Microfinance and Moneylenders: Long-run Effects of MFIs on Informal Credit Market in Bangladesh

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ABSTRACT

Using two surveys from Bangladesh, this paper provides evidence on the effects of microfinance competition on village moneylender interest rates and households' dependence on informal credit. The views among practitioners diverge sharply: proponents claim that MFI competition reduces both the moneylender interest rate and households' reliance on informal credit, while critics argue the opposite. Taking advantage of recent econometric approaches that address selection on unobservables without imposing standard exclusion restrictions, we find that the MFI competition does not reduce moneylender interest rates, thus partially repudiating the proponents. The effects are heterogeneous; there is no perceptible effect at low levels of MFI coverage, but when MFI coverage is high enough, the moneylender interest rate increases significantly. In contrast, households' dependence on informal credit tends to go down after becoming MFI member, which contradicts part of the critic's argument. The evidence is consistent with a model where either MFIs or moneylenders engage in cream skimming, and fixed costs are important in informal lending.

Key Words: Microfinance, Moneylenders, Microcredit, Interest Rates, Informal Borrowing, Long-run Effects, Bangladesh, Identification through Heteroskedasticity
JEL Codes: O17, O12, C3

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INTRODUCTION

Concerns about exploitative moneylenders and usurious interest rates have motivated a variety of government interventions in rural credit markets for centuries in many countries: anti-usury laws, debt settlement boards, credit cooperatives (IRDP in India, 'Comilla Model' in Bangladesh), and specialized rural banks are among the well-known examples.[2] From its inception in the early 1970s in Bangladesh, a central goal of the current microfinance movement has also been to free the poor from the "clutches" of moneylenders, as Muhammad Yunus, the founder of Grameen Bank, puts it.[3] Unlike the standard banks that rely on collateral for screening and enforcement, the microfinance institutions (MFIs) focus on rural poor without collateral, previously served only by informal financiers: friends, family, and especially village moneylenders. The number of poor served by MFIs globally has increased exponentially from 10,000 in 1980 to more than 150 million in 2012. The goal of this paper is to analyze the effects of MFI expansion on the informal credit market with a focus on the moneylenders.

The available evidence shows that government interventions in the rural credit market in the 1960s and 1970s largely failed to drive out the moneylenders (For discussion on the performance of government policy interventions, see McKinnon (1973), Von-Pischke et al. (1983), Hoff et al. (1993), Armendariz and Morduch (2010), Karlan and Morduch (2010)). Has the microfinance movement fared any better in delivering the rural poor from the "clutches" of moneylenders? The proponents of microfinance note that while the government credit programs were captured by the large landholders (Von-Pischke et al. (1983)), MFIs target land-poor households, usually bypassed by the formal banks, who also constitute the bulk of the clientele for the moneylenders. Unlike the government banks, the MFIs thus can create effective competition for the moneylenders. The availability of microcredit at relatively lower interest rates without any collateral allows poor households to substitute away from the high interest rate loans from traditional moneylenders and landlords. Microcredit thus is expected to drive down the

[2] References to moneylenders appear throughout history, for example in the Hindu religious Vedic texts in ancient India dating back to 1500 BC. The Bible tells a story in which Jesus "overthrew the tables of the moneychangers" (Matthew 21:12-13). Perhaps the most colorful reference to a moneylender is that of Shakespeare's Shylock who demanded his pound of flesh in exchange for a late repayment (Merchant of Venice).

[3] Recounting the origin of Grameen Bank, Yunus states: "(W)hen my list was done it had the names of 42 victims. The total amount they had borrowed was US $27. What a lesson this was to an economics professor who was teaching about billion dollar economic plans. I could not think of anything better than offering this US $27 from my own pocket to get the victims **out of the clutches of the moneylenders."** Yunus (2009, 7th Nelson Mandela Lecture. Emphasis added).

moneylender interest rate and eventually drive them out of business as the microcredit market deepens.[4]

Many critics and observers of MFI movement, however, contend that microfinance in fact leads to a higher demand for moneylender loans which drives up the interest rates. A household might find it necessary to borrow from moneylenders or other informal sources after becoming a MFI member, for example, to keep up with a rigid repayment schedule even though it did not borrow from them before.[5] The demand for informal loans may also increase because of indivisibility of investment projects; MFI borrowers may require additional loans to achieve economies of scale in their microcredit financed investment.[6] It is often argued that the ability to borrow from multiple sources may lead to unsustainable debt accumulation and condemn the poor to a vicious cycle of poverty and indebtedness.

While many practitioners would probably concur with one or the other contrasting views noted above, the interactions between the informal credit market and MFIs may be much more complex and nuanced; the price and quantity of informal credit may respond in opposite directions when MFI coverage increases in a village. For example, there can be a "cream skimming" effect where an MFI poaches away the better borrowers from the moneylender, and facing riskier borrowers the moneylender needs to charge a higher interest rate. Note that cream skimming by MFIs is more likely in our context compared to the case of formal banks, because many MFIs rely on group liability lending, while the banks rely on individual lending. Since joint liability generates incentives to exclude someone who poses greater risk, the households left in the pool of potential clients for the moneylender are likely to be particularly high risk.[7] Another channel that gives rise to a positive effect of MFI penetration on moneylender interest rates, along with a reduction in rural poor's dependence on moneylenders, is noted by Hoff and Stiglitz (1998): if

[4] Although this argument is made by proponents of MFIs, existing theoretical models can be used to provide theoretical foundations for this view. See the discussion in section (4) below.

[5] See Jain and Mansuri (2003) for a theoretical analysis, and Sinha and Matin (1998) for a discussion in the context of Bangladesh.

[6] This seems plausible given the recent evidence that the entrepreneurial MFI borrowers cut their consumption to undertake indivisible investments (see Banerjee et al. (2013)).

[7] Although we focus on the cream skimming by the MFIs, theoretically it is possible that the MFIs attract the high risk borrowers, and moneylenders cream skim as they hold on to the low risk (high return) borrowers and can extract the surplus due to market power (see Mookherjee and Motta (forthcoming) for a formalization). For a discussion on the relevant empirical evidence that points more to cream skimming by the MFIs in the context of Bangladesh, see P. 39 below.

there are significant fixed costs in screening and enforcement, competition from MFIs may force a moneylender to increase the interest rate to cover fixed costs as the number of borrowers declines.

Since moneylenders have always been at the core of policy discussions on rural financial sector reform, one would expect the interactions between MFIs and moneylenders to be a fruitful ground for empirical research. It is thus surprising that there is little systematic evidence on the effects of MFIs on the informal credit market in general and on the moneylenders in particular. The only paper of which we are aware is Mallick (2012) that uses data from 106 villages in Bangladesh, and reports evidence of a positive effect of MFI competition on moneylender interest rates, but the effects on households' demand for informal loans are not analyzed.[8] A positive effect on moneylender interest rates in itself, however, does not tell us that it is an outcome of higher demand as claimed by the critics of microcredit; it may also result from a change in the composition and size of the pool of borrowers in the informal markets, as noted above. To sort out these contrasting views, we thus need to estimate the effects of MFI membership on the household borrowing. If we find that MFI penetration leads to higher incidence of household borrowing from moneylenders along with higher interest rates, this is more consistent with the demand shift explanation of the critics. In contrast, if we find that MFI membership reduces the probability of a household borrowing from the moneylender, but the moneylender interest rates increase with MFI competition, the evidence would be more consistent with the view that emphasizes the cream skimming effect and fixed costs in informal lending.[9]

Using two surveys from Bangladesh, this paper provides evidence on the effects of MFI penetration in the rural credit markets on moneylenders' interest rates and households' demand for informal loans. Bangladesh offers an excellent opportunity to understand the long run effects of MFI penetration on informal credit markets, because it is among the most mature MFI markets in the world with almost 40 years of microcredit lending. In 2011, there were 35 million MFI borrowers in Bangladesh with 248 billion taka in outstanding loans (Microfinance Regulatory Authority, Bangladesh Bank). According to estimates from various available data sources,

[8] The small sample size also raises the possibility that the results may be driven largely by something specific to these villages.

[9] It is important to emphasize here that the primary goal of our paper is to discriminate between the two contrasting views held by the practitioners. We also provide a discussion on the implications of the empirical results for alternative theoretical models in the literature, but the evidence on the interest rate and demand for informal credit is not sufficient to discriminate among all different theoretical possibilities. Please see the discussion in section (4) below.

approximately 40 percent of the households in rural areas are MFI members (for example, Household Income and Expenditure Survey, 2010). We use two rich data sets for the empirical analysis: (i) an exceptionally large cross section data set that includes almost 800 villages in North-Western Bangladesh for the years 2006-2007, collected by the Institute of Microfinance (InM) in Dhaka and (ii) a panel dataset that covers from 2000 to 2007, collected by BIDS-BRAC.[10] The large cross-section data-set with almost 800 villages provides adequate power to estimate the effects on village level moneylender interest rate with a measure of confidence, because there is ample variation in the degree of MFI penetration across different villages.

For identification of the effects of higher MFI coverage on the moneylender interest rate in a village, the main challenge is unobserved village-level heterogeneity. When we run an OLS regression of moneylender interest rates on MFI coverage, the estimated effect is likely to be biased, because the MFIs do not choose the location and intensity of credit programs across villages randomly, and the households do not decide to participate in the microcredit programs randomly either.[11] A standard approach to tackling the omitted variables bias is to design an instrumental variables strategy. However, it is extremely difficult, if not impossible, to find credible exclusion restrictions required for the instrumental variables approach in our application, and there has been increasing skepticism about the validity of the exclusion restrictions imposed in many related contexts. We thus take advantage of advances in econometrics that provide alternative ways to address possible biases in non-experimental data without imposing exclusion restrictions. To enhance credibility and ensure robustness of the conclusions, we report estimates from a rich array of recent econometric approaches.

As part of our preliminary exploration, we use three estimators that rely on conditional independence assumption (CIA): (i) normalized inverse propensity reweighting estimator (IPW due to Hirano and Imbens (2001)), (ii) bias corrected matching (Abadie and Imbens (2002)), and distance weighted bias corrected radius matching (Lechner et al. (2011)). These estimators provide estimates that are valid under weaker assumptions than the OLS, but they still rely on the assumption that there is no selection on unobservables.

[10] The InM survey was led by Baqui Khalily and Abdul Latif, and the BIDS-BRAC surveys by Mahabub Hossain and his collaborators.

[11] Note that the spatial heterogeneity observed in the MFI activities across villages in Bangladesh is an outcome of MFI choices, donor policy, historical accidents, and path dependence over a period of almost 40 years. This also implies that it may not be feasible to study the long-run effects of MFI competition by randomized interventions across villages.

Central to our empirical strategy are two estimators that relax the conditional independence assumption and correct for possible biases due to selection on unobservables: the minimum-biased (MB) propensity score reweighting estimator proposed by Millimet and Tchernis (2013), and heteroskedasticity based instrumental variables scheme developed by Klein and Vella (2009a).[12] While the MB estimator is based on normalized IPW, it is attractive because it minimizes the bias arising from possible violation of the CIA due to selection on unobservables. Heteroskedasticity based identification approach was developed in a series of papers by Rigobon (2003), Klein and Vella (2009a, 2010) and Lewbel (2012).[13] The intuition behind heteroskedasticity-based identification is that when there is substantial heteroskedasticity in the treatment equation, the changing variance in the residual acts as a "probabilistic shifter" of the treatment status, similar to the shifts induced by a standard instrumental variable satisfying exclusion restriction.[14] As emphasized by Lewbel (2012) and Klein and Vella (2009a, 2010), heteroskedasticity based identification is useful when the standard exclusion restrictions are not available. We implement the heteroskedastic instrumental variables approach developed by Klein and Vella (2009a) which performs well when omitted variables bias is the main concern, as is the case in our application (see Millimet and Tchernis (2013) for the relevant Monte Carlo evidence).[15] The heteroskedasticity in the treatment equation in our case is based on clear theoretical reasoning; it results from interactions between fixed costs in establishing a new branch and private information of loan officers on potential borrowers.[16] For the household level analysis, we exploit a two-round panel data set spanning seven years, and combine a difference-in-difference model with household fixed effects (DID-FE), and then implement different estimators including alternative matching,

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[12] A few recent papers have used heteroskedasticity based identification to analyze the effects of microcredit; see, for example, Schroeder (2014), and Mallick (2012)).

[13] While all three rely on second moments in the data for identification, their approaches differ. For recent applications of the specific approach implemented in this paper (i.e., Klein and Vella (2009a)), see Maurer et al. (2011), Klein and Vella (2009b), Farre et al. (2012, 2013), Schroeder (2014), Emran et al. (2014), among others.

