in the cost of crime. The model thus suggests that the introduction of microcredit affects the cost of crime of all households; the effect is unambiguous only for the richest and poorest non-borrowers, and the least poor borrowers. The size and sign of the average household treatment effect therefore depends, and is a function both of the effect on the “treated” (borrowers) as well as on the “control group” (non-borrowers).

How does microcredit affect the village level intensity of threat? It can be solved, using steps analogous to those above, from

$$\lambda^2 = \frac{1}{2cD} \times \left\{ \begin{aligned} &\int_0^{\frac{1}{2}} \left[\frac{\lambda v_{MC} c y(a, mcB)}{\lambda v_{MC} c + 2y(a, mcB)^2} \right]^2 m(a) dF(a) + \\ &\int_0^{\frac{1}{2}} \left[\frac{\lambda v c y(a, mcNB)}{\lambda v c + 2y(a, mcNB)^2} \right]^2 (1 - m(a)) dF(a) + \\ &\int_{\frac{1}{2}}^A \left[\frac{\lambda v c y(a, mcNB)}{\lambda v c + 2y(a, mcNB)^2} \right]^2 dF(a) \end{aligned} \right\}$$

This can, *ceteris paribus*, go either way. If the "weighted aggregate exploitable income" of the village increases because of the credit (the R.H.S. of the previous equation increases for any given λ), then crime intensity increases, i.e., the equilibrium λ increases.

3.3 Simulation results

Here we show that microcredit can increase the costs of crime at the village level even though it improves the situation (=reduces the cost of crime) of the households obtaining the credit. To begin with, we use the following density for the land distribution

$$f(a) = \frac{\beta}{\varsigma + \chi a}.$$

This we have (roughly) calibrated to the average village data in our data. The productivity effect of microcredit is assumed to be 5 per cent, i.e.,

$$\mu = 0.05.$$

We assume the cost of protection for borrowers to be just modestly lower than for other non-borrowers. This is just to make sure that our results do not hinge on extremely large crime externalities created by the microcredit. We also want to give a small cost advantage to gangs in their activities over the households in their protection activities¹⁶. Thus we set

$$\nu = 1.51$$

$$v_{MC} = 1.47.$$

For simplicity we have set

$$A = 1$$

¹⁶Keeping the other parameters the same but setting $\nu = c = 1.5$ still gives negative impacts on non-borrowers but the aggregate impact is positive.

and

$$\alpha = 0.5, l = 5, c = 1.5, D = 0.5.$$

The share of poor households receiving credit is estimated by fitting a polynomial to the average data from program villages and normalizing the aggregate share to unity (i.e., ignoring the fact that some formally ineligible households have received credit).

The first result is that microcredit reduces the average cost of crime for the borrowers by a small amount: Their cost of crime is 0.2019 without credit, 0.2016 with credit. Not all borrowers benefit as can be seen in Figure 1. The non-borrowers' cost of crime increases. The cost of crime of the eligible non-borrowers increases from 0.0770 to 0.0772 while the cost of crime for the households with more than 0.5 acre land increase from 0.0929 to 0.0931. The cost of crime of the eligible non-borrowers are without microcredit smaller than the cost of borrowers as with our fitted borrower share function the share of borrowers among the wealthier households (below the 0.5 threshold) is relatively large. These figures are population share weighted figures, (explaining the small figure for large landowners) so that by adding them one can see that the aggregate costs of crime increases when microcredit is introduced to the village. The relatively large numbers for the borrowers are due to the relatively large share of borrowers with large land holdings (even though below 0.5 acres). In the simulated model it is the poorest and richest non-borrowers that are especially hurt by crime (as measured by the change in the level of cost of crime), though most non-borrowers are hurt. Even among the poor the gain by borrowers is outweighed by the loss of non-borrowers. Interestingly, also the poorest borrowers face higher costs of crime.

[Figure 1 here]

4 Data

4.1 NGOs in Bangladesh

Non-governmental organizations (NGOs) have expanded significantly their activities in Bangladesh, with an estimated 750 NGOs now present. Most of them are small, and have limited managerial and staff capacity. For instance, 90 percent of those NGOs have programs in less than five out of the 64 districts of Bangladesh. NGOs in Bangladesh provide a strikingly homogeneous set of services like health-care and sanitation, child education with microcredit dominating. Microcredit now reaches almost 43% of households and covers about 70% of rural poor in Bangladesh. This sector is dominated by the Grameen Bank, BRAC (Bangladesh Rural Advancement Committee), and ASA (Association for Social Advancement), which collectively cover about 81% of the microcredit market in Bangladesh (see Figure 2). Therefore, we considered only these three credit programs in our survey.

[Figure 2 here]

All microcredit organizations use the same land-holding - based rule on allocation of credit: Households who own more than one half an acre of land are ineligible for credit. As will become clear below, our data is similar to the BIDS-World Bank survey data collected in 1998 in that this rule is not strictly enforced.

4.2 Data collection

During the period of 2006-2007, a household survey was conducted in 69 Bangladeshi villages using a multi-stage stratified random sampling technique. In the first stage, 487 police stations¹⁷ of Bangladesh were divided into five strata according to presence of different microcredit organizations:

¹⁷Police stations also serve as local judicial units and define geographical areas.

Grameen Bank, BRAC, ASA, mixed program and non-program strata.¹⁸ We randomly selected 4 police stations from Grameen Bank, and BRAC strata, and 5 police stations from the remaining three strata. In this way, we chose 23 randomly police stations.

From each police station, we randomly selected three villages for the survey. A census was conducted in each of the selected villages. The purpose of the census was to identify eligible (less than 50 decimals, i.e., half an acre, of land) and ineligible (50 or more decimals of land) households for microcredit, as well as participating and non-participating households among the eligible ones in the program villages. In the non-program villages a random sampling technique was used to draw 15 eligible and 7 ineligible households. Using our census data, we categorized the village households into program participants, eligible non-participants, and ineligible non-participants. We drew 15 households randomly from the program participant and 5 households from the eligible non-participant category. 2 ineligible households were also drawn randomly. Overall, 1 518 households were drawn for the survey, of which 810 (53.2%) were program participants and 708 (46.8%) were non-participants. 1188 of the households were in the program villages. These households constitute our household level sample. In producing our household level descriptive statistics, we use weights to correct for the within-village sampling scheme. For village level descriptive statistics and estimations, we use weights that also take into account the variation in village size.

