Impact of Microfinance on Food Security, Informal Credit, and Agricultural Wages: The Case of Bangladesh

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A Dissertation submitted to

The Faculty of
The Columbian College of Arts and Sciences
of The George Washington University
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy

January 31, 2014

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Dedication

This dissertation is dedicated to the memory of my father, Klaus Berg, in whose footsteps I follow and to my mother, Isabelle Girardot-Berg, for encouraging me every step of the way.

Acknowledgements

Just as it takes a village to raise a child, so too does it take a community to craft a Dissertation. Needless to say, this Dissertation would not have been written without the support of a community of Professors, friends, and family.

First, and foremost, I must gratefully acknowledge my dissertation advisor, Shahe Emran who, like a lighthouse, patiently shined a light illuminating the path ahead. I have come a long way and learned a lot through this odyssey.

I am thankful for Bryan Boulier who stepped forward as my co-advisor and guided me along the stages of pulling three disparate pieces into one coherent whole.

Thank you Stephen Smith, for looking out for me early on in the program, and for remaining supportive throughout. Thanks Ben Williams, for patiently answering various econometric questions, no matter how difficult to understand or how challenging to explain. I gratefully thank James Foster for organizing the Development Workshop which gave us a chance to develop our research ideas and practice our presentation skills. I really enjoyed being a member of this team. Thank you Jorge Muñoz for accepting to be my external adviser despite your many obligations, and for sharing your wisdom on the topic of agricultural economics during the home stretch.

This dissertation began with an adventurous trip to Dhaka in the Summer of 2008. Together with Chrysanthi Hatzimasoura, I journeyed to this distant part of the globe to intern at the Institute of Microfinance. I am infinitely grateful to Baqui Khalili, at that time Director of the InM, for this wonderful opportunity and for generously sharing the data which became the foundation for my research. Thanks as well to Mahabub Hossain for sharing his panel. Thank you Sabin Ahmed for your hospitality during my stay in

Dhaka. I am very thankful to Zabid Iqbal for clarifying many issues relating to the data set. I am most grateful to Nazmul Hoque for translating my Bangla questionnaires and answering my various inquiries into what life in Bangladeshi villages is like.

For moral support and an understanding ear, I have greatly relied on my good friends: Saher Asad, Subika Farazi, Melanie Allwine, Marina Gindelski, Amy Guisinger, Sarah Niedergall, Daniel Broxterman, Feno Maret, Virginia Robano, and Courtney Lotfi. I could not have gotten this far without your help, support, and understanding.

Great thanks go as well to the members of the Economics Department for sharing with me your precious time, no matter how scarce. Thank you Tara Sinclair for teaching me Gauss, thank you Tim Moore for helping me understand why a tricky model did not work. I wouldn't have lasted this long in the program had it not been for Steven Suranovic who recommended me for the GTA fellowship and for mentoring me during my many years as a TA. Thank you Irene Foster for some challenging time working as a TA. The stipend helped pay the bills, but the experience working with students was invaluable and enriched me greatly during my time at GW. And thanks to Google, for always being available to answer my burning questions…even at 3 am.

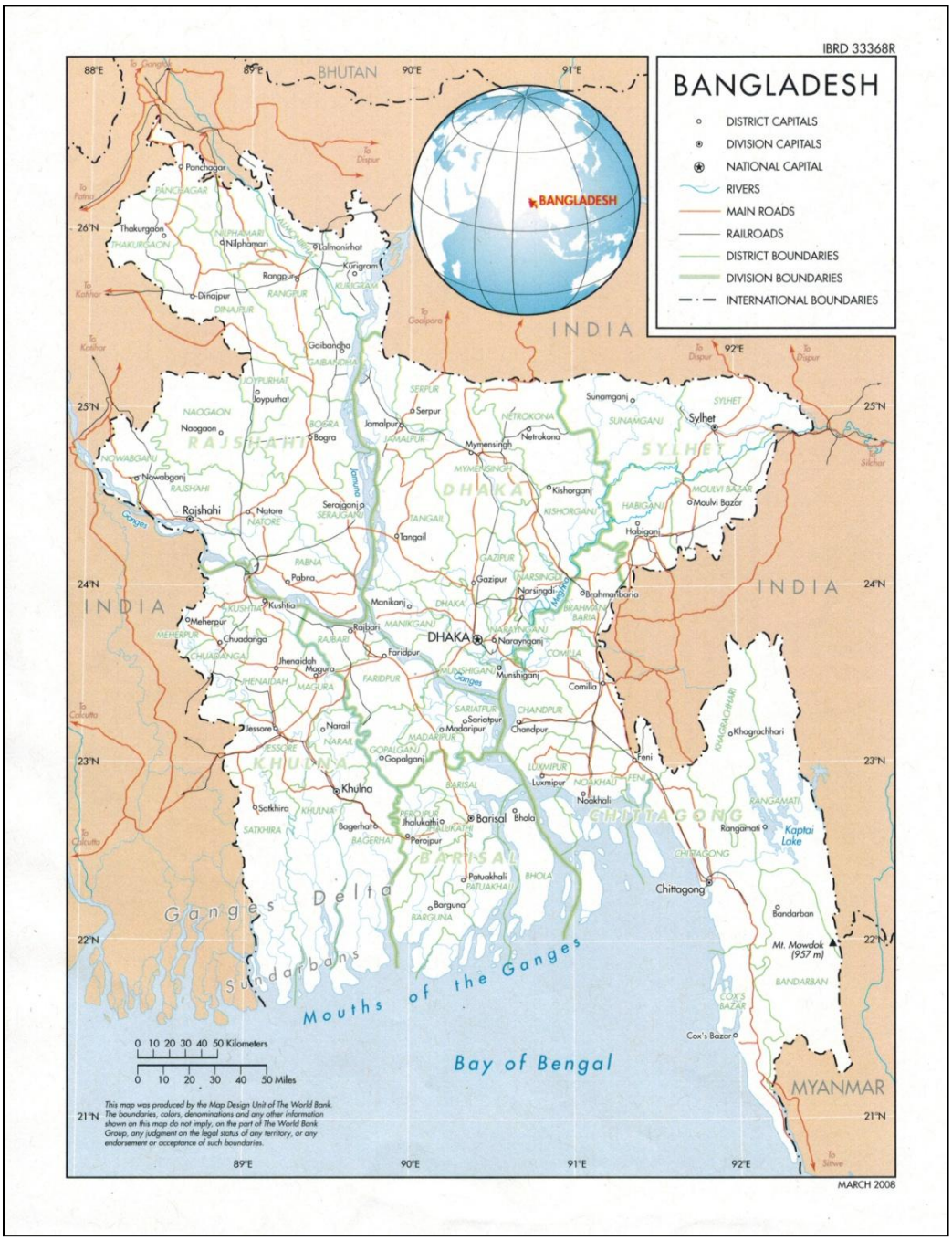
I am thankful to my family for their support. Thanks to my mom, Isabelle Girardot-Berg, for being unfailingly supportive and for proofreading an endless procession of drafts. Thank you Zoubida Allaoua for inspiring me to reach higher.