[14]The parallel to the standard instrumental variables is, however, less than perfect. In particular, the factors that generate heteroskedasticity in the treatment equation can also generate heteroskeasticity in the outcome equation, because no exclusion restriction is imposed on the explanatory variables. As we discuss in detail later, identification remains valid in general even when there is heteroskedasticity in the outcome equation. For a more complete discussion, please see section 2.2 below.

[15] For applications of an alternative heteroskedasticity based identification approach developed by Lewbel (2012), see Emran and Shilpi (2011), Emran and Hou (2013), and Emran and Sun (2014).

[16] In this sense, the hetoroskedastic probit of the treatment equation can be thought of as a convenient model of the MFI selection process that focuses on the second moment. We, however, note that the existing theoretical models on the interactions between the MFIs and the moneylenders, and competition among MFIs do not yield any predictions regarding the second moment of the error term in the selection equation in our context. We thus discuss some plausible informal theoretical reasoning that remains to be formalized.

propensity score reweighting, and MB estimators in the DID-FE model.[17] We discuss in detail the plausibility of the parallel trend assumption in our application (please see section 3.1 below).

Our main findings are as follows. The evidence strongly suggests that penetration of microfinance in a village *increases* the moneylender interest rate when the MFI coverage is high enough. At low levels of MFI coverage, there is no perceptible effect on the moneylender interest rate; the effects of microfinance on rural credit market are thus heterogeneous. The 'proponent's view' that competition from MFIs brings down the 'exploitative' interest rates thus seems to be contradicted. However, the results do not support the alternative view that when a household becomes an MFI member it is more likely to take additional loans from moneylenders and other informal sources. Evidence on a household's propensity to borrow from informal sources based on panel data analysis shows that the MFI membership reduces significantly the probability that a household would borrow from them. Thus the moneylender interest rate may go up in a village even though MFI borrowers substitute away from moneylenders as argued by the proponents of microfinance. The fact that MFI membership reduces the demand for moneylender loans contradicts the 'crowding in' effect of the Jain and Mansuri (2003) model. The coexistence of higher interest rate with a lower propensity to borrow is consistent with higher transactions costs in serving a smaller number of clients (fixed costs) by the moneylender (Hoff and Stiglitz (1998)), and cream skimming by moneylenders (Mookherjee and Motta (forthcoming)). We discuss the available evidence in the context of Bangladesh that casts doubts on cream skimming by the moneylenders and points to cream skimming by the MFIs instead.

The remainder of the paper is organized as follows: Section 2 is devoted to the analysis of the effects of MFI competition on moneylender interest rate at the village level; Section 3 deals with the effects of MFI membership on household borrowing. In each section, we first discuss the empirical issues and our identification approach, then data, and finally present the results. The last section is devoted to a discussion of the predictions of five theoretical models regarding the effects of MFI competition on the demand for moneylenders' loans and the interest rate. The evidence presented in section 3 is used to discriminate among alternative models. The paper concludes with a brief summary of the results.

[17] For discussions on the advantages of combining matching with a DID design, see Heckman et al. (1998) and Blundell and Costa-Dias (2009).

1. THE SPREAD OF MICROFINANCE AND MONEYLENDER INTEREST RATE

1.1. EMPIRICAL STRATEGY

To understand the identification issues, consider the following triangular model:

$$ML_j = \beta_0 + \beta_1 MF_j + X_j^{'}\gamma + u_j \qquad (1)$$

$$MF_j = 1(\alpha_0 + X_j^{'}\delta + v_j > 0) \qquad (2)$$

Where, ML_j is the moneylender interest rate, MF_j is an indicator of MFI coverage in village j, and X_j is a set of village controls as well as regional fixed effects. We use binary indicators of MFI activities in a village at different thresholds of coverage. This is motivated by two considerations. First, a binary treatment allows us to take advantage of recently developed econometric approaches for non-experimental data in the evaluation literature (for example, the Minimum Biased (MB) propensity score reweighting estimator). Second, and no less important, it provides a simple way to analyze potentially heterogeneous effects of MFI penetration; the treatment effect β_1 is thus assumed to potentially heterogeneous. The effects of MFI coverage on informal interest rates are unlikely to be constant across the distribution; its strength will, in general, depend on the extent of coverage with possible threshold effects. One would not expect much of an impact of MFI entry into a village on the informal interest rate if, for instance, only a small fraction of the potential informal borrowers get access to microcredit.[18] A focal threshold for defining the binary 'treatment' is the mean coverage rate. We also use other thresholds for defining the treatment variable. Note that one has to be careful about the appropriate treatment and comparison groups and the interpretation of the estimates when the binary treatment is defined in terms of other thresholds. For example, consider the case when the treatment is defined as villages that have MFI coverage in the top quartile of the sample. To keep the comparison group same as the case of binary treatment defined at the cut-off of mean coverage rate, we need to exclude the villages that fall in the third quartile of coverage distribution.

Another relevant issue is the implication of possible general equilibrium effects across villages. One might worry that MFI interventions in a village may affect the households in the

[18] One might wonder whether a continuous treatment variable in a quadratic specification could better capture the heterogenous effects. The evidence presented later shows that the effects on interest rate are insignificant for the first three quartiles of MFI coverage, and becomes both statistically and numerically significant only at the fourth quartile. Fitting a quadratic model in this case could lead us to erroneously conclude that there is a positive effect for the third quartile, for example. Moreover, a quadratic model involves two endogeneous variables, complicating the identification and estimation substantially.

neighboring village, and the estimated treatment effect will be biased downward, leading to incorrect conclusion that there is no impact of MFIs on rural credit market. This, however, seems a highly unlikely possibility in the context of rural Bangladesh, both on theoretical and empirical grounds. A large body of theory emphasizes that rural markets, especially the credit market, are segmented due to adverse selection and moral hazard problems arising from information imperfections (Hoff, Braverman, and Stiglitz (1993), Banerjee (2003)). The textbook model of spatial arbitrage is not appropriate in this context. The empirical evidence also shows that there is significant spatial heterogeneity in interest rates, and very limited arbitrage (for a survey of the evidence on lack of arbitrage in rural credit market, see Banerjee (2003)). Note that even if there are some spill-overs across villages, this would make it more difficult to find any impact of MFI intervention, and the evidence of a significant effect presented later cannot be explained by this.

The main identification challenge in estimating the effect of MFI penetration on moneylender interest rate is that, in general, the correlation between u_j and v_j is non-zero due to unobserved village and borrower characteristics such as productivity and risk. For concreteness, consider the implications of unobserved productivity heterogeneity across villages. As noted above, the rural credit markets are in general segmented because of inadequate infrastructure and the local information advantages enjoyed by moneylenders (Hoff and Stiglitz (1993), Ghosh, Mookherjee and Ray (1999), Banerjee (2003), Siamwalla et al. (1993), Aleem (1993)). In a segmented market, interest rates charged by the moneylenders in a village depend on its productivity characteristics; the moneylenders in a more productive village are able to charge higher interest rates as they extract the surplus from borrowers. If the MFIs also prefer to locate in villages with higher productive potential, then we would observe Cov $(u_j, v_j) > 0$. This implies that if one runs OLS regressions, the estimated effect of MFI presence on moneylender interest rate across villages will be biased upward; one may find a spurious positive "effect", even if the causal impact of MFIs on moneylender's interest rate is in fact negative. However, the omitted productivity heterogeneity in OLS regressions may as well lead to a *downward* bias in the estimated effect of MFI penetration; this happens when the location choices of MFIs are primarily driven by poverty alleviation objectives. In this case, the MFIs target relatively less productive villages and we expect Cov $(u_j, v_j) < 0$. This implies that the OLS estimate may spuriously find a zero or even a negative effect, when the true effect is positive and large in magnitude. Possible measurement errors in the MFI coverage variable would also bias the estimated effect towards zero due to attenuation.

A standard solution to the bias caused by omitted variables and measurement error is to employ an instrumental variables strategy. To develop an instrumental variables strategy for credible identification, we need an exogenous source of variation in the placement of MFI branches which does not affect the interest rate across villages. The available studies on the location choices of MFIs in Bangladesh suggest that MFIs take into account both profit and poverty alleviation in their location choices (Salim (2013)). The evidence also indicates that the MFIs prefer villages closer to the market centers (usually the Thana center where the branch office is located) (see, Mallick and Nabin (2013), and Zeller et al. (2001)). However, any area characteristics that may have determined the placement of MFI branches (e.g. population density, infrastructure, poverty indicators) can potentially affect moneylender interest rate as well. Thus they are not likely to satisfy the exclusion restrictions required for identification. In our empirical analysis we thus do not impose any exclusion restriction on the village characteristics.

(1.2) ALTERNATIVE ECONOMETRIC APPROCAHES

(A) Preliminary Analysis under the CIA Assumption: Matching and Propensity Score Reweighting

To reduce potential bias in the OLS estimates, we use two matching estimators and a propensity score weighting estimator. The matching estimators are: bias-corrected matching due to Abadie and Imbens (2002), and distance-weighted radius matching with regression based bias correction developed by Lechner, Miquel and Wunsch (2011) (henceforth called "LMW Radius Matching"). The LMW radius matching combines the following: (i) weighting of the matched controls within the radius according to their distance to the treated observation, (ii) bias-adjustment based on OLS or logit regression depending on the support of the outcome variable, (iii) partially data-driven choice of the radius size as a function of the distances in pair matching and (iv) asymptotically unbiased propensity score trimming to ensure common support in the propensity score across treatment groups. Extensive empirical Monte Carlo evidence reported in Lechner et al. (2013) shows that this procedure with a relatively wide radius yields reliable estimate of average treatment effect on treated.

The propensity score reweighting estimator we use is the normalized inverse propensity score weighted (IPW) estimator which weighs the observations on the treatment group by the probability of being treated (the inverse of the propensity score) and weighs the observations on the control group by the probability of not being treated (one minus the inverse of propensity score). Busso et al. (2014) provide Monte Carlo evidence that the normalized IPW estimator performs best among a wide set of matching and propensity score based estimators in applied settings.

Choice of Variables for Matching

The choice of conditioning variables is critical for estimation under the assumption of conditional independence. Although the estimates from matching and IPW are treated as preliminary in our empirical analysis, we choose the set of control variables to reduce the bias as much as possible. Our approach is motivated by the suggestion of Heckman and Navarro-Lozano (2004) for choosing variables for matching. As Heckman and Navarro-Lozano (2004) emphasize the variables that determine selection into the treatment and also affect the outcome are appropriate for matching. Our choice of control variables in the empirical analysis thus focuses on the determinants of the MFI program location and intensity across different villages.

The existing literature on the MFI branch placement in Bangladesh identify village productivity (economic potential) and risk characteristics as first order determinants (Salim (2013), Nabin and Mallick (2013). As noted earlier, productivity and risk are also among the most important factors in determining moneylender interest rates. Some of the most important productivity characteristics such as soil quality and elevation are effectively time invariant, and we employ upazilla fixed effects to sweep them off. Given the natural endowment, access to markets and quality of infrastructure determines the technology choices and productivity in a village. We thus include measures of access to markets and other services such as distances to bazar (market), bus stop, and secondary school. Distance to formal bank branch is introduced to capture potential competition from and linkages to the formal financial sector, and thus affect the choice of MFI branch location (Bell (1993)). Irrigation increases productivity and reduces risk of agricultural production, affecting both risk and returns in the credit market. Accordingly, we include percentage of households using irrigation as a control. We also include the number of households surveyed in a village as a scale variable which is important due to fixed costs involved in establishing a new branch.

Vulnerable Group Development (VGD) is a major public safety net program targeting the poor in Bangladesh; many MFIs use the VGD cards as an indicator of moderate poverty. For example, BRAC excludes a household from its ultra-poor program (CFPR/TUP) if it has a VGD card. We use percentage of households with VGD cards as an indicator of moderate poverty in the village.[19] As the analysis of Salim (2013) on the branch locations of BRAC and Grameen Bank shows, the existence of a sizable group of moderate poor households is important for location choices of MFIs.[20] Land ownership is used by most of the MFIs as a salient selection criterion. While many MFIs including BRAC, Grameen Bank, and BRDB in principle lend only to households owning less than 50 decimal of land, mis-targeting due to both type 1 and type 2 errors is not rare. In particular, the evidence indicates that landless ultra-poor (owning less than 10 decimal of land) are largely excluded from the standard MFI lending programs. Thus the landless constitutes an important clientele of moneylenders. We include the percentage of landless (less than 10 decimal) in the village to capture this effect.