To formulate our own questionnaire we followed the BIDS-World Bank (1998) household survey questionnaire to which we included crime related questions. Our survey is described in detail in Aktaruzzaman (2009).

4.3 Measurement of cost of crime

Our measure of cost of crime includes wage loss due to crime, medication cost for injuries suffered in a gang attack, price of confiscated household goods, and the value of cash payments to the gang. We define the wage lost by the cost that a household has to bear because of inability to sell labor after being injured in an attack by a gang. To calculate the wage loss, we asked the victims ‘how much could you have earned per day (on average) during those days when you were

¹⁸A large number of other microcredit organizations were present in these villages. As explained above, their market shares are very small however.

unable to work because of injury due to gang attack?’ To compute medication costs, we include all the expenses regarding medication, such as doctor fees, government hospital/ health center or private clinic bills and cost of medicine. To find out the price of stolen household goods we asked the following question: ‘Have any household members been evicted or have any household goods been stolen by the gang during the last 12 months?’ We considered more than 17 categories household items, such as goats, chicken, crops, and bicycles. If the answer to this question was ‘yes’ we asked ‘how many times has the incidence occurred and what is the estimated value of the stolen goods?’.

We also include the amount of money given by a household directly to a gang member or to someone who negotiated with the gang. To estimate the cash payments we asked ‘have you or any members of your household given any money to the gang in the last 12 months?’ If the answer was yes, we then asked how many times the household gave money to the gang and the amount each time. We asked similar questions to measure the negotiation costs with gang.¹⁹

4.4 Descriptive statistics of household characteristics

At the household level, we collected data on a number of household characteristics and, critically, on household land. Regarding land, we not only collected information on the amount of land, but also an estimate of its value per acre. Table 4 presents descriptive statistics of these. The average age of the household head is 44 years old (s.d. 12), average land-holding is 0.8 acres (s.d. 1.6), value of land per acre is on average 10 600 taka and average consumption is 57 000 taka per year. More than 60% of households have less than half an acre of land (the threshold for microcredit); almost all household heads are male;²⁰ and 85% of households are Muslim.

Some of the household characteristics are statistically different for borrowers and non-borrowers. Borrowers own less land on average (0.24 as opposed to 1.10 acres) and are also more likely to be landless (17% versus 13%); they are slightly less educated (3.4 compared to 4.6 years for the household head); are younger (41 compared to 44 years old); their home is a dwelling more often (90% compared to 75%); they are located further from the entry point to the village (730 meters

¹⁹When households are threatened by extortion, they often seek help from a person who is well connected to gang. This is done in order to negotiate with the gang. Some cost is involved to complete this procedure, and this cost we call the negotiation cost.

²⁰A woman is the household head essentially only if she is a widow.

instead of 590) and also further from the village center (403 as opposed to 335 meters); are much more often eligible for credit, i.e., own less than half an acre of land (88% versus 49%); and their household annual consumption is lower (52 000 taka compared to 59 000). In addition to the figures reported in the Table 4, we calculated the probability of obtaining credit conditional on being eligible. The probability of obtaining credit is 33% for eligible, and 7% for ineligible households.

[Table 4 here]

As with crime, there is considerable heterogeneity between villages in some household characteristics. Looking at village level statistics in presented in Table 5,²¹ we find that the standard deviation of village-level average household land is 0.66 when the mean is 0.87. When looking at average village level consumption (standard deviation of means 13 000 taka, mean 51 000), average education of household head (s.d. 1.9 years, mean 4.3 years), the proportion of land-less households (s.d. 0.1, mean 0.17) or land value / acre (s.d. 9800 taka, mean 11 000 taka), we again find considerable heterogeneity. Heterogeneity across villages in family size (s.d. 0.6., mean 4.8) and age of household head (s.d. 4.6 mean 44) is much smaller.

[Table 5 here]

4.5 Verification of the RD design

In the language of the regression discontinuity literature, our forcing variable is the amount of land a household owns. The critical threshold is 0.5 acres (see Section 4.1). We now analyze whether this threshold satisfies the criteria of the RD design (RDD).

A crucial issue is manipulation of the threshold. Imagine that, contrary to what is the case, the microcredit organizations strictly enforced the 0.5 acre rule. Then households with landholdings

²¹As in Section 2, due to the small number of villages surveyed, we include non-program villages into the village level statistics.

just exceeding the critical 0.5 acre value would have an incentive to sell a small part of their land in order to become eligible. Figure 3 shows a histogram of the proportion of households with different landholdings, conditional on the village being a program village. The Figure clearly shows that while program and non-program villages seem to have a very different distribution of land-holdings, the program villages also have a suspiciously high proportion of households just below the 0.5 acre threshold. This could be the outcome of households selling enough land to get under the threshold in order to become eligible (to increase the probability of getting credit).

[Figure 3 here]

We first tested for the effect of the threshold.²² The probability of obtaining credit is 0.33 for program village households under the threshold, and 0.07 for households over the thresholds. Thus, in line with the World Bank survey data, our data reveals that microcredit organizations do not enforce their announced eligibility policy. The difference in the probability of obtaining credit is highly significant however (p-value 0.000). Thus the data suggests that there is an incentive to manipulate the threshold.

To check whether manipulation has really taken place, we resorted to two approaches. Uncharacteristically for data used in an RDD setting, we have a control group of non-program villages. In those villages, there is no need to manipulate the threshold. To utilize them to test for manipulation, we did the following: First, we divided land-ownership into $B = 11$ bins.²³ Second, we calculated the proportion of households in each village belonging to each of the bins. This resulted in B “observations” of the variable $prop_{bi}$, the proportion of households in bin b in village i per village. We then regressed $prop_{bi}$ on $B - 1$ bin dummies, and interactions between the B bin dummies and a program - village indicator. The results suggest that while the proportion of households in the bin just below the threshold is higher than the proportion of households in the bin just above the threshold, the difference in this between program and non-program villages is not statistically significant: The p-value of a Wald-test is 0.13. An interpretation of this result is

²²Of course, the real test of the threshold is the significance of the eligibility dummy in our first stage regression. It is highly significant at 1% level.