Thank you all for always encouraging me when I got discouraged and celebrating with me when success finally arrived!

Figure 1: MFI Members in Bangladesh

Source: Taken by the author, during a field visit while an intern at the Institute of Microfinance in Bangladesh, summer 2008.

Figure 2: Map of Bangladesh



Area studied is Northwestern Bangladesh, Districts of Gaibandha, Lalmonirhat, and Nilphamari.

Source: World Bank (2013)

Abstract of the Dissertation

Impact of Microfinance on Food Security, Informal Credit, and Agricultural Wages: The Case of Bangladesh

Since its beginning in Bangladesh in the 1970s, the spread of microfinance worldwide has been impressive, estimated at over 100 million members in 2009. While proponents argue that microfinance has improved the lives of millions of poor people, critics have raised doubts about its efficacy as a poverty alleviation strategy. Despite the doubts, few rigorous studies of impact have been completed. My dissertation is a contribution to the ongoing debate, and focuses on Bangladesh as a case study. It consists of three empirical research essays: (i) Chapter 2 estimates the impact of microfinance on seasonal food security of the ultrapoor in Northwestern Bangladesh; (ii) Chapter 3 assesses its impact on the informal credit market; and (iii) Chapter 4 looks at its impact on women's and men's agricultural wages. We take advantage of a unique dataset of 280,000 ultrapoor households generously shared with us by the Institute of Microfinance (InM) in Bangladesh and we apply novel econometric techniques to address the endogeneity of microfinance.

Chapter 2 uses a subset of 150,000 ultrapoor households in Bangladesh to analyze whether microfinance helps a household cope with aggregate shocks such as seasonal famine, known as *Monga* in Bengali. To address selection on unobservables, we use the "Minimum-Bias Bias-Corrected" estimator due to Millimet and Tchernis (2012) that corrects for endogeneity bias without exclusion restrictions. The empirical results suggest that microfinance improves food security of poor households by increasing food consumption during the Monga season. Also evidence is strong that microfinance helps

households avoid distress sale of labor, and reduces the probability of short-term migration in search of work during the seasonal famine.

The expansion of microfinance programs through the developing world has raised some interesting questions regarding its impact on the existing informal credit market. Chapter 3 analyzes this question by looking at both the impact on the village moneylender interest rate and on informal borrowing by households. We use two data sets from Bangladesh: (i) a large cross-section that includes more than 800 villages (extracted from the above InM data set); and (ii) a nationally representative panel with household-level data from 62 villages from BRAC. Relying on heteroskedasticity and matching to achieve identification (Klein and Vella 2009a, 2010; Millimet and Tchernis 2012), our results suggest that the spread of microfinance has had a positive and statistically significant effect on the moneylender interest rate. Microfinance membership seems to decrease the probability of borrowing from informal lenders but increase the average amount borrowed. We consider three alternative hypotheses to explain these results: increased demand, cream skimming, or fixed costs. The theory of cream skimming is most consistent with our results: as MFIs reach villages, they attract the better borrowers, leaving behind a riskier pool, leading the moneylenders to raise their interest rates accordingly.

Chapter 4 investigates the impact of microfinance coverage on women's agricultural wages, looking into both the impact on the general, "Normal", agricultural daily wage and the wage prevailing during the Monga. To address the endogeneity of microfinance coverage, we employ the Klein and Vella (2009a) instrumental variable and the Minimum Bias estimator of Millimet and Tchernis (2012). The results suggest that

microfinance expansion tends to increase the average wage earned by women in agriculture, both during the Monga and Normal seasons, a significant poverty alleviation measure since only ultrapoor women work as agricultural laborers. The wages of men are found to increase as well. As microfinance expands, women tend to substitute their time away from the wage market towards their microenterprise. Consequently, the labor supply curve shifts to the left thus increasing the wage rate for those who continue to work in the labor market. Also by improving the situation during Monga, microfinance has an even greater impact during the non-Monga season, when more laborers—both men and women—now work at the going wage.

In brief, the results of our research suggest that microfinance does have a significantly positive impact on the welfare of the ultrapoor. Microfinance membership reduces the likelihood that households will be forced to skip meals and practice distress sale of labor during the hungry season, while also reducing the poor's reliance on informal "exploitative" sources of finance, and increasing the agricultural wages earned by both men and women in the villages. At the same time, by capturing the less risky borrowers, MFIs do not bring down the interest rates for those fewer villagers who continue to borrow in the informal market. But higher average interest rates in the informal market do not necessarily worsen the situation of this group since they were risky borrowers in the first place, likely facing higher interest rates regardless. In fact they may even have easier access to informal credit as suggested by the larger average loan size.

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1 Introduction

Microfinance has become an integral part of the anti-poverty strategies of many developing countries over the last three decades. Since its debut in Bangladesh in the 1970s, the growth of microfinance membership worldwide has been phenomenal, expanding from 10,000 in 1980 to over 100 million in 2009 (Microcredit Summit Campaign 2009); from 1997 to 2007 alone, the total number of clients reached by microfinance institutions (MFIs) grew ten times (Armendáriz and Morduch 2010, Table 1.1). While the proponents argue that microfinance has improved lives of millions of poor people (especially women) by providing access to credit without collateral, the critics have raised doubts about its efficacy as a poverty alleviation and development strategy (for a recent survey of the literature, see Armendáriz and Morduch (2010)). Yet in spite of the controversy, "relatively few rigorous studies of impact have been completed and the evidence on statistical impacts has been mixed so far" (ibid, p. 5). This dissertation research aims at filling some of the gap in our understanding of the impact of MFIs on the ultrapoor, by examining its effect on food security, the informal credit market, and women's agricultural wages, taking Bangladesh as a case study. Filling this gap is especially important since helping their clients escape poverty is among the stated goals of MFIs, and could have important policy implications.