(B) Identification with Selection on Unobservables but No External Instrument: Two approaches

In this subsection, we discuss two approaches recently developed in econometrics literature that do not rely on the CIA assumption, and correct for possible biases due to selection on unobservables when there are no credible exclusion restrictions that can be imposed.

The Minimum-Biased Normalized IPW (MB-IPW)

The MB-IPW estimator due to Millimet and Tchernis (2013) builds on the normalized IPW, and exploits a result due to Black and Smith (2004) to minimize the bias in estimates that arises from selection on unobservables. Black and Smith (2004) show that the bias minimizing propensity score is equal to 0.5, and the estimates that use observations in the neighborhood of the

[19] We emphasize again here that we are using VGD card instead of a village level "poverty line" to define the extent of moderate poverty, because the MFI loan officers do not rely on village level poverty line estimates (if available).

[20] For an excellent theoretical analysis for the rationale behind targeting moderate poor (just below the poverty line) by client maximizing MFIs in a country such as Bangladesh, please see McIntosh and Wydick (2005).

bias minimizing propensity score perform well in tackling omitted variables bias.[21] This, however, implies that the MB provides estimate for local average treatment effect (LATE), similar to the standard instrumental variables under the assumption of monotonicity. Also, there is a trade-off between bias and efficiency: smaller radius reduces the bias, but at the cost of higher variance. For the empirical implementation, we employ alternative radii (0.25 and 0.10) around the bias minimizing propensity score.[22] The MB estimates reported later in this paper also correct for deviations from normality assumption using Edgeworth Expansion. Monte Carlo evidence shows that the MB estimator provides reliable estimates of causal effects for the relevant treatment group even when the conditional independence assumption is violated because of omitted variables (Millimet and Tchernis (2013)).

Heteroskedasticity Based Identification: Klein and Vella (2009a) Approach

We noted earlier that it may not be impossible to find plausibly exogenous characteristics of a village that are important determinants of location and intensity of MFI programs, but such village characteristics are unlikely to satisfy exclusion restrictions imposed in the interest rate equation. As discussed by Klein and Vella (2009a) and Lewbel (2012), existence of significant heteroskedasticity in the treatment equation provides a plausible source of identification in such cases. A substantial econometric literature has developed that exploits heteroskedasticity for identification when no credible instrument is available (Wright (1928), Rigobon (2003), Klein and Vella (2009a, 2010), Lewbel (2012)).[23]

We utilize an approach developed by Klein and Vella (2009a) to estimate the effects of MFI penetration on moneylender interest rate. Evidence from a number of recent Monte Carlo exercises shows that the Klein and Vella (2009a) approach is effective in correcting for biases from omitted variables and measurement errors (Ebbes et al. (2009), Millimet and Tchernis (2013), Klein and Vella (2009a, 2010)). The main sources of heteroskedasticity in the treatment equation

[21] At propensity score of 0.50, an MFI is indifferent between treatment statuses in terms of the observables. The role played by the unobservables is like the flip of a fair coin to determine the actual treatment status.

[22] A radius of 0.10 implies that 20 percent of the observations around the propensity score of 0.50 are used for estimation.

[23] A limitation of the heteroskedasticity based identification is that it is not applicable when the dependent variable is not continuous. Also, since identification exploits variations in second moment, it is more inefficient when compared to a standard IV (Lewbel, 2012).

need to be identified from a priori theoretical reasoning based on intimate knowledge of the selection process.[24]

For identification, an essential requirement in Klein and Vella (2009a) approach is that the error term in equation (2) exhibits substantial heteroskedasticity. Let $S_v^2(\hat{X}_i'\pi)$ be the conditional variance function for v_j satisfying the following condition:

$$v_j = S_v(\hat{X}_i'\pi)v_j^*, \qquad (3)$$

Where v_j^* is a zero mean homoskedastic error, $\hat{X}_i'$ is a subset of X_i' consisting of variables that generate heteroskedasticity and $S_v(\hat{X}_i'\pi)$ is a non-constant function. Then one can write the treatment equation as follows:

$$Pr(MFj = 1 \vdots X) = Pr(X_j'\delta; \hat{X}_i'\pi) = P(Z),$$

where P (.) is the density function, and $Z = X/S_v(\hat{X}_i'\pi)$. The identification result follows from the fact that when $S_v(\hat{X}_i'\pi)$ is not a constant function, as is the case when there is heteroskedasticity, the variables Z determine a household's participation in MFI program, but do not influence the mean impact of MFI membership on moneylender interest rate as specified in equation (1) above. If $S_v(\hat{X}_i'\pi)$ is constant, Z = X (up to a scaling factor), implying Z cannot be excluded from the interest rate equation, and there is no identifying information, especially if one uses 2SLS.[25] As discussed by Klein and Vella (2009a, 2010) and Millimet and Tchernis (2013), this approach provides credible identification when there is substantial heteroskedasticity in the treatment equation. It is also important to appreciate that the identification remains valid in general even though the same X variables can generate heteroskedasticity in the outcome equation (no exclusion restriction is imposed on X), a point mentioned in the introduction. Denote heteroskedasticity in the outcome equation by $u_i = S_u(\hat{X}_i'\theta)u_i^*$, where $u_i^*$is a mean zero homoskedastic error. Except for the special (and unrealistic) case when the ratio of $S_u(\hat{X}_i'\theta)/S_v(\hat{X}_i'\pi)$ is a constant, the Z variables are excluded from the outcome equation and provide identifying variations (for a more complete discussion, please see Klein and Vella, 2009a,

[24] The Klein and Vella (2009a) approach is implemented using het prob and iverg2 commands in Stata.

[25] In a Probit model, the effects of MFI are identified by the nonlinearity of the normal CDF. However, it is well-understood in the literature that such identification is very weak and unreliable, especially because it relies on a small proportion of the observations in the tails (see Altonji et al. (2005)). In contrast, heteroskedasticity allows one to use the observations from the thick support region, where the normal CDF is approximately linear.

2010). In the empirical analysis we provide evidence that the ratio $S_u(\hat{X}_i'\theta)/S_v(\hat{X}_i'\pi)$ is not a constant.

The relationship in equation (3) above has clear economic interpretation in our application. Suppose v_j^* is a measure of the intrinsic productivity attributes of area j observed and used by MFIs for the branch location decisions, but unobserved by the econometrician. What condition (3) above implies is that although MFIs (the central office) base their decisions on indicators of intrinsic productivity of area j, the actual outcome (e.g. coverage rate) is determined by interactions between productivity and other physical and socio-economic conditions (e.g. infrastructure, land distribution, poverty incidence) as determined by the S_v function. In the context of our application, the S_v function captures primarily the effects of screening by loan officers based on their private information (for more on this, see below). In this sense, the heteroskedastic Probit model can be thought of as a convenient structural model of the selection process that exploits heteroskedasticity for identification.[26]

What are plausible sources of heteroskedasticity in equation (2) above? The variables potentially giving rise to heteroskedasticity can be identified from a model that focuses on the interaction among fixed costs in program placement (such as establishing a branch office), MFI screening and households' self-selection. The basic argument is simple and grounded on the available evidence; given fixed costs, once a branch is placed in a village by the central office,[27] the branch manager tries to achieve a minimum scale for the viability of the program.[28] In fact, 'building volume' and retaining borrowers are among the most important challenges faced by MFIs when opening branches in new locations.[29] The set of potential clients is determined by the intersection of self-selection by households and MFI program selection criteria (set at the central office). When the potential client base is not large, to achieve scale economies, the loan officers have incentives to ignore private information on households' credit worthiness or eligibility. Because the private information of loan officers on households is probably the most important component of the error term v_j, ignoring this private information reduces the variance in observed

[26] The link between structural approach and heteroskedasticity based identification is more explicit in the control function approach developed in Klein and Vella (2010).

[27] The central offices ("head office") of most of the MFIs in Bangladesh are located in the capital city, Dhaka.

[28] Recent evidence shows that there are significant scale economies in microfinance (Hartarska et al. (2013)).

[29] In the context of Bangladesh, Rahman (2003) notes "(A)chievement of financial sustainability of a branch of MFI requires an increase in the number of clients within the branch". To achieve scale economies, many MFIs provide incentives to loan officers to increase number of borrowers through bonuses linked to number of new clients.

coverage.[30] In other words, the coverage rate would tend to bunch at around the minimum viable scale, similar to a corner solution. In contrast, when a large proportion of households satisfy the program-specified criteria, the loan officers do not worry about minimum viable scale, and their private information plays an important role in determining the actual coverage rate, resulting in a higher variance. Variance in the coverage rate across villages in this case would reflect closely the variance in the village and household characteristics relevant for repayment capacity and poverty alleviation, and observed by the program manager and loan officers, but not observed by the econometrician. One may argue that an MFI will enter into a village only if it can cover the fixed costs. This, however, assumes that the MFIs have almost perfect information about the potential clientele in a village, which is unrealistic, and not consistent with the available evidence. If the MFIs had enough information to know ex-ante whether they can recoup the fixed costs, then we should not observe closure of branches. But even the best NGOs such as BRAC had to close branches in Bangladesh, because they found out that they are non-viable, through a learning process.

In the context of Bangladesh, there are plausible reasons to expect that indicators of poverty incidence and of landlessness in a village would generate heteroskedasticity in the treatment equation. The recent evidence on "revealed objective functions" of MFIs based on the branch locations of Grameen Bank and BRAC in Bangladesh suggests that the MFIs take into account both poverty alleviation and financial sustainability in their branch location decisions (Salim (2011)). The MFIs thus primarily target the moderate poor, and exclude the extreme poor or so-called ultrapoor (Rabbani et al. (2006), Rahman (2003)). The extreme poor may also self-select out of such programs, because they lack the required human capital, and the substantial time commitment required for group meetings etc. may be too onerous when they are working long hours on low-return activities for survival (Matin et al. (2008), Rabbani et al. (2006), Emran et al. (2014)). Thus the set of potential clients available to a loan officer is expected to be higher in areas with high incidence of moderate poverty, but lower where extreme poverty is prevalent. Many MFIs including Grameen Bank and BRAC use land ownership as a salient targeting mechanism, a household with more than half acre (50 decimal) of land is in principle not eligible for the

[30] In some cases, the loan officers may even bend the formal program criteria to attain the minimum viable scale. This may explain part of the "targeting errors" observed in MFI programs. Also, note that the self-selection by the household is necessary but not sufficient for MFI membership, because the loan officer is the "final arbiter" in selection into a program.

microcredit programs. However, extreme poverty is closely linked to landlessness, and one widely used indicator of extreme poverty is whether a household owns less than 10 decimal of land (for example, it is used by ultra-poor programs such as BRAC CFPR/TUP). Thus households with lower than 10 decimal land may be more likely to be excluded from and/or opt-out from the microcredit programs. Many MFIs also use possession of a VGD card as an indicator of moderate poverty; for example, a household with VGD card is not eligible for the ultra-poor program of BRAC.[31] Thus one would expect that the client base for standard microfinance is higher in a poor village (with higher proportion of VGD card), but lower where proportion of landless (less than 10 decimal land) households is higher. As discussed above in section (2.2), this implies that the error term in the MFI coverage equation will have lower variance where the proportion of landless households is higher, and higher variance where the proportion of the moderately poor (with VGD card) is higher (the actual coverage is to the right of the minimum viable scale, determined by loan officers' private information). It is important to appreciate that the *a priori* signs of the heteroskedasticity-generating variables in the selection and heteroskedastic probit models together provide economic rationale to our identification approach. The heteroskedastic probit model used to capture the interactions between the fixed costs and loan officers' private information thus can be thought of as a model of the selection process used by the MFIs and provides the basis for identification in this approach.[32]

(2.3) DATA

The village level data for the econometric estimation of the impact of MFI coverage on informal interest rate come from the baseline survey conducted during 2006-2007 by Institute of Microfinance (InM) for the Programmed Initiative for Monga Eradication (PRIME) of Palli Karma

[31] One might wonder if some other measures of moderate poverty based on standard poverty line estimates would be more suitable for our analysis. However, note that we are trying to capture the information set available to and used by the loan officers. While VGD card status is used by NGOs for screening, we are not aware of loan officers in any NGO in Bangladesh using village specific poverty line estimates for screening and selection.