²³We constructed the bins by 10 decimals, i.e., 0.1 acres of land.

that around the threshold, the distribution of households is not statistically different between the program and non-program villages, suggesting that no (large scale) manipulation has taken place.

As a second test, we looked at the value of land of households just above and just below the threshold in program villages. The idea behind this test is that (given some imperfections in the market for land in rural Bangladesh), a household that originally owned more than 0.5 acres of land would sell its marginal and thus least valuable land to get under the threshold. An implication of this would be that the land value (per acre) of households just below the threshold should be higher than that of households just above the threshold. The raw data does not support this, as the land value per acre just below the threshold in the program villages is 7331 taka, and just above 9489 taka. To perform a more formal test, we ran a regression where the dependent variable was $landvalue_{bik}$, the value of land (per acre) of household k in village i and bin b , where bins were determined according to amount of land owned by the household. The explanatory variables were bin dummies and interactions between them and a program village indicator. We then tested for the significance of the difference in the coefficients of the bin-dummies just above and just below the threshold. The coefficient for program villages is, in line with the raw data, negative with a p-value of 0.68. The result is robust to alternative ways of constructing the bins.

5 Estimation and results

5.1 Household level analysis

Our main household level analysis utilizes data on program village households. Given the relatively small number of households, we resort to a parametric fuzzy regression discontinuity (as in e.g. van der Klaauw 2002) and employ polynomials of the (scaled) forcing variable (land). Our instrument is the indicator variable for eligibility that takes value 1 if the household owns at most 0.5 acres of land and is zero otherwise. As is well known, this set-up amounts to 2SLS estimation. Our theoretical model strongly suggests heterogenous effects, in which case we identify the local

average treatment effect of microcredit on crime. Following Lee and Lemieux’s (2010) suggestion, we estimate the model using polynomials of different powers, always including interactions between the instrument and the polynomial terms.²⁴

The estimation equation takes the form:

$$CC_{ik} = X_{ik}\beta + \delta D_{ik} + g(land_{ik}) + \epsilon_{ik}, \quad (10)$$

where CC_{ik} is (the log of) our measure of the cost of crime faced by household i in village k , X_{ik} is a possible vector of covariates (village fixed effects and household characteristics), D_{ik} is the indicator variable for obtaining microcredit or alternatively, the (log of the) amount of credit, $land_{ik}$ is the amount of land owned by household i , ϵ_{ik} is the error term, $g(.)$ a (polynomial) function to be specified, and (β , and especially) δ the coefficient(s) of interest. We only use observations (households) from the program villages.

We include in the reported specifications household characteristics and village fixed effects for efficiency reasons,²⁵ but our results are robust to excluding (either or both of) them. Our vector of household characteristics is the following: A dummy for religion (Muslim vs. non-Muslim), years of schooling of the household head, a dummy for the gender of the household head, a dummy for dwelling type, number of adult male members, distance to the nearest neighboring household, distance to the entry point to the village, distance from the center of the village. We follow a general to specific testing procedure and start with a 4th order polynomial.

5.1.1 First stage results

We report our first stage results in Table 5. In column one we include no control function terms, and the eligibility dummy obtains a positive and highly significant coefficient, with a t-value of over 8. Both household characteristics and village fixed effects are as groups each jointly significant in all specifications. In column two we add a first order polynomial in scaled land. The coefficient of

²⁴We scale land so that it takes value zero at the threshold. This is done in order for our model to satisfy the fundamental assumption behind regression discontinuity (See Hahn, Todd and van der Klaauw 2001). We orthonormalize the polynomial terms and the interactions between the eligibility dummy and the polynomial terms.

²⁵This is in line with Hoxby (2000) who argues that in a situation where the number of observations close to threshold is limited, a “within” RDD approach is more powerful and less biased.

the eligibility dummy is still significant with a t-statistic of almost 8. Scaled land and its interaction with the eligibility dummy are jointly significant. In the third column we add a second order term and its interaction. Now the t-statistic of the eligibility dummy is almost 7. The second order terms, and all polynomial terms are jointly significant. Adding third order terms in column 4 gives otherwise a similar picture (t-statistic of the eligibility dummy 5), but the third order terms are not jointly significant. Column 5 repeats this, with a t-statistic of 4 for the eligibility dummy, and jointly insignificant fourth order terms.

Testing the restricted models against our most general specification, we cannot reject the Null that 4th order terms are jointly insignificant, nor the Null that 4th and 3rd order terms are jointly insignificant. The 2nd - 4th order terms are however jointly significant at the 6% level, suggesting we reject the 1st stage specification against the general model. The same applies to the most restricted model without any control function terms. Testing the restricted versions against each other we cannot reject the Null that 3rd order terms are jointly insignificant, but do reject the Null that 2nd order terms are jointly insignificant.

We conclude from these first stage results that a second order polynomial is sufficient for the first stage specification. Our instrument, the eligibility dummy, is however strong even if we use higher order polynomials.

5.1.2 Second stage results

The first issue we have to confront regarding the second stage specification is the order of the polynomial. We have done the following: We first use a 4th order polynomial in the first stage and perform general to specific testing of the second stage polynomial. What we find is that we cannot reject the most restricted specification (i.e., the one without any control function terms) against the more general alternatives. Second, we use the same polynomial in both the first and the second stages. It is these latter results that we report here.