The region studied covers parts of Northwestern Bangladesh where ultrapoor households suffer a seasonal shortfall of income resulting in hunger, a period known locally as *Monga*. Many are forced to skip meals, borrow from moneylenders, or migrate in search of jobs.

Taking advantage of a unique dataset of 280,000 ultrapoor households collected by the Institute of Microfinance (InM), a non-profit research institution in Dhaka, Bangladesh, the first chapter of my dissertation examines whether microfinance membership helps the ultrapoor in Northwestern Bangladesh cope with seasonal famine. Using the same source of data, the second chapter examines the impact of microfinance on the moneylender interest rate at the village level and on informal borrowing at the household level. For a more complete picture of the impact on informal borrowing, we analyze a second dataset: a nationally representative two-period panel (2000 and 2007) from Bangladesh.[1] By examining the effect of microfinance on the moneylender interest rate and informal borrowing, one is able to develop a clearer understanding of the impact on the informal credit market equilibrium. The third chapter of this dissertation uses the same InM village data to analyze the impact of microfinance coverage on agricultural wages earned by men and women during the Monga and Normal seasons.

In each of the chapters, identification of the causal impact of microfinance is challenging due to omitted variables. Since we cannot control for everything that would influence both microfinance and the outcome of interest, ordinary least squares (OLS) estimation would likely yield biased results. In the absence of a credible instrumental variable, we turn to novel econometric techniques to overcome the endogeneity of microfinance. In particular, we apply recently developed matching techniques: the "Minimum Bias (MB)" and "Bias Corrected (BC)" estimators of Millimet and Tchernis (2012). Where appropriate, we employ heteroskedastic-based identification: the Klein-

[1] While this panel has information on the amount households borrowed from informal sources in 2000 and 2007, it does not contain information on either the moneylender interest rate or on meals consumed by households.

Vella IV (Klein and Vella 2009a) and the Klein-Vella Control Function (Klein and Vella 2010).

Overall, the results suggest that microfinance does have a significant impact on the welfare of the poor. Chapter 2 concludes that microfinance membership reduces the likelihood that households will be forced to skip meals during Monga, the hungry season. Chapter 3 finds that microfinance reduces the poor's reliance on informal sources of finance. Microfinance membership decreases the incidence of informal borrowing at the household level as MFIs attract the better, less risky borrowers. Those remaining in the informal credit market are on average riskier borrowers, and so we see an increase in the moneylender interest rate as MFI coverage increases. Chapter 4 finds that microfinance coverage increases the agricultural wages earned by both men and women in the villages. As microfinance expands, women are able to get loans to start or expand their microenterprise. Thus, the labor supply in the agricultural wage market shifts to the left. Those ultrapoor who continue to work as laborers earn a higher wage on average. Finally, Chapter 5 addresses the policy implications of our findings.

2 Does Microfinance Help the Ultrapoor Cope with Seasonal Shocks?

2.1 Introduction

Although the initial focus of the literature on microcredit had been on the implications of missing credit markets and the potential effects of relaxing binding credit constraints on household outcomes, it is now well appreciated that microcredit may at least partially be filling in for a number of other missing markets. For example, Emran et al. (2009) show that microcredit addresses simultaneously two missing markets: credit and labor. Microcredit may also work as an imperfect substitute for missing insurance and consumer credit markets. There is evidence that many households use microcredit for consumption smoothing (an insurance market role), and also for financing indivisible consumer durables such as bicycle and television (missing market for consumer credit), or other lumpy expenditures (such as financing migration or investment in education). Microfinance NGOs are also increasingly offering explicit savings and insurance products to poor households (see Karlan and Morduch (2008) and Banerjee and Duflo (2011) discussions). Taking advantage of a large data set on 280,000 ultrapoor households supplied by the Institute of Microfinance in Bangladesh (InM) and using the seasonal famine in Northwestern Bangladesh known as Monga as a case study, this paper provides evidence on the effectiveness of microfinance programs in coping with aggregate seasonal shocks.

That the credit market can play an insurance role, especially when the credit contract is renegotiable, has been well-understood in the literature on consumption smoothing in developing countries (Udry (1990, 1994), Besley (1995), Morduch (1995)).

There is evidence that microcredit programs may help mitigate idiosyncratic shocks at the household level such as health shocks (see Gertler et al. (2009)). However, there is limited work in the current literature on the role played by microcredit in coping with more aggregate shocks at the village or regional level. Probably, the closest precursor to this paper is Pitt and Khandker (2002) which provides evidence on the effects of microfinance membership on consumption and labor supply across different seasons. The other closely related papers are Morduch (1998) and Khandker (2009). Morduch (1998) finds evidence that microfinance reduces consumption volatility, although a recent paper by Morduch and Roodman (2009) raises doubts about the validity of this conclusion. Khandker (2009) uses HIES data from Bangladesh and analyzes implications of microfinance membership and other anti-poverty programs such as vulnerable group development (VGD) for consumption smoothing and coping with the hardship of the lean season. However, isolating the effects of microfinance is not a focus of the study, and thus it does not address the endogeneity of microfinance membership.

Almost every year during the months of September-November (before the Aman harvest), a large part of rural Northwestern Bangladesh, especially in the Rangpur region, becomes vulnerable to seasonal famine or near famine situation. During this lean season, a large number of poor households cannot find any employment. The poor and ultrapoor households thus turn to desperate measures to cope with the seasonal famine such as reducing daily food intake and distress sale of assets (Rahman (1995)). Since most of the poor households own little assets other than their labor endowment, selling labor in advance during Monga is among the few options they might have to avoid starvation.

When households own land, they can also sell their crops in advance.[2] Such distress sale of labor or crops implies that the households receive very unfavorable prices and thus may be trapped in a vicious cycle of poverty. The average wage received for advance labor sale is about 50 percent of the wage in the spot market (Rahman (1995)). Access to credit in such a situation can potentially make a big difference.