[32] A reader may wonder at this point whether a fully developed structural model would be better for our analysis. Note, however, that the literature on structural modeling of MFI location and program intensity choices is at its infancy. The only paper we are aware of is Salim (2013) that analyzes the location choices of two NGOs: Grameen Bank and BRAC in Bangladesh. Salim's analysis, however, is restricted to only the "ex-ante" choice, i.e., whether the head office decides to go to a village or not, but cannot address the "ex-post" choice, i.e., the extent of coverage in a village, which is determined by the loan officers and branch managers, given their incentive scheme. As we discussed above, our focus here is on the variations in the intensity of the program coverage (proportion of households who are MFI members) across villages, and thus Salim's model is inadequate to form the basis for a structural econometric analysis.

Sahayak Fundation (PKSF). We call the dataset the InM-PKSF survey. The baseline survey consists of a census of all households meeting certain income, employment and land ownership criteria as well as a village level survey.[33] The village level survey collected information on moneylender interest rates and availability of infrastructure and services. Empirical analysis of this paper is based on this village level dataset supplemented with MFI coverage rates calculated from the household survey.[34] The dataset covers three districts (Lalmonirhat, Nilphamary and Gaibandha) in Rangpur division where the earliest baseline surveys of the PRIME program were conducted. Out of 18 upazillas (sub-districts) in these districts, survey was undertaken in 12 upazillas. There are 804 villages in our dataset.[35] To make sure that our estimates are not unduly influenced by a few outliers, we exclude a small number of villages reporting unusually high interest rate (above 120 percent) from our sample giving us a final sample of 793 villages. We, however, emphasize that none of the qualitative conclusions from the empirical analysis are affected if we use the full sample (results are available from the authors).

The InM-PKSF survey is particularly suitable for our empirical analysis for a number of reasons. First, the survey was primarily targeted to poor households which are usually more dependent on the moneylenders in the absence of MFIs. Second, interest rate data were collected for standardized loan products. The interest rate analyzed in this paper is the money lender interest rate in normal times (not the lean season) for loans of maturity up to one year (reported as monthly rate).[36] We do not include interest rates on longer maturity loans, because the maturity of the standard MFI loans in Bangladesh is one year. The standardized rates ensure that variations in interest rates across villages are not due to heterogeneity in loan duration or seasonality. The summary statistics in appendix Table A.1 show considerable variations in both MFI coverage and informal interest rates. The average monthly informal interest rate in our sample villages is about 19 percent, and the median is 10 percent (simple rate). We also divide villages into quartiles in terms of MFI coverage rate. The average monthly interest rate in the three lower quartiles is about

[33] Households meeting any of the following three conditions were included in the survey: households should have monthly income of Tk. 1,500 or below, or are dependent on day-labor, or have less than 50 decimal of land.

[34] The household level dataset available to us does not contain the interest rate information on informal loans.

[35] To appreciate the richness of the data set, recall that the only available study on the effects of MFIs on moneylender interest rate is based on 106 villages (see Mallick (2012)).

[36] The questionnaire clearly asked about moneylender interest rate ("Mohajoni Rin" in Bengali). So it is highly unlikely, if not impossible, that the households confused moneylender loans with loans from friends and family. Also, it is standard to ask about monthly rather than annual interest rate (simple rate) in the household surveys in Bangladesh.

16 percent, but rises to 27 percent in the top-most quartile. Note that the moneylenders charge interest on loans at a flat rate, and thus the effective interest rate is higher when the declining balance over time is taken into account. As is widely discussed in the microcredit literature, MFIs also calculate flat rate interest charges on the loans. It is thus appropriate to use the flat-rate moneylender interest rates as reported in the InM-PKSF data set for our analysis. The average annual interest rate charged by MFIs in Bangladesh has been around 15-18 percent (flat rate) in recent years, according to CGAP. Estimates based on data from Credit and Development Forum for the year 2000 show that 80 percent of MFIs in Bangladesh charge 11-15 percent annual interest rate, and about 1 percent charges more than 20 percent (Rahman (2003)). Starting from July 2004, the wholesale microcredit fund provider PKSF capped the interest rate at 12.5 percent flat (annual rate).

The average MFI coverage rate is about 42 percent in our sample of villages (Table A.1) which is comparable to coverage rate from our panel data (38 percent). According to the Household Income and Expenditure Survey (HIES) 2010, about 45 percent of households with less than an acre of land in the Rangpur division covering areas included in our sample are active borrowers from MFIs. The summary statistics for all other variables used in the regression are also reported in Table A.1.

(2.4) PRELIMINARY ESTIMATES: OLS, MATCHING, and PROPENSITY SCORE WEIGHTING

We discuss here the results from a number of alternative estimators that provide us unbiased estimates only under the (restrictive) assumption that there is no selection on unobservables. These estimates are useful in two ways: (i) they provide a benchmark for the estimates reported later from approaches that correct for selection on unobservables, and (ii) the pattern of the magnitude of the estimates may help understand the nature of omitted variables bias.

The simplest specification is where the moneylender interest rate is regressed on the MFI coverage dummy (D=1 if coverage in a village more than the mean coverage rate) without any controls. The OLS estimate, reported in column (1) of Table 1, shows a statistically significant and positive correlation. This positive ‘effect’, however, could result from common unobserved village characteristics. If better infrastructure and higher productivity of a village lead to both higher informal interest rate and better coverage of MFIs, then one would expect this correlation to weaken when we add controls for village productivity and infrastructure.

In the next specification, we add several controls for village productivity and risk characteristics which can also potentially affect MFI placement. The set of control variables were discussed earlier in section 1.2 above. When these controls are added to the specification, the results (column 2) indicate a much *larger* effect of MFI coverage in the interest rate regression (OLS estimate). In columns (3) and (4), we add district and upazilla fixed effects as catch-all controls for time-invariant unobserved village heterogeneity respectively. The coefficient of MFI coverage becomes slightly larger in column (4) compared with column (1). Both estimates (columns (3) and (4)) are statistically significant at the 1 percent level. What is striking about the OLS estimates from different specifications is the fact that instead of weakening, the partial correlation between informal interest rate and MFI coverage has become numerically and statistically more significant when village productivity controls are added. This suggests that, in our application, MFI location choices are driven largely by poverty alleviation objectives, and thus OLS coefficients are likely to be biased downward. As we discuss later, the conclusion that the OLS estimates are downward biased is strongly supported by the evidence from all other different approaches.[37]

The estimates from matching and propensity score reweighting estimators are reported in the last three columns of Table 1. The reported confidence intervals are generated using bootstrapping procedure, following Millimet and Tchernis (2013) and Lechner et al (2011, 2013). Columns (5) and (6) in Table 1 report the bias corrected matching estimate (Abadie and Imbens (2002)) and LMW radius matching estimate respectively, while columns (7) reports estimates from normalized IPW estimator. Interestingly, all three estimates from matching and inverse propensity weighting suggest a numerically larger effect of MFI penetration into village credit market on moneylender interest rate compared to the OLS estimate from the comparable specification in in column (4) of Table 1 (the average estimate is 8.90, and the OLS estimate in column (4) is 6.05). Also, note that the estimates are numerically similar across columns (5)-(7), implying a measure of robustness.

[37]While some readers may not be fully convinced about a specific point estimate, we would like to emphasize that, the pattern of the estimates from different approaches provide very strong evidence in favor of the conclusions reached.

Although we present the matching estimates as part of our preliminary results, a reader may be curious whether matching is useful in reducing the bias compared to the OLS estimates. To this end, we checked the covariate balance both with and without matching.[38] The results are presents in upper panel of appendix Table A.2. The evidence is interesting; they show that while there are statistically significant and numerically substantial differences in *all* of the observable characteristics without matching, matching achieves covariate balance between treatment and comparison for all variables, except for irrigation. We also note that the set of control variables has reasonable power in the first stage probit model which correctly classifies 71 percent of the observations.[39]

(2.5) ADDRESSING SELECTION ON UNOBSERVABLES

Estimates from MB-IPW Estimator

Column (1) in Table 2 reports the estimated effect of MFI coverage dummy on moneylender interest rate from the MB-IPW estimator. The estimated effect of the high MFI dummy is higher in magnitude compared to the estimates based on CIA assumption in Table 1, implying that the bias due to possible selection on unobsevables is negative. The estimate from MB-IPW reported in column (1) of Table 2 is 12.51. In fact, the lower cut-off estimate of 95 percent confidence interval for the MB-IPW estimate is larger in magnitude than the point estimate from OLS in column (1) of Table (1). The MB-IPW estimate reported in column (1) is based on a radius of 0.25; one might wonder if the conclusion changes when we use a smaller radius which is expected to reduce the bias more effectively, but may also reduce the efficiency. The MB-IPW estimate when radius is 0.10 (not reported in Table 2) is 11.93, and the 90 percent confidence interval is [3.857, 21.580]. The estimate is thus very close to that in column (1) of Table 2 using a radius of 0.25.

Recall that matching and Normalized IPW estimates reported in Table 1 above reduce the bias in OLS estimate by making the comparison(s) more similar to a treatment, and the MB-IPW

[38] We thank an anonymous referee for suggesting this.

[39] Note that a first stage probit model that predicts almost all of the observations correctly violates the common support assumption, because obeservations with similar observable variables then are classified as either treatment or control and there is no overlap. This is similar to the problem of overfitting the first stage in the IV regressions; a first stage with $R^2 = 1$ implies that the predicted value is same as the actual endogeneous variable. For a discussion, please see Emran and Hou (2013).

estimator, in addition, minimizes the bias due to the failure of CIA (possibly due to dynamic learning effects) in the normalized IPW by trimming the sample around the bias minimizing propensity score. The fact that MB-IPW estimator is more effective in reducing the bias can be seen from the covariate balance test reported in the lower panel of appendix Table A.2; all of the covariates are balanced including irrigation in this case.

The relative magnitudes of the estimates discussed so far, i.e., MB-IPW > Matching and IPW > OLS, strengthens substantially the argument that the direction of omitted variables bias is *downward*. The results thus suggest strongly that the effect of MFI coverage on moneylender interest rate is most likely to be positive and significant in magnitude.

Estimates from Klein and Vella (2009a) Approach

The specification of the estimating equation used for the Klein and Vella (2009a) approach is the same as in column (4) in Table 1. The implementation of the K-V estimator involves the following steps. First, a heteroskedastic probit is estimated to generate the predicted probability of participation in MFI programs. For heteroskedastic probit regression, we follow Farre et al. (2012, 2013) and assume that the heteroskedasticity function $S_v(\hat{X}_i'\pi)$ has the following parametric form due to Harvey (1976):

$$S_v(\hat{X}_i'\pi) = \mathrm{e}^{-(\hat{X}_i'\pi)}$$

Then the predicted probability from heteroskedastic probit model is used as an instrument for the MFI coverage dummy. Since the standard terminology uses "first stage regression" to denote the first stage of a two stage least squares, we call the first step heteroskedastic probit model described above the "zero stage".

We start the discussion of the results with probit estimation of the treatment equation (2). The results in column (4) of Table 2 show that the probability of a higher coverage rate (more than the mean coverage which is 42 percent) correlates significantly with the percentage of households using irrigation, the distance to markets and facilities, the percentage of households with VGD cards, and the percentage of functionally landless households. MFI coverage rate is positively correlated with the percentage of households with irrigation. This is to be expected when the repayment rate is important to MFIs. A stable source of income is needed to ensure that household can meet the rigid repayment schedule which starts after a few weeks of the loan disbursement. Since productivity (and thus average income) is higher in a village with more irrigation (green revolution) and income variability is lower because of less dependence on rainfall, the repayment objective implies that more MFIs would locate in such a village. Thus the proportion of households that are MFI members would increase with the irrigation in a village. The coefficient of distance to markets and other facilities is negative implying that MFI coverage is higher near markets. This is expected as returns to investment and income tend to be higher for households located closer to the market centers (Emran and Hou (2013)). Mallick and Nabin (2013) also report similar evidence on the preference of MFIs in Bangladesh to locate in villages near markets. The MFI coverage is higher in villages with greater percentage of households with VGD card. This positive partial correlation is indicative of targeting the moderate poor in the location choice of MFIs. Finally, MFI coverage rate is lower in villages with higher proportion of functionally landless households. Emran et al. (2014), Rahman (2003) and Zeller et al. (2001) also report that though MFIs target their lending to poor households (a common land cut-off is 50 decimal)[40], the ultra-poor landless households have by and large not been reached by them.