We report the results in Tables 6 and 7 and concentrate on the coefficient of the treatment variable. In Table 6 the treatment variable is an indicator variable for the household having a microcredit loan; in Table 7 the log of the loan size, measured in taka ($=\log(1+\text{taka})$). We report

results from estimations that always include household characteristics and a full set of village fixed effects.²⁶

[Table 6 here]

In column one of Table 6 where we don't include any control function terms our estimate of the treatment effect is -3.7 and statistically significant at better than 1% level. Adding 1st order terms does not change the estimate, nor the significance level, much. The control function terms are jointly insignificant. Adding 2nd order variables changes the picture. The coefficient of the treatment variable decreases in absolute value and is very imprecisely measured. However, both the 2nd order terms, and all control function terms are jointly insignificant. Adding 3rd order terms in column four brings no change to the results of column three: The estimated treatment effect is again highly insignificant, as are both the 3rd order and all the control function terms. In column five we report results from using a 4th order polynomial in both the first and the second stages. The estimated treatment effect is now -1.24 and very imprecisely measured. However, again the added 4th order polynomial terms are jointly insignificant, as are all the control function terms. The tests reported in the Table suggest that we should either not use any control function terms, or at most a first order polynomial, in the second stage specification.

Our specification tests suggest using a 2nd order polynomial in the first stage, and either no control function terms, or a 1st order polynomial in the second stage. When we do that, we obtain a treatment effect of -3.98 (-4.02) when using no control function terms (a 1st order polynomial) in the second stage, with a t-value of 3.05 (2.67). The joint significance levels of the polynomial terms, village fixed effects and household characteristics are similar to those reported in Table 6 for the corresponding second order specifications.

Taken together, these results provide some support for a negative causal effect of obtaining microcredit on the cost of crime. These results are tempered by the fact that the point estimate of the treatment effect is reduced in absolute value, and loses significance, when we move to use

²⁶Our results are robust to excluding either of or both of these.

higher order polynomials. The interpretation of there being a (significant) negative causal effect gets however support from our testing procedure on what order polynomial to use. Thus, our interpretation is that the preferred specification is the one using a 2^{nd} order polynomial in the first stage, and either no control function terms, or a 1^{st} order polynomial in the second stage. Both specifications yield a negative and statistically significant causal effect of microcredit on the cost of crime.

As robustness tests, we have done four things: First, we have estimated the model using a 4^{th} order polynomial in the first stage: Our results are essentially unchanged. Second, we re-estimated all the above models using data from all villages, i.e., by including the non-program village households into the estimation sample. The results are in line with those reported: The coefficients of the treatment variable are somewhat smaller in absolute terms, but their statistical significance is higher. Third, we have estimated the model without either or both the village fixed effects and household characteristics. Our results are robust to excluding them. Finally, we have used the estimation approach of Pitt and Khandker (1998; see Pitt 1999) which utilizes data on both treatment and non-program villages,²⁷ has two fixed effects per village, and imposes some constraints on the data. The results are in line with those reported in that we find a negative and a statistically significant treatment effect.

[Table 7 here]

Moving to Table 7 where the treatment variable is continuous, we find that our results regarding the order of the polynomial when using the credit indicator carry over to using a continuous treatment variable: The data suggests to either not use any control function terms, or to only use a 1^{st} order polynomial in the second stage, and to use a 2^{nd} order polynomial in the first stage. The biggest change on the testing front is that household characteristics become jointly insignificant in the second stage when we use a 4^{th} order polynomial. The point estimate of the treatment variable is always negative, varies between 0.13 and 0.40 in absolute value, and is statistically significant

²⁷We follow Pitt and Khandker also in not including polynomials of (scaled) land, nor interactions with the eligibility dummy.

when we do not include control function terms, and when using a 1st order polynomial (in the second stage). Concentrating on these two estimates, we find an elasticity of -0.4.

5.2 Village level analysis

The household level analysis leaves open the question of whether the estimated negative treatment effect of microcredit on cost of crime is due to the cost of borrower households' decreasing or due to the cost of crime of non-borrower households increasing, or both. Figure 4 below plots the cost of crime of borrowers, non-borrowers in program villages, and households in the non-program villages that by definition are all non-borrowers, as a function of land holdings. As is clear from the Figure, the cost of crime of borrowers is lower but the cost of crime of program village non-borrowers is higher than that of non-program village households. The mean cost of crime for non-borrower households in program villages is 1600 taka while it is 800 taka in the non-program villages. A t-test suggests though that the difference between the non-borrowers in program and non-program villages is not significant when measured in absolute or in relative terms. Nonetheless, the Figure suggests that the estimated negative treatment effect may be due to negative spillovers from microcredit to non-borrowing households, i.e., due to the diversion effect of the criminal gang reallocating its activities towards non-borrower households.

[Figure 4 here]

To identify the effect of microcredit on village level crime, we exploit two sources of variation: First, we use the variation across villages in the proportion of households that are microcredit customers. As the proportion of households that are microcredit customers is potentially linked to unobservables that also affect village level crime (e.g. location of the village, fertility of the soil etc.), we need an instrument. The second source of variation that we exploit yields our instrument: We use the proportion of households that are eligible for microcredit, i.e., own at most 0.5 acres of land. Our identification assumption is thus that, conditional on covariates (which include controls

for land ownership and its distribution), the proportion of households with at most 0.5 acres of land does not affect the level of village level crime.

While both the average amount of land owned by households, its value per acre, and the distribution of land-ownership all are potentially correlated with the level of crime, it seems unlikely that our instrument is. The reason we think this is the case is that the 0.5 acre threshold is essentially arbitrary and should have no effect on the propensity of a household becoming the target of a criminal gang. To control for the level and distribution of land ownership, we include the mean amount of land owned by households in village i and its square, as well as the proportion of households with no land. The latter is potentially important as there is significant variation over villages in the proportion of landless households, and presumably they are unattractive targets of crime.

Our estimation sample consists of the 54 program villages included in our survey, and we thus have to work with a very small sample. It is well known that 2SLS suffers potentially from small sample problems. There is little we can do about this, and the results therefore have to be interpreted with some caution. Our model is just identified, and therefore the alternative strategy of estimating the reduced form of the model does not work. Instead, we have estimated the model with different transformations of both the endogenous explanatory variables. Because of the small sample size, we include only a limited set of control variables in addition to the land-based variables. These are: Highest grade of education completed by the household head; dwelling type; the number of adult male household members; distance to the nearest neighbor; and distance to the entry point to the village. All are measured as village-level averages. We report bootstrapped standard errors. Our dependent variable is the log of the cost of crime for the average household in the village (i.e., we take the average of the cost of crime over all households in the village).