One would expect that better access to credit through microfinance membership can only help households in coping with adverse village/regional shocks such as seasonal famine. Microcredit may yield higher income when used in productive activities, and fungibility of credit means that loans taken ostensibly for investment can be used for consumption smoothing. As emphasized by Pitt and Khandker (2002), most of the microcredit projects are non-farm activities, and thus are less subject to seasonality or weather shocks, compared to agriculture. Moreover, microcredit may be effective in mitigating the effects of low demand for labor in agriculture during the lean season, because it creates employment opportunities within the household (see Chapter 4).

The implications of microfinance for a household's ability to cope with seasonal (aggregate) shocks is, however, not unambiguous. One can easily find reasons to suspect that microcredit may not be very effective in addressing regional shocks such as the seasonal famine in Northwestern Bangladesh. First, microcredit loans are not short term consumption loans, so that a household may not be able to get new loans during the Monga period. In fact, the rigid loan repayment schedule might make it difficult to both buy enough food and also repay the loans at the same time. Second, although microfinance groups may be helpful in the face of idiosyncratic shocks at the household

[2] In our data set the incidence of advance crop sale is very low, less than 1 percent. So we do not use it as an indicator of a household's ability to cope with seasonal famine.

level (such as health shocks as found by Gertler et al. (2009)), Monga is a more aggregate shock (at the village or sub-district level) that affects many (or even most of the) households in a given village at the same time. Aggregate shocks are likely to make the 'solidarity group' aspect of microcredit programs such as Grameen Bank and BRAC less effective to cope with Monga and other similar aggregate shocks to a village. The income level of most of the households in the affected regions suffers adversely during Monga, and the resulting local demand constraint can make nonfarm activities financed by microcredit nonprofitable. Thus it is not obvious that access to microcredit necessarily makes it easier for a household to cope with seasonal adversity such as Monga. Whether or not microfinance helps a household cope with Monga (and other similar aggregate shocks) is an empirical issue. Only when the positive income generation from self-employment and consumption smoothing effects dominate, we would expect microfinance to play a positive role in coping with the seasonal shocks.

This paper analyzes the impact of microfinance membership on a number of economic indicators that are informative about a household's ability to cope with famine. They are: indicators of food security (number of meals a day during Monga), advance sale of labor as an indicator of distress sale, and short term migration for work during Monga. An important advantage of our study is that we rely on the InM exceptionally large and rich data set on 280,000 ultrapoor households with monthly household income less than Tk. 1,500 ($21 in 2006). For our analysis, we retain roughly 150,000 households for which we have complete household and village characteristics (see Section 2.4 for a description of the Data). The large sample size gives our analysis an

edge in terms of external validity.[3] Also, note that our sample covers many different microfinance NGOs working in Northwestern Bangladesh including Grameen Bank, BRAC, ASA and BRDB. Our estimates give average effects of the different programs, and thus can lay claim to a higher level of generality compared to most of studies that focus on one specific microfinance program.

Identification and estimation of the effects of microfinance membership is difficult because of two levels of selections: the self-selection into a microfinance program by the households and the screening process of an MFI. We address the bias in the estimated effects that arise from selection on unobservables by using the recent "Bias Corrected" (BC) estimator due to Millimet and Tchernis (2012) that corrects for the bias without imposing exclusion restrictions.

Unlike other matching estimators such as inverse probability weighted matching estimator (IPW) of Hirano and Imbens (2001), the BC estimator does not rely on the conditional independence assumption. The BC estimator provides an estimate of the bias due to selection on unobservables using a trimmed sample around the bias minimizing propensity score and then subtracts the estimated bias from the "Minimum Bias" estimate to arrive at the relevant causal effect. The Monte Carlo evidence in Millimet and Tchernis (2012) shows that the BC estimator does an excellent job in terms of correcting the bias that arises from selection on unobservables.

The results from our empirical analysis provide robust evidence in favor of a beneficial effect of microfinance membership on a household's ability to cope with

[3] We are not aware of any other work that utilizes such a large data set to analyze the effects of microfinance on ultra poor households. As part of robustness checks, we use a much larger sample of more than 240,000 households. We do not use the larger sample for the main analysis because of missing information about village characteristics.

Monga. The evidence is strong that microfinance membership improves the ability of a household to have three meals a day during Monga.[4] According to our preferred estimate, microfinance improves the probability by about 0.015 that a household can afford 3 meals a day and thus escape from hunger and starvation during Monga. This improvement is a substantial effect considering that only 6 percent households are able to manage three meals a day during Monga in our data set.[5] Microfinance helps the relatively better-off households to achieve three meals a day during Monga (i.e., the households for which the relevant margin is two versus three meals a day), and also improves the food-security of poorest of the ultrapoor (i.e., the households for which the relevant margin is one versus two meals a day). There is convincing evidence that microfinance reduces substantially the probability that a household needs to sell labor in advance during Monga. Microfinance membership also negatively affects the probability of short term migration during Monga in search for work.

The rest of this paper is organized as follows. Section 2.2 provides a brief background of the persistent seasonal famine (Monga) in Bangladesh. Section 2.3 discusses our empirical strategy. Section 2.4 is devoted to a discussion of the data and main variables. The empirical results are reported in section 2.5. The paper concludes with a summary of the empirical findings.

[4] We use three meals a day as an indicator of food security, as it is the norm in rural Bangladesh to have three full meals when a household has enough wealth. It is important to appreciate the fact that even the three meals are not likely to supply enough nutrition (especially protein) and calorie during Monga for most of the poor households. Because the meals usually consist of coarse rice and a meager amount of vegetables and lentils.

[5] This estimate is based on the large sample with about 240,000 households.

2.2 Monga: The Season of Deprivation and Starvation

Despite the enormous social and economic progress made in recent years, Bangladesh remains a poor country. While the poverty headcount rate fell nationwide from 49 to 40 percent between 2000 and 2005 (World Bank (2008)), the rural poverty rate in Rangpur district and surrounding areas in Northwestern Bangladesh was 56 percent in 2005 (Khandker et al. (2010b)). Five million of Bangladesh's poor live in the 'Greater Rangpur' region, an area plagued almost every year by Monga, a season of near famine (World Bank (2008)).