Column (5) of Table 2 reports the estimates of sources of heteroskedasticity when we assume that all of the explanatory variables in the treatment equation may potentially contribute to heteroskedasticity of its residual, i.e., $\hat{X}_i = X_i$ in equation (2) above.[41] The estimates in column (5) suggest two statistically significant determinants of heteroskedasticity apart from the Upazilla dummies. The residual variance increases significantly with an increase in the proportion of moderately poor households (i.e., households with VGD cards). As noted above, the MFI coverage rates are also higher in these villages (see column (4) Table 2). A village with high incidence of landlessness, on the other hand, has lower coverage rate, according to the estimates in column (4) in Table 2. Higher landlessness also results in lower variances in MFI coverage rates across villages (column (5)). These results are consistent with the model of MFI coverage discussed above that focuses on the implications of fixed costs in program placement and private information of loan officers and branch managers as important components of the error term in the selection

[40] The moderate poor are sometimes called "borderline poor", i.e., households marginally below the poverty line. See for example, Rahman (2003).

[41] This "kitchen sink" formulation where all the variables are assumed to generate heteroskedasticity is standard in the applications of K-V estimator including the empirical papers written by the originators of this approach: Roger Klein, Frank Vella, and their coauthors; see, for example, Klein and Vella (2009b) which estimates returns to education using this approach.

equation (2) above. The log-likelihood ratio test for homoskedasticity can be rejected resoundingly at less than 1 percent significance level as reported in the lower panel of column (5).

However, when the full set of explanatory variables are included in the vector $\hat{X}_i$ generating heteroskedasticity, some of the regressions reported later on 'heterogenous treatment effects' in section (2.6) below suffer from non-convergence problem. For the sake of comparability, we thus repeat the estimation procedure with a heteroskedastic probit model that exploits only the two most important sources of heteroskedasticity, i.e., the percentage of households with a VGD card and the percentage of landless households. The results reported in column (6) of Table 2 show that indeed both of these variables are statistically highly significant in explaining the variance of the residual term in the treatment equation. The Likelihood ratio test of the null of homoscedasticity can also be rejected unambiguously at the 1 percent significance level when only these two variables are assumed to generate heteroskedasticity.

The estimation results from heteroskedasticity based identification are reported in columns (2) and (3) of Table 2. The instrument in column (2) (denoted as KV1) is the predicted probability from a "zero stage" heteroskedastic probit model when all explanatory variables are assumed to contribute to heteroskedasticity. The instrument used in column (3) (KV2) is the predicted probability when percentage of households with VGD card and percentage of landless households are assumed to be the sources of heteroskedasticity. The heteroskedasticity based instruments have substantial strength in explaining the variations in MFI coverage across villages; the Angrist-Pischke F statistic is 119.83 in KV1 and 62.29 in KV2. A test for the null hypothesis that the ratio $S_u(\hat{X}_i'\theta)/S_v(\hat{X}_i'\pi)$ is a constant is rejected at the 1 percent level for both specifications, implying that identification is valid even if the same control variables generate heteroskedasticity in the interest rate equation. The estimates of the effect of higher MFI coverage on moneylender interest rate are positive, large in magnitudes and statistically significant at the 5 percent level or less. Both estimates are larger than the corresponding MB estimate, with the estimate from KV2 (restricted set of controls in $\hat{X}_i$) being lower compared with that from KV1 (full set of controls in $\hat{X}_i$).[42]

[42] One might argue that the difference between KV1 and KV2 estimates suggests that our identification is not valid, because a Hansen's J test would reject the overidentifying restriction. However, Hansen's J is not a valid test when the treatment effect is heterogeneous, as is the case in our application. The different estimates from different instrument are relevant LATEs, and there is no reason for them to be same which is the null hypothesis in Hansen's J test.

(2.6) HETEROGENEOUS EFFECTS ON MONEYLENDER INTEREST RATES

The empirical analysis so far is based on a definition of 'high' vs. 'low' coverage by MFIs that takes the mean coverage rate as the threshold. While the results based on this commonly-used threshold are interesting and informative, this is likely to be only part of the story. In this subsection, we use a number of different cut-off points in defining the 'high' and 'low' coverage rates which allow us to understand potentially heterogeneous effects of MFI penetration in village credit markets. We sort and divide the total sample of villages into four groups in terms of the MFI coverage rate. The average coverage rate in the lowest group (first quartile) is 13 percent, 34.3 percent in the second quartile, 50.7 percent in the third quartile and 70.4 percent in the fourth quartile. We define the treatment and comparison groups using different combinations of these groups. For Klein and Vella (2009a) approach, the percentage of households with VGD cards and percentage of landless households are assumed to be the sources of heteroskedasticity in the treatment equation. As mentioned before, when the full set of control variables are assumed to generate heteroskedasticity in the heteroskedastic probit specification, estimation was not feasible in the first and third cases discussed below due to non-convergence.

The first exercise is motivated by the following question: when MFI activities increase moderately starting from a low base, does that influence the moneylender interest rate in any significant way? We focus on the sample from the lower half of the MFI coverage distribution, and define the lowest group (first quartile) as our comparison group and the second quartile as the treatment group. The OLS and KV estimates for this sample are reported in the first two columns of Table 3. We omit the matching and minimum biased (MB-IPW) estimates for the sake of brevity, but we emphasize that the conclusions are supported by these alternative approaches. The results in Table 3 show that there is substantial heteroskedasticity in the treatment equation; the null hypothesis of homoscedasticity is rejected at less than 1 percent significance level. This provides confidence that the Klein and Vella (2009a) approach is suitable for estimation. The F-statistic for exclusion restriction on the instrument derived from the heteroskedastic probit is 38.5, which substantially exceeds the rule of thumb F-statistic of 10. The signs of both OLS and KV estimates are positive, but the magnitudes are small relative to the estimates in Tables 1 and 2. Perhaps, more importantly, none of the estimates are statistically significant even at the 20 percent level. This evidence suggests no significant impact of a moderate increase in MFI coverage on moneylender interest rate when the initial coverage rate is low.

For the next exercise, we take the third quartile as our treatment group, and use two alternative comparison groups. The first comparison group consists of the first quartile, and the results are reported in columns (3) and (4) in Table 3. The OLS and KV estimates contradict each other, and both the estimates are not significant at the 10 percent level. The second comparison group consists of the first and second quartiles. The OLS and KV estimates are reported in columns (5) and (6) in Table 3 respectively. The diagnostic test shows that heteroskedasticity in the residuals of the treatment equation is not strong, which leads to low explanatory power of the instrument (the Angrist-Pischke F is 8.29, much lower than the ones reported in Tables 1-2. It is also smaller than the rule of thumb cut-off 10). This raises concerns that the estimates from this specification may not be reliable. To avoid weak instrument bias, we thus report results from an alternative specification that includes the full set of control variables as sources of heteroskedasticity; the estimation results are reported in column (7). The LR test of the null of homoskedastcity in this case is rejected resoundingly, and the instrument is also not weak (the Angrist-Pischke F statistic is 81.65). However, the conclusion does not depend on the specification; the results in columns (6) and (7) both show no statistically significant effect of higher MFI coverage on moneylender interest rate. The results on the third quartile as the treatment group suggest that the positive effects of MFI penetration on moneylender interest rates reported earlier in Tables 1-2 are likely to be driven by the fact that a perceptible effect on the informal interest rate is observed only when MFI activities cover a large enough proportion of the households in a village. This plausible conjecture is validated by the results reported in the last two columns of Table 3.

For the estimates reported in the last two columns (Columns (8) and (9)), we again take the first and second quartiles as the comparison group, but the fourth quartile is the treatment group. The effects of MFI coverage are positive and large in magnitudes in both the OLS and KV regressions. The coefficients are statistically significant at the 1 percent level. Both of these estimates are larger than those reported in Tables 1 (column 4) and Table 2 (column 4). The KV estimate indicates a large effect of higher MFI coverage on moneylender interest rate.

(2.7) IMPLIED MAGNITUDES and ECONOMIC SIGNIFICANCE

While the estimates reported in Tables 1-3 provide strong evidence in favor of the conclusion that higher microcredit coverage in a village ends up increasing the moneylender interest rate, the magnitudes of the effects may not be readily apparent to a reader.

A comparison of the different estimates in Tables 1 and 2 shows the following interesting pattern in the estimated marginal effects of high MFI dummy. The OLS estimate implies a 6 percentage point difference in informal interest rate between high and low MFI coverage areas. The MB-IPW estimate suggests a 12.5 percentage point difference between the two areas, and the conservative estimate from the Klein and Vella (2009a) estimator (KV2) implies about 19 percentage point difference.[43] To get a sense of the magnitudes, we need to know the MFI coverage in high versus low areas. The MFI coverage is 60.75 percent in high and 23.74 percent in low areas respectively. Taking for example, the conservative estimate from KV-2 in Table 2, this implies that an increase in coverage by 37 percentage points led to an 18 percentage point increase in the moneylender interest rate. The evidence thus indicates economically significant effects on the moneylender interest rate. One might interpret this evidence to imply that, on an average, a one percentage point increase in the MFI coverage increases the interest rate by about half a percent. But this interpretation may not be quite appropriate given the evidence in Table 3 that the effects of MFI penetration become visible only in the fourth quartile.[44]

(3) MFI MEMBERSHIP AND HOUSEHOLD BORROWING FROM INFORMAL SOURCES

As discussed in detail before, a higher moneylender interest rate following the spread of MFI programs in a village credit market is consistent with alternative hypotheses regarding the household borrowing. To distinguish between these alternative explanations, in this section we provide an analysis of household's borrowing from informal sources including moneylenders. The focus of the analysis is on the question whether MFI membership in fact increases the probability that a household borrows from informal sources, even though it did not borrow from them before, as argued by the critics of microcredit. We take advantage of household level panel data for the empirical analysis. We also shed light on the average informal loan size of the MFI members compared with non-MFI members.

[43] We reiterate here that the differences in the estimates from MB-IPW and KV reflect that fact that they are providing estimates for different groups.
[44] This also means that it may not be informative to calculate the implied elasticities in our context.

(3.1) IDENTIFICATION ISSUES AND EMPIRICAL STRATEGY

Estimation of the effects of MFI membership on the propensity to borrow from informal sources faces challenges arising from household self-selection, MFI placement and screening choices. For example, households in a village may participate more in MFI programs and also take more loans from the moneylenders, both driven by higher aggregate demand for credit due to higher productivity potential in that village. Selection bias can also be due to unobserved household characteristics, as the households that participate and that do not may be systematically different. Two of the salient unobserved household characteristics in the context of our analysis are entrepreneurial ability and risk preference. According to the standard models of occupational choice (Kanbur (1979), Kihlstrom and Laffont (1979)), less risk-averse and high ability households would choose to experiment with new economic activities such as non-farm microenterprises. Also, a household with higher entrepreneurial ability is more likely to join the MFI. Households with higher ability and risk preference would thus need more loans from the moneylender, especially if the investment projects are indivisible. The fact that it is impossible to find reliable information on household ability and preference heterogeneity implies that the OLS estimates are likely to suffer from omitted variables bias. For example, we do not have good measures of ability, it is subsumed in the error term, and the omitted ability can create a spurious positive effect of MFI membership on the probability of moneylender loans taken by the households. However, note that the direction of bias from unobserved heterogeneity cannot be pinned down from *a priori* theoretical reasoning alone. For example, omitted ability heterogeneity can instead result in a negative bias if high ability reduces the probability of joining an MFI because the outside option is higher (for example, higher educated women becoming teacher in the village school).

To deal with the biases resulting from MFI program placement and selection of households into MFI membership, we take advantage of a two-round panel data that span seven years, from 2000 to 2007. We implement household fixed effects in a difference-in-difference (DID) framework. Consider the following DID specification:

$$B_{it} = \theta_0 + \theta_1 d_{07} + \theta_2 T_i + \theta_3 (d_{07} * T_i) + e_{it} \qquad (5)$$

Where T_i is the treatment dummy which takes on the value of 1 if household i is an MFI member in the year 2007, but was not a member in the initial survey year 2000, B_{it} is a binary variable which takes the value of unity if household i borrowed from informal sources in 2007, but did not borrow in 2000, d_{07} is a dummy that equals 1 for 2007, and e_{it} is the residual term. This specification exploits household fixed effects in a DID framework by defining the treatment and outcome variables appropriately. It effectively differences out the time invariant household characteristics (ability and risk aversion); it also wipes out the effect of time invariant village characteristics that may have affected MFI placement decisions.

However, one can argue that there may be important time varying unobservables that could potentially bias the estimates; perhaps the most important time-varying factor in our context is dynamic learning effects that could potentially vary across households. For example, ability to learn, and deal with "disequilibria" may depend on the education level and experience as emphasized by Schultz (1975). It is, however, important to appreciate that the violation of parallel trend assumption in our context requires that, at the time of the self-selection decision, the women knew about their ability and could form an accurate estimate of the slope of the learning curve, and this self-knowledge played a decisive role in their participation decision into microcredit. This is an extraordinary assumption especially because most of the women who borrow from MFIs in Bangladesh have very little education, and they are unlikely to have any experience in managing a microenterprise. As noted recently by Chowdhury et al. (2015), a more appropriate assumption in this context is that of "symmetric ignorance" (Emran and Stiglitz (2009)), where at the time of participation (selection) decision, both the MFI and the potential borrower do not have much of any idea about the likely shape of the learning curve in the microcredit financed economic activity.