[Table 8 here]

Table 8 contains the results of our estimations. Our instrument works fine, with 1st stage F-tests well in excess of the rule of thumb - value of 10. No matter whether we use the levels or logs of the endogenous explanatory variable, we find that at the village level, an increase in the proportion

of borrower households has a positive causal effect on the level of crime. Results in column two suggest that the elasticity of crime at the village level is rather high at 1.2 - this contrasts with the estimated household level elasticity (on the amount borrowed) of -0.4. Additionally we find that of our controls, only land obtains a significant coefficient. In line with expectations, the coefficient is positive, indicating that richer villages face more crime. As a (limited) way of dealing with the small sample size we also estimated the reduced form of the village level model. There, the coefficient of our instrument is 6.2, and significant at 3% level.

These results suggest that while the causal (local average treatment) effect of microcredit on the cost of crime at the micro level is negative, it is positive at the macro level. This suggests that microcredit creates a crime externality: It may attract more crime to the village, and certainly diverts crime to other households. This then hits non-borrowing households (and, potentially, those borrower-households not at the threshold) more, as the participating households (affected by the treatment at the threshold) are better able to protect them, due to e.g. the group-mechanisms of microcredit. It is also plausible that the joint liability mechanism of microcredit plays an important role here, forcing households to internalize the costs of crime of other households in the same borrower group.

6 Conclusions

Crime is facilitated by weak and/or corrupt official institutions. The unfortunate situation is that many developing countries' institutions are both weak and corrupt. These circumstances may give rise to unofficial institutions that seek to improve the situation. Microcredit has traditionally been seen as an endogenously arisen institutional remedy to the imperfections of the "official" financial structures. As a byproduct, it may however provide more than just that, affecting other areas of life, too. The objective of this paper was to study the effect of microcredit on crime.

Our survey documents the high frequency and the severe economic consequences of crime in rural Bangladesh. Some 30% of households were victims of some type of crime in the last 12

months that had economic consequences. The consequences, relative to consumption, were severe: Typically, a household would suffer losses worth several days' household consumption. We believe this to be important, and alarming, new information. Microcredit borrowers face less crime than non-borrowers.

The theoretical model we use allows us to study the capacity allocation decision of a crime gang, the investments in protection by households, and the household (micro) and village (macro) effects of crime. We model microcredit as having two effects: First, it increases household income for poor households, possibly also of non-borrowing households through a labor-market externality (an example is that non-borrower households are employed by borrower households in their new micro enterprises), but decreases the income of rich (non-borrower) households through the same externality. Second, it reduces the cost of investing in protection against crime. The key insight we take from the model is that one of the many possible outcomes is one where the effect of microcredit on cost of crime is different at the micro and macro levels. In particular, it is possible that the effect at the household level is that the cost of crime decreases (on average) for borrower households, while at the village level crime increases through the diversion effect alone.

We employ a regression discontinuity design to estimate the causal effect of microcredit on cost of crime at the household level. We find a significant negative effect. Employing a continuous measure of microcredit participation, we find an elasticity of -0.4. While our household level result is not robust to using higher order polynomials, we cannot reject the null hypothesis of using low order polynomials. The results hold in the robustness tests we perform.

We then extend the identification used in regression discontinuity design to the village level. To the best of our knowledge, this is a new way of solving the endogeneity problem, thereby allowing us to identify spillovers from aggregate data. Its benefit is that one can use it with cross-section data; its cost, at least in our case, is that the number of villages (and hence the number of observations) in our survey is rather small. We find that at the macro level, microcredit increases the cost of crime. The estimated elasticity of village level cost of crime with respect to the proportion of microcredit borrowers is 1.4.

Putting together our micro (household) and macro (village) level results suggests the following:

First, the various microcredit mechanisms - efforts to increase the “citizenship” of participants, regular sharing of information, and the joint liability mechanisms that forces participating households to internalize negative shocks of other participating households - mitigate crime among microcredit borrowers. Second, microcredit creates a crime externality on the non-participating households, diverting criminal activity towards non-borrower households, and possibly increasing the level of criminal activity. Thus, while in many ways beneficial, microcredit is not without unwanted side-effects that so far have been unappreciated.

Our paper thus contributes to the research on externalities associated with private protection against crime. The results show that the protection can have significant aggregate negative externalities, consistent with the theoretical work focusing on publicly observable protection.

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Appendix A: Microfinance and externalities

To understand the impacts of microcredit on crime at the village level a straight forward way to proceed is to assume that microcredit has externalities, either positive or negative. In the following we concentrate on externalities microcredit creates through local labor markets. In our sample most of the landless households and households with small landholdings have family members employed by households with large landholdings. We assume that microcredit is used to improve the productivity of family's own land. This reduces the supply of labor to other families, increasing the local wage. There is thus a positive externality to other poor households, but a negative externality to richer households. This non-linearity in externalities together with the non-linearity in self-protection with respect to income is the key to understand why village level and individual level impacts of microcredit can be of opposite sign.