Monga is a season of severe food deprivation that strikes parts of Bangladesh with disturbing regularity. Also known as *Mora Kartik*, or October the month of deprivation, it is a season when household food stocks have run out and jobs are scarce. It is "the bane of the rural poor, the season of half-meals and debt bondage" (Rahman (1995), p. 234). Every mid-September through mid-November there is a negative shock to income, and consequently households find it difficult to buy enough food. It is important to note, that seasonal hunger is the consequence of seasonal income fluctuations among people whose income is barely enough to survive during regular times. It is not merely the result of a shortage of food. While it would certainly help if farmers could produce enough to build up buffer stocks, the real problem is one of seasonal 'failures of exchange entitlement' in the sense of Sen (1976, 1981): According to Sen, "Exchange entitlements are concerned with what a person can, in fact, get through exchange and not with what he *could* get if he *could* buy and sell at given prices." (Sen 1976, p. 1,274). During the Monga in Greater Rangpur, there is a seasonal entitlement failure due to unfavorable terms of exchange faced by poor laborers who, unable to find work at a decent wage during this time, cannot

exchange their labor at a rate adequate to purchase enough food for themselves and their families. In rain-fed areas, the agricultural calendar in Bangladesh is divided into two main growing seasons. *Aus*, the wet season first crop is grown when enough rainfall occurs (April to August). *Aman*, the wet season second crop lasts from July to December. In addition if irrigation is available, a third rice crop, called *Boro*, can be planted after Aman. The hunger months occur between the planting and harvest of Aman, the autumn rice crop, when there is a shortage of employment and wages are very low but grain prices are high (Rahman (1995)). Thus Monga repeats itself almost every year around September to November after the previous season's food has run out, before the transplanted rice is harvested in December. These months, and especially October, give rural people a harder time than usual because of extremely limited job opportunities (Muqtada (1975), Hossain (1990)). Evidence suggests that this variation in income is more pronounced in Greater Rangpur area which is the focus on our study than it is in other parts of the country (Khandker (2009), Khandker et al. (2010a)).

The Monga-affected region of Greater Rangpur, encompasses the districts of Gaibandha, Kurigram, Lalmonirhat, Nilphamari, and Rangpur. In the Monga of October 1991, Greater Rangpur experienced an average 50 percent drop in the daily wage rate compared to the rest of the year (Rahman (1995)). The existing evidence shows that the inhabitants of Greater Rangpur are poorer than the rest of the country in terms of a variety of indicators including income, expenditures and poverty level. Extreme poverty in Greater Rangpur is 42 percent compared to the national rural average of 27 percent. Also, the daily wage rate for male agricultural worker in Greater Rangpur is 46 taka

compared to 64 taka found elsewhere (Khandker et al. (2010b)). During Monga, the poor are especially hard hit.

Seasonal variation in income is, however, not unique to Bangladesh, it is common to agrarian economies. With monsoon-dependent crops and a lack of irrigation, agricultural households in Indian villages receive on average 75 percent of their annual income in the span of a three-month period (Chauduri and Paxson (2001)). When combined with extreme poverty, seasonal variation in income translates to seasonal hunger. Dercon and Krishnan (2000) found consumption of rural households in Ethiopia to vary greatly over a short period of time. Malawi has its own hungry season, as one of its citizen recounts: "Come January, most people are forced to tighten their belts and wait until harvest…We call this period 'the hungry season'. In the countryside, people are working the hardest … but doing so with the least amount of food. Understandably, they grow thin, slow, and weak" (Kamkwamba and Mealer, (2009, p. 71)).

2.3 Empirical Strategy

To understand the issues involved in identification and estimation of the effects of microfinance on a household's ability to cope with seasonal famine, consider the following triangular model:

$$C_i = \beta_0 + \beta_1 M_i + X_i'\Gamma + \xi_i \tag{2.1}$$

$$M_i = \alpha_0 + X_i'\Pi + \varepsilon_i \tag{2.2}$$

Where (2.1) is the outcome equation, and (2.2) is the selection equation. The outcome equation shows household i's ability to cope during Monga (C_i), as a function of membership in any Microfinance Institution (M_i), household and village characteristics (X_i), and an error term (ξ_i). As noted earlier, the outcome variables we focus on are

indicators of household food security (number of meals a day), incidence of advance labor sale, and migration in search of work during Monga.

The selection equation captures the two levels of selection processes discussed before, i.e, the self-selection by a household and the screening of the potential borrowers by an MFI. The endogeneity arises from the fact that there are individual, household and village level unobserved factors that may affect both the outcome and the selection equations, and thus the correlation between the error terms is not zero, i.e., $\rho = Cov(\xi_i, \varepsilon_i) \neq 0$. The most obvious individual-level common unobserved heterogeneity in the context of microfinance is ability (or entrepreneurial capability). An individual with higher ability would expect higher net return from participation in the credit program, and thus would self-select into the program. But higher ability may also mean that she will have better economic outcomes in the absence of credit availability. This creates a positive selection effect, and $\rho > 0$ on this account. However, it is also possible that the outside option for a high ability entrepreneur is much better (shadow price of time is higher), and thus she might not be interested in high interest rate micro loans with its web of restrictions (such as group liability, and substantial time commitments for regular group meetings). If this is the case, MFI would attract relatively low ability micro-entrepreneurs and thus the selection would be negative implying $\rho < 0$. There is some econometric evidence that, in fact, the selection into MFI programs in Bangladesh is negative, and thus the OLS and Probit would yield estimates that are biased downward (see, for example, Schroeder (2009), and Pitt and Khandker (1998)).

The correlation between ξ_i and ε_i can also arise because of nonrandom placement of MFI programs across different villages. For example, to ensure high repayment rates,

the MFIs have incentives to select villages with concentrations of moderate poor and eschew the most vulnerable villages with concentrations of ultrapoor. The MFI can also use information about a village's economic potential to pick better endowed villages. This would result in a positive correlation between the error terms in equations (1) and (2) above implying $\rho > 0$. But if the MFIs are true to their objective of poverty alleviation, then they will target relatively unfavorable villages, thus making $\rho < 0$.