As part of a conservative strategy, we include a set of household characteristics from the 2000 round of the survey including the household head's education and age (as a proxy for experience) to allow for differential learning across households. The specification thus becomes:

$$B_{it} = \theta_0 + \theta_1 d_{07} + \theta_2 T_i + \theta_3 (d_{07} * T_i) + X_{00,i}\Pi + e_{it} \tag{6}$$

Where $X_{00,i}$ is a vector of household characteristics from the 2000 round of the panel, thus determined prior to the treatment. Note that our treatment group consists of all of the households that joined MFI programs in any year after 2000 and before the second round survey in 2007.

We also provide evidence from an approach that combines the DID approach with matching in the spirit of Heckman et al. (1998) (in addition to household fixed effects). The combination of matching with DID is called MDID by Blundell and Costa-Dias (2011). The MDID-FE approach utilized here implements the LMW radius matching and Abadie-Imbens bias corrected nearest neighborhood estimator; the IPW estimates are similar and omitted for brevity.

Matching can improve upon the linear conditional DID-FE model in equation (6) above in two ways: (i) it allows for nonlinear effects of the pre-treatment observable characteristics in the DID-FE model which would be able to capture the dynamic learning effects more faithfully (assuming they are significant and were known to the borrower when deciding participation into the microcredit) and (ii) it imposes the common support condition. In addition, we also use the MB estimator in the implementation of the MDID approach in a household fixed effect model (henceforth called MBDID-FE). As noted earlier, the MB estimator minimizes the bias due to potential failure of conditional independence assumption.[45]

The progressively richer and more flexible empirical models from DID-FE to MDID-FE to MBDID-FE allow us to understand the sensitivity of the estimates due to violation of the CIA. It is important to appreciate that if the main sources of unobserved heterogeneity are innate entrepreneurial ability and attitude toward risks which are arguably time-invariant, then the estimates should not vary substantially across these alternative empirical models. This provides a way to gauge the importance of unobserved time-varying factors in our application.

For implementation of the above discussed empirical strategy, we use alternative comparison groups. There are two groups who can serve as comparisons: households which had not been members of MFI on both survey years (termed as "never member") and households who were members in 2000 but not in 2007 (termed as "drop-outs"). The drop-outs are considered by many to be more comparable to the new members as both of these groups are MFI clients ((Alexander-Tedeschi and Karlan (2009)). We also put together the 'never members' with the 'drop-outs' as an additional comparison group, as failure to include the drop-outs may lead to bias in the effects of MFI membership on household outcomes. As noted by Chowdhury et al. (2015), if the assumption of symmetric ignorance is appropriate, then excluding drop outs may cause substantial bias when the borrowers learn about their ability and learning curve after undertaking microcredit financed economic activity.

(3.2) DATA

The household level panel data for two rounds (2000 and 2007) from the BIDS-BRAC surveys are used for our analysis. These two rounds of the surveys have complete information on

[45] Note also that the Klein and Vella heteroskedasticity based IV estimator is not applicable here, because the dependent variable is binary.

1599 households. The sample used for estimation is however a bit smaller (1365), as we exclude the households (234) who had been MFI members in both survey years and thus lack observations on pre-treatment period(s). Out of the sample of 1365 households, 376 households are new members, 142 are drop-outs and rest (844) were never member in MFI institutions. The MFI participation rate in 2007 is 38 percent which is consistent with evidence from representative national surveys such as Household Income and Expenditure Survey 2010 (According to HIES 2010, MFI participation rate in rural Bangladesh is about 30 percent). In the full sample, about 7.11 percent (97) households are new borrowers from the informal sources in 2007. About 4 percent of new MFI members borrow from informal sources compared with 8.3 percent among non-members.

(3.3) EMPIRICAL RESULTS

Table 4 reports the estimation results for the effects of MFI membership on the propensity to borrow from informal sources. The upper panel shows the results when the comparison group is defined to include only those who have not been MFI members in both survey years (i.e., never members). The comparison group in middle panel consists of drop-outs who were MFI members in 2000 but not in 2007. The comparison group in the final panel combines both the drop-outs and never members. We begin by presenting the DID-FE estimate of the effect of MFI membership which is reported in column (1) of Table 4. This specification (equation 5) does not include any household or region level controls. The estimates in column 1 show that the coefficient of 'new' membership in MFIs has a negative sign and is statistically significant at the 1 percent level regardless of the ways comparison groups are defined. The magnitude of the coefficient is larger when drop-outs are taken as the comparison group compared with the case where "never members" are the comparison group. These DID-FE estimates suggest a significant decline (0.04-0.06) in the propensity to borrow from informal sources by the new MFI members.

To check the sensitivity of the DID-FE estimates when we allow for time-varying effects of household and region characteristics, we estimate the specification in equation (6). Column (2) reports the results when household characteristics in 2000 are added and column (3) when both household and region characteristics in 2000 are included as explanatory variables. The household level variables included are log of household head's age, a dummy indicating whether the head has above primary level education, total owned and total cultivable land, number of household members self-employed in agriculture, and household size. To control for region-specific effect, we include a dummy indicating the poorer region in the country (three divisions in the north-west and south). We perform t-tests of differences in means of these characteristics between treatment group and different comparison groups. The results (not reported here) indicate that 'never member' comparison group consists of households whose head are older and which are more agricultural (more land, more members employed in agriculture). There is no significant difference in education, household size or religion between these two groups. In the case of 'drop-out' comparison group, there is statistically significant difference in mean only for household head's age and to some extent for the number of members self-employed in agriculture. If household-level heterogeneity has time-varying effects, then one would expect DID-FE estimates to change significantly when household level controls (pretreatment) are added to the regression. The estimates in column (2) show a slight increase in the magnitude of the treatment coefficients for "never member" and "both drop-out and never member" comparison groups, and a slight decline for "drop-out" comparison group. We find changes in the same directions when region dummy is added in the set of controls (column (3)). However, none of the estimates are statistically or numerically significantly different from those reported in column 1. This can be interpreted as suggestive evidence that probably the most important sources of selection bias in our application are in fact time-invariant.

To probe the issue of potential bias from time-varying omitted variable in more depth, we report estimates that combine the DID-FE with two alternative estimators. The results from the MDID-FE estimator (using Abadie-Imbens bias corrected and LMW radius matching) are reported in columns (4) and (5) of Table 4 respectively. Matching is done using pre-treatment (in other words 2000 survey) household and region characteristics discussed earlier.[46] The estimates in the case of drop-out control (column (4), middle panel) are smaller in absolute magnitude compared with that in column (2), and they are also not estimated precisely. Note that this likely reflects small sample size for this case (521observations). For the other two comparison groups (top most and lowest panels), the estimates in columns (4) and (5) strengthen the conclusion that MFI membership reduces the probability that a household borrows from the moneylender. The estimates from LMW radius matching in column (4) are nearly indistinguishable from those in

[46] We emphasize here that the central conclusions of this paper do not depend on the exact set of variables used as controls or for matching.

column (3) based on DID-FE estimator. The final column in Table 4 reports the results from the MB-DID-FE approach discussed before which minimizes the bias due to the violation of the CIA arising from non-parallel trends in the augmented DID-FE model, which can happen if dynamic learning effects are not adequately captured by the pretreatment household characteristics and regional dummy. The estimates in column (6) are all larger in absolute magnitude and significant at the 1 percent level. The evidence from the MB-DID-FE approach thus provides strong support to the conclusion that the main sources of selection bias are time-invariant factors such as innate entrepreneurial ability and risk aversion, and thus time varying unobservables do not constitute a major threat to internal validity of the DID-FE estimates.

As an additional robustness check, we redo the analysis for a restricted sample that excludes any household with land ownership more than one acre.[47] The idea behind this exercise is to focus on the households who are collateral poor and thus are likely to be excluded from the formal credit market. These are also the target population of most of the MFI programs. The results are reported in Table 5. The estimates in Table 5 reinforce the conclusion that once a household becomes MFI member it is less likely to borrow from the informal sources.

The estimates in Tables 4 and 5 provide robust evidence that the propensity to borrow from informal sources *declines* significantly after households join into MFI programs. The most credible estimate from the MB-DID-FE estimator implies a 6 percentage point decline in the propensity to borrow from moneylenders among the households that became MFI member after 2000. Given that the average propensity to borrow from informal sources is about 7.1 percent, the estimate thus implies that the propensity to borrow from informal sources is 8.78 percent among the non-MFI households, and it declines to 2.78 percent among the new MFI members. The results thus contradict the argument by many critics of MFIs that they do not help the households break free from the "clutches" of moneylenders.

(3.4) LOAN SIZE AND MARKET SHARE OF INFORMAL CREDIT

A simple comparison of borrowing rates between 2000 and 2007 indicates that borrowing from informal sources declined substantially from 12.5 percent in 2000 to 8.8 percent in 2007. Tables 4 provides robust evidence of a negative and significant (numerically and statistically)

[47] This is inspired by land cut-off used in Morduch (1998) to define appropriate samples.

effect of MFI membership (the households that became members after 2000) on the propensity to borrow from informal sources. While the number of households borrowing from informal sources has declined in general and among new MFI members in particular, an increase in informal interest rate is still possible if loan sizes of the few who still borrow from informal sources have gone up sufficiently. If, on the other hand, the market share of moneylenders (and family and friends) in total credit to households has gone down, then that would provide credible evidence against increasing indebtedness of the left-out households due to MFI penetration.

To provide some suggestive evidence on the changes in loan sizes and market shares over time, we utilize the panel dataset. The number of households who reported borrowing from informal sources in either of the two survey years is small (189 in 2000 and 134 in 2007. A closer look at the data reveals some obvious coding mistakes for the loan size data, leading to very large outliers in the amount of loans. For instance, the largest borrower in 2007 borrowed some 1.05 million taka, but it is a household with only 0.14 hectare of land, less than primary education for its head and with only one worker who is self-employed in agriculture. To avoid undue influence of dubious outliers, we restrict our analysis to loan amounts of Taka 50, 000 or less, thus dropping of about 4.4 percent of the sample. The proportions of households which had not been MFI members in both years ("never member") in both full and restricted samples are similar to each other. Note that focusing on the restricted sample may also be desirable because this is indeed the main clientele of MFI lenders. We also performed some robustness checks by restricting our sample to loan amount of Taka 100,000 or less. Overall results reported here remain unaffected. Loan outstanding numbers for both years are deflated using the consumer price index with base year 2005.

Figure 1 plots the average sizes of loans from different sources for both years. The loan size for each category in each year is estimated from data on households which reported positive borrowing. The average loan sizes are substantially higher for MFI loans compared with informal loans in both years. While average loan sizes have increased for both MFIs and informal sources, it declined in the case of bank loans. Even with somewhat larger increase, average size of informal loan is still lower than that of MFI loans in 2007 (Tk. 8,073 vs. Tk. 8,681).

Is the increase in average size of informal loan sufficient to more than offset the decline in the propensity to borrow from informal sources between 2000 and 2007? To answer this question, we report in the upper panel of Table 6 the average loan sizes when households with no loans are also included in the sample. Average loan size in this case thus incorporate any change in the borrowing from each source. For the full sample, the average size of informal loan in 2007 is 38 percent lower than that in 2000. Most dramatic decline in loan sizes happened for the households that became member of MFI after 2000 ("new members", 22 percent of sample). These households were not member of MFI in 2000, and borrowed about Taka 1245 from informal sources in that year. After becoming member, their borrowing from informal sources declined to Taka 251 in 2007. Even for households which were not members of MFIs in either of the years ("never members", 52 percent of the sample), the average size of informal loan declined from Tk. 909 in 2000 to Tk. 721 in 2007. The decline in loan size is smaller only for drop-outs who were member in 2000 but not in 2007 (9.9 percent of sample).