We assume that the distribution of land in the village is given by the cumulative density $F(a)$ where a denotes the acreage of the farm. We further assume (admittedly, against the facts), that microcredit organizations only grant credit to eligible households, i.e., those with less than half an acre of land. The number of eligible households is then $F(\frac{1}{2}) \equiv E$. Consider now a farm with a acres of land. The income of a household is

$$y(a, l; l_o) = Aa^\alpha l_o^{1-\alpha} + w(l - l_o)$$

where l = amount of labor the household has, l_o = amount of labor used in the own farm and A = farm productivity. We assume that in addition to working in their own farm the household members can also work in other farms or in some other employment (the formulation contains also the possibility that in some farms more labor is needed than is provided by the family members) for a wage w . This endogenous wage is the opportunity cost for working in the own farm.²⁸ We assume that all households maximize their income given the amount of land owned. Thus the FOC for optimal labor input is

$$(1 - \alpha) A \left(\frac{a}{l_o} \right)^\alpha - w = 0 \Leftrightarrow \left(\frac{a}{l_o} \right)^\alpha = \frac{w}{(1 - \alpha) A}$$

giving

$$l_o(a) = a \left(\frac{w}{(1 - \alpha) A} \right)^{-\frac{1}{\alpha}}$$

The local labor market clears when the aggregate demand for labor (l_o aggregated over all farms) equals aggregate labor supply (l multiplied by the mass of households):

$$\begin{aligned} N \int_0^{a^{\max}} a \left(\frac{w}{(1 - \alpha) A} \right)^{-\frac{1}{\alpha}} dF(a) &= Nl \Leftrightarrow \\ \left(\frac{w}{(1 - \alpha) A} \right)^{-\frac{1}{\alpha}} &= \frac{l}{\bar{a}} \end{aligned}$$

²⁸ Notice that this means that the demand for labor in each farm is independent of the supply of labor by the household members. For simplicity, we assume households of similar size.

where N = total mass of households in the village, $a^{\max}$ = largest farm size, and $\bar{a}$ = average farm size in the village. The equilibrium wage is

$$w = (1 - \alpha) A \left(\frac{\bar{a}}{l} \right)^{\alpha}.$$

This implies that the household income is given by

$$y(a) = A \left(\frac{l}{\bar{a}} \right)^{1-\alpha} [a + (1 - \alpha) (\bar{a} - a)].$$

Let us then introduce microcredit. We assume that microcredit improves farm productivity by specifying that the farm production function is

$$(1 + \mu) A a^{\alpha} l_o^{1-\alpha}$$

for households that receive a microcredit. Note that with a Cobb-Douglas function it does not matter whether the microloan improves land or labor productivity or total factor productivity. Thus, following the same calculations as above and assuming that share $m(a)$ of the eligible households receive a microloan (we assume loans are of the equal size for all households),²⁹ the labor market equilibrium condition is now

$$\begin{aligned} \int_0^{\frac{1}{2}} a \left(\frac{w}{(1 - \alpha)(1 + \mu)A} \right)^{-\frac{1}{\alpha}} m(a) dF(a) + \int_0^{\frac{1}{2}} a \left(\frac{w}{(1 - \alpha)A} \right)^{-\frac{1}{\alpha}} (1 - m(a)) dF(a) + \\ \int_{\frac{1}{2}}^{a^{\max}} a \left(\frac{w}{(1 - \alpha)A} \right)^{-\frac{1}{\alpha}} dF(a) = Nl. \end{aligned}$$

Here, the first L.H.S. term is the labor demand of those eligible households who obtain microcredit; the second the labor demand of those eligible households that do not obtain credit; and the last L.H.S. term gives the labor demand of households that are ineligible for microcredit. This leads to the equilibrium condition

$$\left(\frac{w}{(1 - \alpha)A} \right)^{-\frac{1}{\alpha}} = \frac{l}{\bar{a}^{mc}}$$

where (the superscript mc refers to microcredit being available)

$$\bar{a}^{mc} = \int_0^{\frac{1}{2}} \left[m(a) (1 + \mu)^{\frac{1}{\alpha}} + (1 - m(a)) \right] dF(a) + \int_{\frac{1}{2}}^{a^{\max}} a dF(a).$$

The equilibrium wage is then given by

$$w = (1 - \alpha) A \left(\frac{\bar{a}^{mc}}{l} \right)^{\alpha}.$$

Thus, microcredit increases the wage rate by increasing the demand for labor. This is the externality created by microcredit. By the envelope theorem, households hiring labor in net terms (the households with large landholdings) experience a negative externality as their wage costs increase while the households with low enough landholdings experience a positive externality. The reduced form expressions for household

²⁹ Many microcredit organizations give loans that are of fixed size, though this fixed size may be a function of the number of past (and repaid) loans.

incomes with microcredit in the village are analogous to the ones without microcredit. The income of a non-borrowing household (superscript $mcNB$ for microcredit being available, but the household being a non-borrower) can be written as

$$y^{mcNB}(a) = A \left(\frac{l}{\bar{a}^{mc}} \right)^{1-\alpha} [a + (1-\alpha)(\bar{a}^{mc} - a)].$$

The income of a household receiving credit (B for borrower) is

$$y^{mcB}(a) = A \left(\frac{l}{\bar{a}^{mc}} \right)^{1-\alpha} \left[a(1+\mu)^{\frac{1}{\alpha}} + (1-\alpha)(\bar{a}^{mc} - a(1+\mu)^{\frac{1}{\alpha}}) \right].$$

This model is used as the basis of the model for analyzing the cost of crime. One should note, however, that there are other potential sources externalities: One could, for example, think of the incentive systems of local police. If the microcredit clients get better protection against crime through the microcredit institutions then local police has more resources to concentrate on the other households. In case the local police is very corrupt and cooperates with the gangs, the non-borrowing households face more harassment from the local police. With non-corrupt police these households get more protection.

Table 1
Household Level Crime Descriptive Statistics

Type of crime	All households - %	Borrower	Non-borrower	Adjusted Wald test
Any crime	36.20	22.82	41.90	25.26***
Affected 1 type of crime	23.99	17.99	26.55	6.41**
Affected 2 types of crime	10.20	4.01	12.84	12.37***
Wage loss	4.42	2.02	5.44	6.43**
Medical costs	6.45	2.99	7.93	8.86***
Lost goods	27.17	17.58	31.26	14.74***
Money	12.93	5.98	15.89	12.80***
#Incidences, conditional on being a victim	1.41	1.25	1.44	6.39**
Sample size	1188	810	378	1188

Notes: 344 households were affected by crime.