When the outcome variable is binary, as is the case in our application, one can estimate the triangular model using MLE under the assumption that ξ_i and ε_i are approximately bivariate normal. However, such identification relies on the nonlinearity of Normal CDF, and is regarded as non-robust (Altonji et al, (2005)). In the absence of any exclusion restrictions, one can also use various matching methods (Heckman et al. (2004), Todd et al. (1998), Hirano and Imbens (2001)). However, the matching methods rely on the assumption that there is no significant selection on unobservables conditional on matching on the observable characteristics. This is a strong assumption which is unlikely to hold in many applications including ours. Recent advances have developed ways to minimize and correct for the bias that results from the failure of the conditional independence assumption (CIA). We use the 'Minimum-Bias Bias-Corrected' (BC) estimator recently proposed by Millimet and Tchernis (2012) which provides a way to correct for the bias. The Minimum-Bias (MB) estimator builds on the normalized Inverse Probability Weighting (IPW) estimator of Hirano and Imbens (2001); it modifies the IPW by restricting observations to those with a propensity score in a "neighborhood" around the Bias Minimizing Propensity Score (BMPS). Note that the normalized IPW relies on the CIA and thus estimates are biased when it is violated, for example due to selection on

unobservables. The 'BMPS' is the propensity score which minimizes this bias, which yields the minimum bias (MB) estimator. The MB-BC estimator subtracts the estimated bias from the MB estimate. Millimet and Tchernis (2012) define the neighborhood around the BMPS as observations with a propensity score within a radius θ, such that at least θ percent of both treatment and control groups are included (trimming observations with a BMPS below 0.02 and above 0.98). They set this radius at 0.05 and 0.25. The Monte Carlo simulations reported in Millimet and Tchernis (2012) show that MB-BC estimator with a large radius (0.25) performs very well in terms of correcting for the endogeneity bias even when there is significant selection on unobservables.[6]

The choice of the control variables is motivated by the objective of minimizing omitted variables bias in the regressions. Since omitted variables bias arises only when a variable affects both the selection and outcome equations, we include observable characteristics that belong to the intersection set of the determinants of the outcome and selection equations.

The household variables we control for in the X_i vector include age of the household head, age squared, number of family members over the age of 12, total owned land, total cultivable land, number of household members occupied in self-employed agriculture, number employed as day laborers, and a dummy for whether the household has a Vulnerable Group Development (VGD) card. Unfortunately, we do not have data on education of the household head.

Age and age squared are included as an indicator of social and human capital (e.g. experience, wisdom, and physical strength). The social and human capital might be

[6] Note that we cannot use the recent approach developed by Klein and Vella (2009a, 2010) that exploits restrictions on second moment for identification, because our dependent variables are binary.

important for access to informal finance in the absence of microcredit, and thus may affect the opportunity cost of not joining into a MFI program. Also, MFI NGOs may target households with relatively young and energetic borrowers, and households whose heads are too young or too old age will be less likely to get selected into the program. We include measures of land and labor endowment of a household, as they determine the shadow price of labor in the household. As discussed by Emran et al. (2009), in a rural economy where the labor market is imperfect or effectively missing, especially for women, the shadow price of labor is a critical determinant of the participation decision of household. The land and labor endowments obviously affect the outcome variables such as ability to have 3 meals a day during seasonal famine. The number of family members over the age of 12 is included to control for the household's labor endowment and total owned land is included to reflect the household's land endowment. Total cultivable land is included to take into account the fact that households may lease land in or out. The number of household members self-employed in agriculture and employed as day laborers capture the household's labor market opportunities, and also represent an important source of income, especially for the landless households. We control for VGD (vulnerable group feeding program) cards, because most of the NGOs use it as an exclusion criteria when screening potential borrowers. A VGD card also should improve the ability of a household to cope with Monga.

The village-level control variables include percent of electricity usage in a village, the average agricultural wage for men and women, [7] distance to the nearest bank, distance to the market or business center, and distance to the secondary school. All of these variables are indicators of the level of development of a village. Percent of electricity

[7] We use the average of the Monga and Normal wages.

usage is a good measure of wealth that is not determined by microfinance. The average male and female wages in agriculture reflect unobserved land productivity, and are important as indicators of labor market opportunities in a village. The distance to bank captures access to formal credit markets, and distance to business center captures access to urban markets. A better access to urban market increases the profitability of non-farm activities financed by microcredit. Since the data lack information concerning the education level of the household head, we include distance to secondary school as an indicator of the availability of educational opportunities in the village.

Finally, we include two dichotomous variables to capture in part the two components of the selection bias: i.e. from both the household and the MFI. For a household to become a MFI member, it must (i) self-select into the microfinance program and (ii) be accepted by the MFI. To account for a household's self-selection into a MFI program, we include a dummy taking the value of one if the household is in a village with a relatively "high" moneylender interest rate, where high is defined as larger than the average of all the villages' interest rates. The moneylender interest rate is the price of credit if a household decides not to apply for microcredit. This is especially true for the poor and ultrapoor households, with little or no access to the formal credit market, which we are focusing on in this study. When the moneylender interest rate is high, the households have more incentive to join a MFI program. To capture the MFI selection process, we include a binary indicator of land ownership. This is motivated by the fact that most of the MFIs use land ownership as a salient targeting variable. Targeting land-poor or landless households is consistent with the poverty alleviation objective of the MFI NGOs in Bangladesh. The lower the land owned the higher is the probability that a

MFI will accept a household as its member. To capture this, we include a binary variable which takes the value of one if the household has less than half the average land owned among all the households overall, and zero otherwise.

2.4 Data

The InM and Palli Karma Shahayak Foundation (PKSF), non-profit government organizations, jointly conducted a census of households in the district of Lalmonirhat in 2006 and in the districts of Gaibandha, Kurigram, Nilphamari, and Ranpgur in 2007. The sample was limited to those households meeting at least one of the following three criteria: less than 1,500 taka of monthly income, dependent on day labor, or having less than 50 decimals (half an acre) of land (Uddin (2008)).

The questionnaire used to collect the data covered a broad range of topics including employment, family size, assets, migration for work during Monga, food security, and membership in any microfinance institution. The census was conducted during normal (non-Monga) time and Monga-values refer to the previous seasonal famine. An example of a question asked of households is "During the last Monga how many times a day did you eat (how many meals)?" This provided information on whether a household could consume three meals or was facing starvation with only one or two meals a day during Monga.