Household borrowing data are used to define the relative market shares of different sources of loans for both years. The market shares are plotted in Figure 2. In 2000, 47 percent of total credit to households came from MFIs, 27 percent from formal banks and 26 percent from informal sources. The market shares have changed dramatically by 2007, with MFIs accounting for 72 percent of total credit. Shares of informal sources halved to only 13 percent, and bank's share fell to15 percent. In terms of absolute volume of loans, total volume of MFI loans nearly doubled between 2000 and 2007 while it declined for both bank loans and informal loans. In the case of informal loan, its level in 2007 was about 62 percent of its 2000 level. We find similar trends in market shares if we restrict our sample to all households with Tk. 100,000 or less loan outstanding. The evidence thus shows clearly that total loans from informal sources have declined in both absolute and relative terms between 2000 and 2007. The MFIs have driven not only informal lenders out of rural credit markets but also largely filled the gap left by withdrawal of public banks from rural areas.

(4) TAKING THE EVIDENCE TO THE THEORY

Although our analysis is motivated by sharply opposing views held by proponents and critics of MFIs, the evidence on moneylender interest rate and household's demand for informal loans (extensive and intensive margins) may also be useful in discriminating among the existing theories on the interactions between MFIs and moneylenders. In Table 7, we provide a summary of the predictions about the effects of MFIs on moneylender interest rate and household's dependence on loans from moneylenders. Note that four of the six papers listed in Table 7 analyze explicitly the interactions between MFIs and informal moneylenders; they are Jain and Mansuri (2003), McIntosh and Wydick (2005), Demont (2014) and Mookherjee and Motta (forthcoming). Although the other two papers (Bell (1990), Hoff and Stiglitz (1998)) do not directly deal with MFIs, they provide results or insights that can be fruitfully used to understand potential effects of MFI interpretation of the village credit market.

Two of the models: McIntosh and Wydick (2005) and Bell (1990) can be used to provide theoretical foundations for the proponents' view that MFIs reduce the demand for moneylender loans and the interest rate. In an interesting paper, McIntosh and Wydick (2005) model the effects of entry by a client-maximizing MFI (with access to grants) on the moneylenders who in the initial equilibrium offers loan contracts (loan size and interest rate) that extract most of the surplus (leaving net returns for a borrower arbitrarily close to zero). The MFIs enjoy lower cost of funds, but higher fixed costs compared to the incumbent moneylender. Entry by the MFI attracts the better borrowers (cream skimming by MFI), and the loan size of the MFI borrowers is larger than that of the households who stay with the moneylenders. The entry by the MFI also lowers the moneylender interest rate. The model in Bell (1990) deals with the interactions between formal banks and moneylenders, but the bank can be reinterpreted as an MFI for our purpose. Similar to the bank in Bell (1990), MFIs also have lower cost of funds (compared to moneylenders), and offers a contract that specifies the loan size and interest rate. The MFI loan offer acts as the outside option for the borrower in her interactions with the moneylender. Bell (1990) shows that, when contract exclusivity can be enforced,[48] the MFIs can lower the interest rate charged by a moneylender and reduce a household's propensity to take informal loans. A theoretical justification for the critic's view that MFIs may increase demand for moneylender loans (crowding in) and increases the interest rate is laid out in a model by Jain and Mansuri (2003). They focus on the rigid repayment schedule enforced by most of the MFIs and show that when a household becomes MFI borrower, it may increase its demand for loans from moneylenders and thus result in higher interest rates. As noted earlier, our evidence provides only partial support to these models. We do not find any evidence of crowding in effect for moneylender loans (unlike Jain and Mansuri

[48] Exclusivity (borrowing from only either MFI or moneylender) seems to be a realistic assumption in our context, as the households in general do not borrow from moneylenders once they get credit from an MFI.

(2003), but we also find that MFI entry can increase moneylender interest rate, especially when MFI coverage is high enough (unlike Bell (1990) and Mcintosh and Wydick (2005)).[49]

Demont (2014) develops a model where both the moneylender and the MFI have same information, earn zero profit due to competition, but MFIs offer group liability contract while the moneylenders offer individual liability contract. The model predicts cream skimming by MFIs, and a reduction in demand for moneylender loans with MFI penetration in a village. But it also predicts that the effects of MFI coverage increase follow an inverse U shaped response which is not consistent with our finding where there is no significant effect before the MFI coverage reaches a threshold, and there is significant positive effect for the highest quartile of coverage.

Our findings are consistent with the models of Hoff and Stiglitz (1998) and Mookherjee and Motta (forthcoming). A recent paper by Mookherjee and Motta (forthcoming) builds a model which predicts that the MFI entry may, under certain conditions, increase the moneylender interest rate, although it reduces the demand for moneylender loans.[50] The model is based on the assumption that the MFIs suffer from informational disadvantage for the low risk borrowers (moneylenders enjoy market power), but they do not suffer from such informational disadvantage when competing for the high risk borrowers. Thus the MFIs attract all the high risk ones when they open a branch in a village, and the moneylenders are left with the low risk (high return) clients. With market power, the moneylender can extract the higher surplus and thus charge higher interest rate. However, as we discuss below, there is substantial independent evidence that casts doubts on cream skimming by the moneylenders as a possible explanation in the context of Bangladesh.

A second explanation for our results can be provided by an adaptation of the Hoff and Stiglitz (1998) model to our application. Although they focus on the interactions among the moneylenders, and trace out the implications of subsidized credit from formal banks to the trader-moneylenders, Hoff and Stiglitz (1998) point to the importance of fixed costs in screening and enforcement in moneylender's operation. If these fixed costs are significant, then when MFIs enter into village and steal some of the clients, the moneylenders face higher average costs with a low scale of operation. With competition driving moneylender's profit to zero (Hoff and Stiglitz (1998)

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[49] Note that the prediction from McIntosh and Wydick (2005) model that the MFIs cater to demand for larger loans is in fact supported by the evidence we discussed earlier.

[50] Like Bell (1990), they also assume that contract exclusivity can be enforced.

assume monopolistic competition), one would observe higher average moneylender interest rates to go up following entry by MFI, but propensity to borrow from moneylenders by households will go down, as we find in our analysis. Unfortunately, we do not have data or secondary evidence from other sources in the context of Bangladesh to resolve whether fixed costs or cream-skimming are more important.[51]

Cream Skimming: by Moneylenders or by MFIs?

The theoretical model developed by Mookherjee and Motta (forthcoming) implies that the higher interest rates charged by moneylenders are the result of MFIs attracting the high risk borrowers. They cite suggestive evidence from Maitra et al. (2014) in the context of India that is consistent with this result.[52] Demont (2014), however, provides conflicting evidence in the context of India, where he finds that MFIs attract the better credit risks. The existing evidence in the context of Bangladesh, however, may not be consistent with MFIs attracting the high risk borrowers.

A substantial theoretical literature on joint liability and group lending (for a survey, see Armendariz and Morduch (2010)) identifies a number of reasons to expect that the MFIs such as BRAC and Grameen Bank in general attract the relatively more credit-worthy households. A large empirical literature provides evidence in favor of this view in the context of Bangladesh. First, as discussed earlier, a substantial empirical literature shows that the poorest of the poor (so-called ultra-poor) are not reached by standard MFI credit programs in Bangladesh (see the discussion in Rabbani et al. (2006), and Emran et. al. (2014) for example). This partly reflects the demand on the loan officers to maintain high repayment rates and rigid repayment schedule. It is widely discussed that the loan officers exclude households if they do not have a steady source of income to ensure weekly repayments. In fact, recent evidence from multiple data sets show that a household with less than 10 decimal land has a much lower probability to become a MFI member (Berg and Emran (2015), Chowdhury et al. (2015)). The fact that the ultra-poor were bypassed by the microcredit in Bangladesh led BRAC to design specialized asset transfer programs for them

[51] The evidence reported by Aleem (1993) shows that the fixed costs can be high; they are higher than the costs of funds.

[52] Note that although the estimate in Maitra et al. (2014) suggests that the risky borrowers are attracted by joint liability loans, it is not statistically significant at conventional levels.

(The Targeting the Ultra-Poor (TUP) program started in 2002).[53] An important implication of Mookherjee and Motta (forthcoming) model is that the relation between land and informal interest rate has to be opposite to that between land and MFI participation to generate higher informal interest rate following entry by an MFI. The relation between land and MFI participation in the context of Bangladesh is approximately inverted U-shaped; which implies that the moneylender interest rate has to exhibit a U-shaped relation with land. We are not aware of any such evidence, and future research needs to provide credible evidence on this relation.

The second important piece of evidence comes from Zaman (2004). He reports that as MFI coverage increases in a village in Bangladesh, progressively richer households become MFI members. In fact, the tendency to attract relatively richer households with MFI penetration has been widely noted in other countries, giving rise to a substantial literature on "mission drift" among MFIs (see, among others, Mersland and Oyesten Strom (2010)).[54]

The above evidence suggests that, in the context of Bangladesh, it is more likely that MFIs attract the less risky borrowers with more land and steady sources of income. This implies that the moneylenders are likely to retain relatively poor and risky borrowers. In this case, we can still observe a higher moneylender interest rate if facing the competition from MFIs, moneylenders earn zero profit (similar to Bell (1990). In this case, a higher moneylender interest rate can result from higher risk premium required to break even with the residual high risk borrowers (ultra-poor), as MFI coverage increases in a village.[55]

CONCLUSIONS

Using two survey datasets from Bangladesh, we provide evidence on the effects of microfinance penetration into the village credit market, focusing on the effects on moneylender interest rate and household borrowing from informal sources. The effects of MFIs on rural credit market have been a topic of intense debate among practitioners and policy makers, with sharply

[53] It is interesting that BRAC TUP program uses 10 decimal land ownership to define an ultrapoor household, i.e., a household is eligible only if it does not have more than 10 decimal land. The standard microcredit programs use 50 decimal (half acre) as the cut-off.
[54] For a theoretical explanation that the change in composition of borrowers in favor of richer households may not reflect any mission drift, but is a consequence of imperfect labor market, see Emran, Morshed and Stiglitz (2011).
[55] A more complete model needs to identify the conditions under which a higher informal interest rate is due to cream skimming by the moneylenders (the India evidence reported by Mookherjee and Motta (forthcoming)), and by the MFIs (the Bangladesh evidence).

opposing views. However, a careful empirical analysis of the effects of the spread of MFIs on moneylender interest rate and household informal borrowing is lacking in the literature.

We consider the possible biases that can result from non-random program placement by MFIs and self-selection by households. It is extremely difficult, if not impossible, to find credible exclusion restrictions to solve identification challenges in the context of microfinance programs. It may also not be feasible to analyze the long-run general equilibrium effects of MFI penetration into rural credit markets by designing randomized interventions. To address selection biases, we develop an empirical approach that takes advantage of recent advances in econometrics that do not rely on exclusion restrictions required in the standard instrumental variables strategy. In particular, we implement the minimum biased normalized IPW estimator proposed by Millimet and Tchernis (2013) and heteroskedasticity based identification approach due to Kelin and Vella (2009a). For the analysis of household borrowing from informal sources, we take advantage of panel data and implement a fixed effect difference-in-difference approach and combine it with alternative matching and propensity score reweighting estimators. The objective is to present an array of evidence using a rich menu of state-of-the-art econometric approaches, so that a reader can judge the robustness of the conclusions reached.

The empirical evidence on the effects of MFIs on moneylender interest rates based on an exceptionally large cross section data set with almost 800 village shows that moneylender interest rates do not go down when microfinance comes to a village; in fact, the interest rate increases when the MFI penetration into the village credit markets is high enough. The effect is heterogeneous; at low levels of MFI coverage, there does not seem to be any perceptible impact, and the effect is strong for the villages in the top quartile of coverage. The evidence based on the panel data demonstrates clearly that a household's propensity to borrow from informal sources declines significantly once it becomes member of an MFI, and that the total volume of credit from informal sources (and formal banks) also decrease substantially in both absolute and relative terms. The evidence on the declining importance of informal sources in rural credit market along with higher informal interest rates contradicts some of the widely held perceptions among contending camps of practitioners. While our results do not support the view of MFI proponents that MFI competition reduces informal interest rates, the evidence also rejects the claim by the critics that MFIs cause increased reliance on informal loans among its borrowers due, for example, to rigid repayment schedules and indivisibility of investment projects. When taken together, the evidence on interest rates and household borrowing is more consistent with cream skimming (by MFIs or moneylenders) and fixed costs in lending by moneylenders. The available evidence in the context of Bangladesh, however, casts doubts on cream skimming by moneylenders as the relevant explanation.