***, ** and * denote significance at 1, 5, and 10% levels.

Table 2
Village Level Crime Descriptive Statistics

Type of crime	%	Village average		
		S.D.	Daily consumption	S.D.
Any crime	38.67	16.92	8.96	28.07
1 type of crime	24.78	14.53	.74	.85
2 types of crime	11.07	11.31	11.60	35.24
Wage loss	5.65	8.80	2.09	1.48
Medical costs	8.25	10.48	1.21	2.42
Lost goods	28.85	17.43	17.13	19.41
Money	13.41	10.69	2.30	3.87
Observations	54		54	

Table 3
Household Level Cost of Crime (Daily Consumption)

	All households	Borrowers	Non- borrowers	Adjusted Wald test
Total cost of crime	5.35 (26.84)	1.83 (8.95)	6.85 (31.43)	7.46**
Wage loss	.23 (1.29)	.07 (.63)	.30 (1.48)	6.99***
Medication	.15 (1.26)	.04 (.35)	.20 (1.48)	5.11**
Lost goods	4.35 (26.11)	1.53 (8.54)	5.55 (30.62)	5.02**
Money	.61 (3.46)	.19 (1.86)	.80 (3.93)	7.86***
Observations	1188	810	378	
Conditional on being affected				
Total cost of crime	14.77 (43.07) N=344	8.04 (17.38) N=185	16.34 (47.01) N=159	3.06*
Wage loss	5.21 (3.48) N=46	3.45 (2.87) N=21	5.48 (3.53) N=25	3.54*
Medication	2.34 (4.43) N=65	1.48 (1.47) N=31	2.48 (4.76) N=34	1.83
Lost goods	16.02 (48.26) N=253	8.73 (18.82) N=134	17.76 (52.90) N=119	2.16
Money	4.74 (8.57) N=104	3.11 (7.04) N=45	5.00 (8.80) N=59	1.77

Table 4
Household Level Descriptive Statistics

Description	Unit of Measuring	All households	Borrower	Nonborrower	Adjusted Wald test
Land	Decimals	84.09 (157.11)	21.09 (42.54)	110.94 (179.10)	49.16***
Landless households	Landless-1	.16 (.36)	.23 (.42)	.13 (.33)	17.23***
Per acre land value	Tk	10728.94 (19710.62)	13086.44 (17976.04)	9848.09 (20274.07)	3.37*
Religion	Muslim-1	.85 (.36)	.86 (.35)	.84 (.36)	0.37
Highest grade completed by household head	Year	4.30 (4.42)	3.51 (4.07)	4.64 (4.53)	9.75***
Sex of household head	Male-1	.94 (.24)	.92 (.27)	.94 (.23)	1.28
Age of household head	Year	43.80 (11.96)	41.83 (11.38)	44.64 (12.11)	8.99***
Dwelling type	Building-0	.79 (.40)	.90 (.29)	.75 (.44)	20.81***
Number of adult male (age above 18)	Number	1.54 (.93)	1.46 (.94)	1.58 (.93)	2.42
Distance of HH dwelling from closest neighbour	Meter	11.84 (16.50)	11.67 (13.87)	11.91 (17.52)	0.04
Distance of HH dwelling from entrance point	Meter	630.22 (450.21)	730.03 (581.44)	587.76 (373.31)	14.30***
Distance of HH dwelling from middle point	Meter	355.46 (273.71)	403.03 (357.97)	335.22 (225.87)	9.54***

Notes: Sample size is 54 program villages and 1188 households.

We use weights to correct for our survey design. For Land value, the sample size is 925.

Table 5
Village Level Descriptive Statistics

Description	Unit of Measurement	Mean	S.D.
Average households land	Decimals	87.37	66.43
Landless households	Landless-1	.17	.10
Per acre land value	Tk	9636.51	9361.77
Religion	Muslim-1	.88	.20
Average highest grade completed by household head	Year	4.29	1.94
Sex	Male-1	.93	.07
Average Age of household head	Year	44.13	4.57
Average dwelling type	Building-0	.81	.17
Average number of adult male (age above 18)	Number	1.56	.29
Average distance of household dwelling	Meter	12.12	6.62
Average distance of HH dwelling from middle point	Meter	626.14	228.06
Average distance of HH dwelling from entrance point	Meter	354.78	114.12

Notes: Sample size is 54 program villages.

We use weights to correct for our survey design and village size.

Table 6
The Effect of Microcredit on Cost of Crime at the Household Level

Independent Variable	0 th	1 st	2 nd	3 rd	4 th
Credit Indicator	-3.70*** (1.43)	-3.89** (1.59)	-2.19 (2.41)	-2.66 (3.58)	-1.24 (5.55)
F-test (First stage)					
Instrument	74.71***	63.72***	47.11***	24.98***	18.08***
All polynomial terms	-	5.06***	5.18***	4.77***	3.85***
Highest order polynomial terms	-	-	3.47	0.675	0.02
Polynomial terms of two highest orders	-	-	-	2.02	0.57
2 nd to 4 th order polynomial terms	-	-	-	-	1.62
Village fixed effects	464.0***	37.20***	32.18***	99.06***	185.0**
Household characteristics	3.09***	4.15***	4.24***	4.10***	4.07***
F-test (Second stage)					
All polynomial terms	-	0.11	0.79	0.76	0.67
Highest order polynomial terms	-	-	0.58	0.124	0.56
Polynomial terms of two highest orders	-	-	-	0.47	1.11
2 nd to 4 th order polynomial terms	-	-	-	-	0.72
Village fixed effects	18.53***	72.88***	40.99***	345.3***	282.4***
Household characteristics	5.71***	4.25***	2.13**	1.92**	1.67**

Notes: Reported numbers are coefficient and robust (standard error).

Standard errors are clustered at village level.

All specifications include village fixed effects and household characteristics.

We employ weights that take into account our sampling design and village size.

Sample size is 54 program villages and 1187 households.

***, ** and * denote significance at 1, 5, and 10% levels.

Instrument = F-test of the instrument in the 1st stage regression.