The outcome variables we focus on in this paper are indicators of food security, distress sale of labor, and short-term migration during the seasonal famine. We use two indicators of food security: binary variables for ability to have three meals and one meal a day during last Monga. We use a dummy for advanced labor sale during last Monga as an indicator of distress sale. Village-level variables were collected in a separate

questionnaire and included information on the moneylender interest rate; agricultural wages; electricity use in the village; and distances to the nearest bank, market, and secondary school. However, unfortunately, for a large number of villages, most of the variables are missing.

This paper focuses on the Districts of Gaibandha, Lalmonirhat, and Nilphamari as they had the most complete data set (Kurigram and Rangpur were lacking village-level variables). These three districts have a total of 280,469 households: 120,608 in Gaibandha, 102,936 in Lalmonirhat, and 56,925 in Nilphamari. However, a large proportion of households lack village level information, and thus we cannot include them if we would like to control for village level heterogeneity. After dropping households with missing variables and excluding those who borrow from both Moneylenders and Microfinance Institutions, we focus on 149,721 households for the main empirical analysis. As part of robustness checks, we also use a much larger sample of more than 240,000 households, but we cannot use village-level controls for these estimates. Table 2.1 and Table 2.2 report summary statistics of the main variables used in our analysis for both samples.

2.5 Empirical Results

2.5.1 Preliminary Results: OLS and Probit

We begin our analysis with OLS and Probit estimates. Given the binary-binary structure of our empirical model, Probit estimates may be more efficient, but the OLS may be more robust, as it does not rely on distributional assumptions. The estimates from OLS and Probit are, however, very similar, and we thus focus on the OLS results in the main analysis (see Table 2.3 and Table 2.4). In addition to the heteroskedasticity robust

standard error, we also report standard errors clustered at the village level. Note that unlike many standard household survey data sets, our data do not come from a stratified random sample. Since we have a census of the ultrapoor households in 12 upazilla's in three districts, the variation used for identification is at the household level. Thus one can argue that the correct standard errors in this case are the heteroskedasticity robust ones. We report the clustered standard errors as a conservative measure of dispersion of the estimates.

The broad picture that emerges from the OLS results reported in Table 2.3 is that microfinance membership seems to have positive effects on a household's ability to cope with Monga. Although the magnitude of the effect varies across different outcome variables, and also depends on the set of controls used, we find that microfinance membership increases the probability that a household can have three meals a day and thus avoid hunger during the seasonal famine. The estimated effect from the most complete specification including household characteristics and Upazilla fixed effects is statistically significant at the 1 percent level according to the clustered standard errors. In terms of magnitude, microfinance membership raises the probability of consuming three meals a day by about 1 percent which is not substantial.[8] The pattern of estimates across different sets of controls indicates that the estimate for three meals is extremely robust; its magnitude barely changes across different sets of controls. The estimates in Table 2.3 suggest that microfinance membership also reduces the probability that a household has to survive on one meal during Monga, the numerical magnitude of the effect is larger (about 3 percent).

[8] Note, however, that the OLS results may be significantly biased downward due to negative selection. The results reported later that correct for the bias due to selection on unobservables seem to confirm this suspicion.

The impact of microfinance membership on "no advance labor sale" is consistently positive, but it loses statistical significance with the introduction of fixed effects (both District and Upazilla levels). The probability of not selling labor in advance during Monga increases with microfinance membership, but the magnitude is very small according to the estimate from the specifications with fixed effects.

Somewhat unexpectedly, the OLS (and Probit) results indicate that Microfinance membership increases the probability that a household member migrates in search of work by about 1 percent during Monga. Since microcredit uses family labor, one would expect that MFI membership would have a negative effect on migration for short term work. However, the estimated effect is not very robust, it is not statistically significant when standard errors are clustered at the village level.

The OLS and Probit results are interesting, and indicate that Microfinance membership may have positive effects on a household's ability to cope with seasonal famine. However, these estimates are subject to potentially serious endogeneity bias due to omitted heterogeneity that affect both the selection into the program and also the outcomes of interest conditional on participation. To address the potential endogeneity bias in the estimated effects of microfinance membership, we report estimates from the Minimum Bias-Bias Corrected (MB-BC) estimator due to Millimet and Tchernis (2012) that corrects for the endogeneity bias without any exclusion restrictions, discussed above in section 2.3. The estimated results are reported in Table 2.5. If not noted otherwise, all the estimates reported in Table 2.5 use the full specification with Upazilla fixed effects that corresponds to the last column in Table 2.3.

2.5.2 Addressing Selection on Unobservables: Minimum-Bias and Bias-Corrected Estimates

In this sub-section, we discuss the results from the Minimum-Bias Bias-Corrected (MB-BC) estimator.[9] The MB-BC estimates are reported in column (1) of Table 2.5. The MB-BC estimator starts from the normalized Inverse Propensity Weighted estimator (IPW) of Hirano and Imbens (2001), and restricts the observations to those with a propensity score within a radius of 0.05 and 0.25 of the bias minimizing propensity score. This yields the Minimum Bias estimator (MB). The MB-BC estimator corrects for the bias in the Minimum Bias (MB) estimate due to the violation of the CIA by using the estimated bias. In all our cases, the MB-BC estimates from alternative radius vary only marginally, so we report the estimates using a radius of 0.25.[10]

The 90 percent confidence intervals reported in column (1) of Table 2.5 shows that the effect of microfinance membership is statistically significant for all four outcome variables (confidence intervals are generated by bootstrapping with 250 replications). None of the confidence intervals contain zero providing clear evidence that microfinance membership matters for a household during seasonal famine.

The estimates show a much larger positive effect of microfinance membership on food security of the household during Monga compared to the estimates from OLS or Probit. The probability that a household can afford three meals per day during Monga increases by 16 percent due to microfinance membership according to the MB-BC estimate. The estimated effect on one meal is negative and much larger in magnitude

[9] The reported estimates are ATE of microfinance membership. The ATT estimates are very similar and thus omitted for the sake of brevity.