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Table 1: Informal Interest Rate and Micro Finance Coverage: Preliminary Estimates

	OLS				A-I BC	LMW	IPW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High MFI Coverage	**5.475***** **(1.87)**	**8.466***** **(1.77)**	**8.546***** **(1.75)**	**6.054***** **(1.46)**	**8.971***** **(1.01)**	**9.181***** **(1.87)**	**8.511***** **(1.77)**
Functionally landless HH (%)		0.029 (0.07)	-0.041 (0.08)	-0.114 (0.07)			
HH with Irrigated land (%)		-0.288*** (0.04)	-0.273*** (0.04)	-0.315*** (0.05)			
Distance to bank		-0.469 (0.32)	-0.612* (0.34)	-0.385 (0.29)			
Distance to market and facilities		1.015** (0.45)	1.005** (0.45)	0.674* (0.37)			
No. of poor HH in village		-0.006 (0.00)	-0.008* (0.00)	-0.007 (0.00)			
HH with VGD card (%)		0.362*** (0.07)	0.383*** (0.07)	0.423*** (0.07)			
Fixed Effects	No	No	District	Upazilla	Upazilla	Upazilla	Upazilla
No. of Observations	793	793	793	793	793	793	793

significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in parentheses. 'A-I BC' reports Abadie-Imbens bias corrected estimate and 'LMW' reports the distance weighted radius matching estimate.

Table 2: Moneylender Interest Rate and Microfinance Coverage: Evidence from MB and Klein-Vella Estimators

	Informal Interest Rate			**MFI Coverage**		
	MB	**KV1**	**KV2**	**Level**	**Residual Squared**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dummy for High MFI coverage in a village	**12.518*** **	**25.935*** **	**18.878** **			
	(3.07)	**(7.18)**	**(7.81)**			
% of functionally landless households			-0.065	-0.011**	-0.001	-0.017***
			(0.08)	(0.00)	(0.01)	(0.01)
% of households with irrigated land			-0.337***	0.005***	0.015	
			(0.05)	(0.00)	(0.03)	
Distance to bank			-0.354	-0.004	-0.022	
			(0.30)	(0.02)	(0.03)	
Distance to market and facilities			1.124**	-0.119***	-0.001	
			(0.46)	(0.02)	(0.001)	
No. of survey households in the village			-0.008*	0.000	0.052***	
			(0.00)	(0.00)	(0.01)	
% of households with VGD card			0.365***	0.014***	-0.019*	0.054***
			(0.07)	(0.00)	(0.01)	(0.01)
Upazilla Fixed Effects	Yes	Yes	Yes	Yes	Yes	No
Zero Stage: Heteroskedastic Probit						
LR test of homoskedasticity						
$\chi2$					71.18	35.33
p-value					0.00	0.00
First State of IV Regression						
Angrist-Pischke F Statistic		**119.83**	**62.29**			
p-value		**0.00**	**0.00**			

* significant at 10%; ** significant at 5%; *** significant at 1%
Robust Standard Errors in Parenthesis in parentheses.
KV1 assumes that the full set of controls generates heteroskedasticity in the treatment equation, while KV2 assumes that two variables are responsible for heteroskedasticity: proportion of landless, and proportion of households with a VGD card.

Table 3: Heterogeneous Effects of MFI Coverage on moneylender Interest Rate

	Treatment								
	2nd Quartile		3rd Quartile		3rd Quartile			4th Quartile	
	OLS	KV	OLS	KV	OLS	KV	KV*	OLS	KV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dummy for High MFI Coverage	3.114	6.474	2.936	-5.845	2.368*	19.784	5.886	9.688***	32.112***
	(2.15)	(6.49)	(1.83)	(10.48)	(1.41)	(22.97)	(7.45)	(2.02)	(8.35)
No. of Observations	400	400	397	397	595	595	595	532	532
Comparison Group	**1st quartile**		**1st quartile**		**1st and 2nd quartiles**			**1st and 2nd quartiles**	
Zero Stage: Heteroskedastic Probit									
LR test of heteroskedasticity									
$\chi 2$		19.13		6.70		3.25	41.69		39.47
p-value		0.00		0.04		0.20	0.00		0.00
First Stage of IV Regression									
Angrist-Pischke F Statistic		38.46		38.09		8.29	81.65		69.44
P-value		0.00		0.00		0.00	0.00		0.00

* significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in parentheses. The KV specification uses proportion of landless and proportion of VGD card holders as the sources of Heteroskedastcity, and KV* uses the full set of control variables.

Table 4: MFI Membership and Propensity to Borrow from Informal Sources

	DID-FE			MDID-FE		MB-DID-FE
				A-I BC	LMW	
	(1)	(2)	(3)	(4)	(5)	(6)
Comparison: Never members						
MFI member	**-0.041*** **	**-0.044*** **	**-0.047*** **	**-0.057*** **	**-0.045* **	**-0.062*** **
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.03)**
No. of Observations	1,223	1,223	1,223	1,223	1,223	1,223
Comparison: Dropouts						
MFI member	**-0.059*** **	**-0.054** **	**-0.053** **	**-0.038**	**-0.043**	**-0.083*** **
	(0.02)	**(0.02)**	**(0.02)**	**(0.03)**	**(0.03)**	**(0.05)**
No. of Observations	521	521	521	521	521	521
Comparison: Never members & Dropouts						
MFI member	**-0.044*** **	**-0.046*** **	**-0.049*** **	**-0.064*** **	**-0.049** **	**-0.059*** **
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.04)**
No. of Observations	1,365	1,365	1,365	1,365	1,365	1,365
Household Controls	No	Yes	Yes	Yes	Yes	Yes
Region Controls	No	No	Yes	Yes	Yes	Yes

* significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in parentheses.
'A-I BC' reports Abadie-Imbens bias corrected estimate and 'LMW' reports the distance weighted radius matching estimate.

Table 5: MFI membership and propensity to borrow from informal sources: Land-poor households (Less than 1 acre of agricultural land)

	DID-FE			DIDM-FE		MB-DID-FE
				A-I BC	LMW	
	(1)	(2)	(3)	(4)	(5)	(6)
Comparison: Never members						
MFI member	**-0.045****	**-0.044****	**-0.050****	**-0.062*****	**-0.052**	**-0.061**
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.03)**	**(0.04)**
No. of Observations	749	749	749	749	749	749
Comparison: Dropouts						
MFI member	**-0.078*****	**-0.074****	**-0.074****	**-0.071***	**-0.071**	**-0.066**
	(0.03)	**(0.03)**	**(0.03)**	**(0.04)**	**(0.05)**	**(0.07)**
No. of Observations	363	363	363	363	363	363
Comparison: & Dropouts Never members						
MFI member	**-0.050*****	**-0.051****	**-0.056*****	**-0.065*****	**-0.058****	**-0.055**
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.03)**	**(0.04)**
No. of Observations	842	842	842	842	842	842
Household Controls	No	Yes	Yes	Yes	Yes	Yes
Region Controls	No	No	Yes	Yes	Yes	Yes

* significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in parentheses. 'A-I BC' reports Abadie-Imbens bias corrected estimate and 'LMW' reports the distance weighted radius matching estimate.

Table 6: Average inflation adjusted loan size (Taka)

	Average loan size (Taka)		Ratio
	2000	2007	(2007/2000)
New member	1245	251	0.20
Always member	478	375	0.78
Drop-out	725	669	0.92
Never member	909	721	0.79
All Households	896	555	0.62
No. of total observations	1528	1528	

Table 7: Taking Evidence to the Theory

Evidence in This Paper: Moneylender interest rate increases if MFI coverage is high enough. Household demand for moneylender loans declines after becoming MFI member.

		Demand for Loans		Cream Skimming by	
	Interest Rate	Extensive Margin	Intensive Margin	Moneylenders	MFI
McIntosh and Wydick (2005)	↓	↓			✓
Jain and Mansuri (2003)	↑	↑			
Mookherjee and Motta (forthcoming)		↓	↑	✓	
Demont (2014)	**Inverted U**	↓			✓
Hoff and Stiglitz (1998)	↓		↓		
Bell (1990)	↓	↓			

Table A.1: Summary Statistics

	Mean	Standard Deviation
	InM-PKSF (2006-2007) Survey (n=793)	
Moneylender Interest rate	19.10	26.42
MFI coverage rate	42.08	22.42
% of household with irrigation	62.00	29.94
Distance to bank (km)	4.53	3.95
Distance to market and facilities (km)	3.31	2.64
No. of survey households in the village	204.69	184.38
% of households with VGD card	6.43	14.55
% of functionally landless household	80.04	12.50
	BIDS-BRAC Panel (2000, 2007) Survey (n=1365)	
'New' Borrowers in 2007	0.07	0.26
'New' MFI members in 2007	0.28	0.45
Log(head's age)	3.74	0.31
Heads Education above primary	0.31	0.46
No. of Agri Workers	0.79	0.81
Agri. Land owned in 2000 (ha)	0.58	1.01
Agri land cultivated in 2000 (ha)	0.41	0.71
Household size in 2000	5.14	2.27

Table A.2: Checking the Covariate Balance

		Mean				
Variable	Sample	Treated	Control	% bias	t-statistic	p>|t|
% of functionally landless households	Unmatched	79.56	80.34	-6.30	-0.89	0.37
	Matched	79.60	79.97	-3.00	-0.41	0.69
% of households with irrigated land	Unmatched	68.57	55.49	44.90	6.36	0.00
	Matched	68.71	65.18	12.10	1.81	0.07
Distance to bank	Unmatched	3.97	5.12	-29.20	-4.14	0.00
	Matched	3.99	4.24	-6.30	-0.96	0.34
Distance to market and facilities	Unmatched	2.90	3.78	-33.80	-4.77	0.00
	Matched	2.89	2.97	-2.80	-0.52	0.61
No. of survey households in the village	Unmatched	181.33	237.07	-27.50	-3.89	0.00
	Matched	181.58	189.71	-4.00	-0.64	0.52
% of households with VGD card	Unmatched	7.70	5.10	18.10	2.56	0.01
	Matched	6.75	5.34	9.80	1.41	0.16
Minimum Bias Trimmed Subsample						
% of functionally landless households	Unmatched	79.56	80.34	-6.30	-0.89	0.37
	Matched	79.97	80.13	-1.30	-0.14	0.89
% of households with irrigated land	Unmatched	68.57	55.49	44.90	6.36	0.00
	Matched	64.79	63.60	4.10	0.47	0.64
Distance to bank	Unmatched	3.97	5.12	-29.20	-4.14	0.00
	Matched	4.39	4.31	2.10	0.22	0.83
Distance to market and facilities	Unmatched	2.90	3.78	-33.80	-4.77	0.00
	Matched	3.14	3.06	3.00	0.42	0.68
No. of survey households in the village	Unmatched	181.33	237.07	-27.50	-3.89	0.00
	Matched	179.08	192.75	-6.70	-0.84	0.40
% of households with VGD card	Unmatched	7.70	5.10	18.10	2.56	0.01
	Matched	5.72	3.78	13.50	1.89	0.06

Figure 1: Average Loan Size (inflation adjusted) from different sources

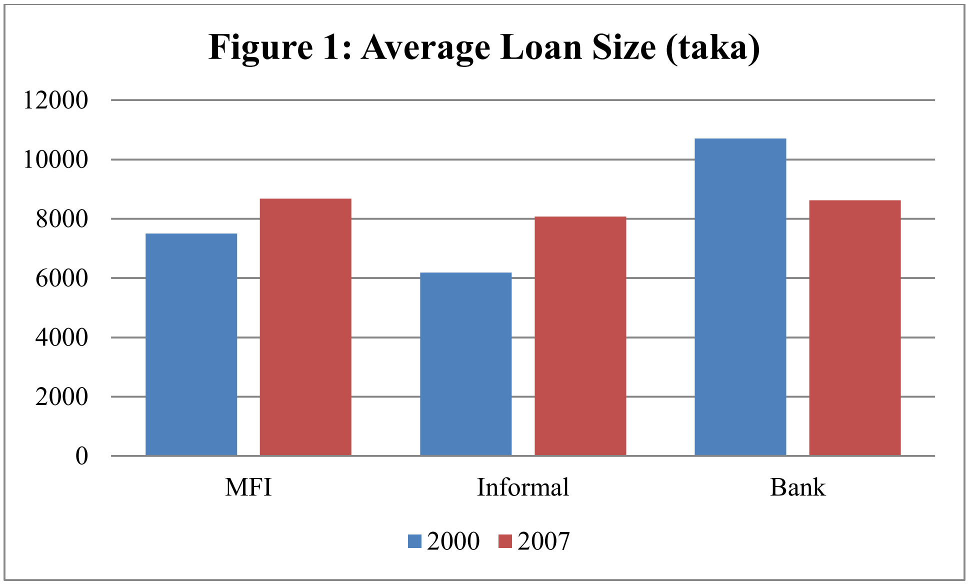

Figure 2: Sources of Rural Credit