Table 7
The Effect of Microcredit on Cost of Crime at the Household Level

Independent Variable	Order of polynomial in scaled land			
	0 th	1 st	2 nd	4 th
Log of amount borrowed	-.38*** (.15)	-.40*** (.16)	-.22 (.25)	-.13 (.60)
F - test (First stage)				
Instrument	71.83***	61.88***	45.30***	23.10***
All polynomial terms	-	4.30***	4.50***	3.71***
Highest order polynomial terms	-	-	3.35**	0.78
Polynomial terms of two highest orders	-	-	-	1.94
2 nd to 4 th order polynomial terms	-	-	-	1.81
Village fixed effects	517.8***	67.78***	71.92***	70.43***
Household characteristics	3.34***	4.41***	4.52***	4.50***
F - test (Second stage)				
All polynomial terms	-	0.14	0.84	0.82
Highest order polynomial terms	-	-	0.60	0.25
Polynomial terms of two highest orders	-	-	-	0.52
2 nd to 4 th order polynomial terms	-	-	-	0.80
Village fixed effects	65.03***	161.3***	52.16***	150.48***
Household characteristics	5.77***	4.08***	2.10**	1.86*

Notes: Reported numbers are coefficient and robust (standard error).

Standard errors are clustered at village level.

All specifications include village fixed effects and household characteristics.

We employ weights that take into account our sampling design and village size.

Sample size is 54 program villages and 1187 households.

***, ** and * denote significance at 1, 5, and 10% levels.

Table 8
The Effect of Microcredit on Cost of Crime at the Village Level

Independent Variables	2SLS		Reduced form
Proportion of borrower households	4.87** (2.29)	- -	- -
Log of proportion of borrower households	- -	1.43** (.73)	- -
Proportion of eligible households	- -	- -	6.17** (2.86)
Household land	.03* (.02)	.03* (.01)	.03* (.01)
Household land square	-.00007 (.00006)	-.00007 (.00006)	-.00007 (.00005)
Age of household head	.03 (.05)	.03 (.05)	.05 (.053)
Proportion of landless households	1.91 (2.58)	-1.98 (2.57)	-2.29 (2.65)
Dwelling type	1.32 (1.22)	1.27 (1.13)	1.09 (1.11)
Highest grade completed by household head	.05 (.12)	.04 (.12)	.09 (.14)
Distance of household dwelling to village entrance point	.0004 (.0009)	.0003 (.0009)	.0005 (.0009)
R^2	-	-	0.22
F- test	41.31***	30.05***	-

Notes: Reported numbers are coefficient and bootstrapped (standard error). We employ weights that take into account our sampling design and village size. All variables are village averages.

The sample size is 54 program villages. ***, ** and * denote significance at 1, 5, and 10% levels. F-test is on the instrument in the 1st stage regression.

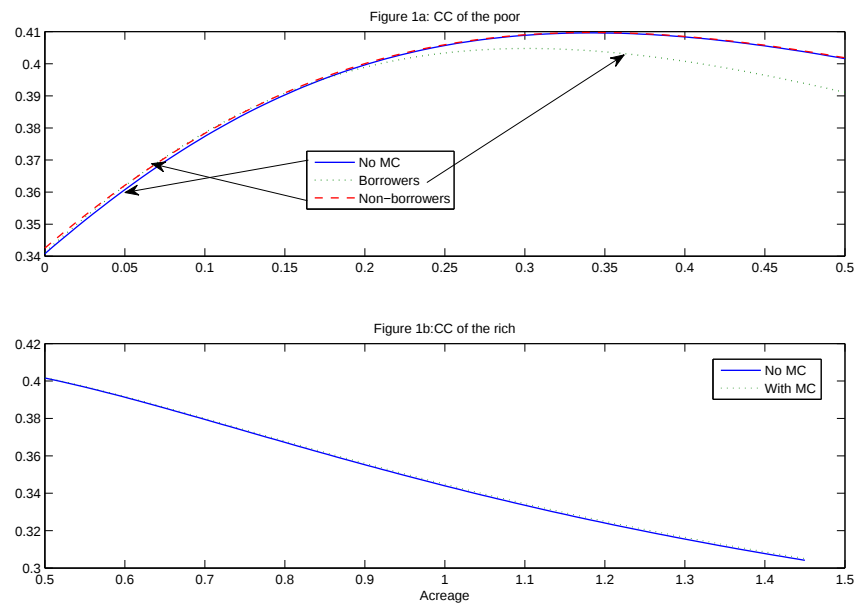


Figure 1. Distribution of Cost of Crime as a Function of Landholdings

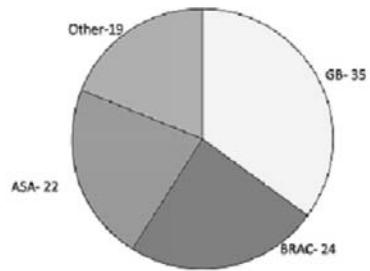


Figure 2. Market shares of the Leading Microcredit Lenders in Bangladesh

Figure 3 Histogram of Distribution of Landholding
Program and Nonprogram Villages (Bin 10)

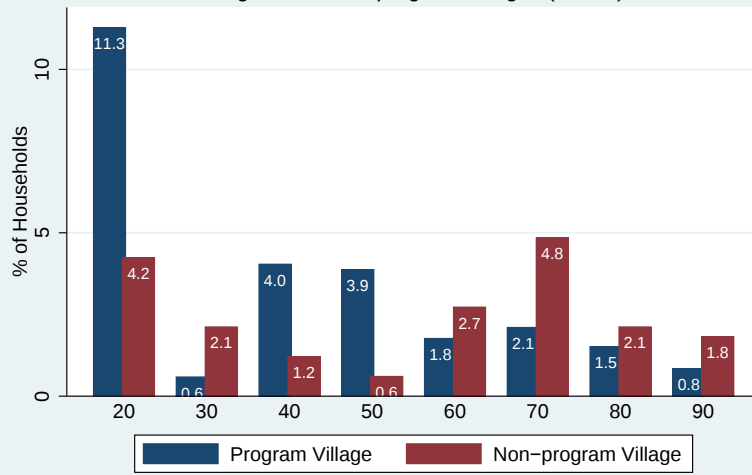


Figure 4 Cost of Crime in Program and Nonprogram Villages