[10] The Monte Carlo evidence presented by Millimet and Tchernis (2012) shows that the MB-BC estimator with a larger radius successfully corrects for the bias due to selection on unobservables.

compared to the effect on three meals. The MB-BC estimate of the effect of microfinance membership on 'not selling advanced labor' during the seasonal famine is 0.19 which is many times larger in magnitude compared to the OLS or Probit estimates (about 1 percent). Interestingly, the conclusion for short term migration for work during Monga is very different when we correct for selection on unobservables using the MB-BC estimator. In sharp contrast to the OLS and Probit estimates that show a positive effect, the MB-BC estimate shows that microfinance membership reduces the probability of short-term migration during Monga which is consistent with the a priori expectations, because, as noted earlier, microenterprises rely on family labor and thus create productive opportunities within the household during Monga when the agricultural labor market virtually shuts down. The estimated effect is, however, implausibly large in magnitude.[11]

For all four outcomes, the MB-BC estimates are much larger in magnitude which suggests that the selection on unobservables is negative in our data set. As mentioned before, this is consistent with the available evidence in the literature on the nature of selection in microfinance programs in Bangladesh (see, for example, Schroeder (2009) and Pitt and Khandker (1998)).

2.6 Conclusions

This paper provides evidence on the role played by microfinance in helping villagers cope with seasonal aggregate shocks, using a cross-section of 150,000 ultrapoor households. We analyze whether membership in microfinance programs helps a household cope with the seasonal famine. To address the bias in the estimate effects due to selection on unobservables, we use the recent Minimum Bias and Bias Corrected

[11] The MB-BC estimates share the problem with OLS that the estimates can fall outside the meaningful bound of unit interval for a probability estimate.

estimators due to Millimet and Tchernis (2012) that corrects for the bias without imposing exclusion restrictions.

The evidence shows that microfinance confers significant benefits to an ultrapoor household in coping with the seasonal famine. The relatively better-off households that operate at the margin of two versus three meals a day clearly benefit from microfinance membership during the seasonal famine. The ultrapoor who struggle at the margin of one versus two meals see their food security improve due to microfinance membership. We find robust evidence that microfinance membership reduces the need for advanced labor sale at low wages during Monga. The evidence is also convincing that microfinance reduces significantly the probability of short term migration for work. This is consistent with a priori expectations that microfinance creates employment opportunities within the household, and thus a member household is less vulnerable to seasonal shock to the demand for agricultural labor.

Table 2.1 Summary Statistics

	Mean	Std. Dev.	Min	Max
Outcome Variables				
Has 3 full meals per day during Monga (yes=1)	0.03	0.17	0	1
Has 1 full meal per day during Monga (yes=1)	0.49	0.50	0	1
Does not sell advanced labor (yes=1)	0.95	0.21	0	1
Migrates in search of work (yes = 1)	0.49	0.50	0	1
Treatment Variable				
Is member of any MFI (yes=1)	0.39	0.49	0	1
Control Variables				
Age of household head (years)	39.68	12.86	0	120
Number of family members over 12 years	2.42	0.96	0	11
Total owned land (decimal)[12]	8.30	12.24	0	363
Total cultivable land (decimal)	4.85	12.67	0	388
Self-employed in agriculture (family members)	0.13	0.36	0	8
Employed as day laborer (family members)	0.61	0.56	0	9
Has VGD card (yes=1)	0.04	0.20	0	1
Percent of electric use in village	32.14	25.58	0	100
Average male agricultural wage (daily, taka)	58.76	19.36	6.50	350
Average female agricultural wage (daily, taka)	35.57	14.21	0	170
Distance from bank (km)	4.33	3.48	0	30
Distance from business center (km)	3.52	2.86	0	17
Distance from secondary school (km)	1.50	2.06	0	22
Moneylender interest rate (%)	24.79	39.12	3	196
Moneylender interest rate > mean (yes=1)	0.14	0.34	0	1
Total owned land < mean (yes=1)	0.74	0.44	0	1
Household in Lalmonirhat (yes=1)	0.11	0.31	0	1
Household in Nilphamari (yes=1)	0.26	0.44	0	1
Observations = 149,721				

[12] The land variables are in decimals, equal to a hundredth of an acre (i.e. 100 decimals=1 acre).

Table 2.2 Summary Statistics, Large Sample

	Obs.	Mean	Std. Dev.	Min	Max
Outcome Variables					
Has 3 full meals per day during Monga (yes=1)[13]	280,400	0.06	0.24	0	1
Has 1 full meal per day during Monga (yes=1)[14]	280,400	0.40	0.49	0	1
Does not sell advanced labor (yes=1)	280,469	0.95	0.22	0	1
Migrates in search of work (yes = 1)	280,469	0.42	0.49	0	1
Treatment Variable					
Is member of any MFI (yes=1)	280,469	0.39	0.49	0	1
Control Variables					
Age of household head (years)	280,467	39.58	12.75	0	120
Number of family members over 12 years	280,469	2.47	1.00	0	14
Total owned land (decimal)	280,468	8.70	12.92	0	1,019
Total cultivable land (decimal)	280,466	5.59	15.86	0	2,500
Self-employed in agriculture (family members)	280,468	0.12	0.36	0	8
Employed as day laborer (family members)	280,468	0.74	0.60	0	17
Has VGD card (yes=1)	280,469	0.07	0.26	0	1
Percent of electric use in village	208,688	32.28	24.71	0	100
Average male agricultural wage (daily, taka)	258,496	56.57	17.94	4.5	350
Average female agricultural wage (daily, taka)	256,991	35.46	12.91	0	170
Distance from bank (km)	238,104	4.67	3.73	0	30
Distance from business center (km)	239,216	3.69	3.17	0	30
Distance from secondary school (km)	218,007	1.80	2.55	0	30
Moneylender interest rate (%)	247,417	23.51	52.22	3	1,200
Moneylender interest rate > mean (yes=1)	247,417	0.14	0.34	0	1
Total owned land < mean (yes=1)	280,468	0.72	0.45	0	1
Household in Lalmonirhat (yes=1)	280,469	0.37	0.48	0	1
Household in Nilphamari (yes=1)	280,469	0.20	0.40	0	1

[13] This dummy takes the value of one if the household consumes three meals per day during Monga and zero if it consumes one or two meals.
[14] This dummy takes the value of one if the household consumes one meal per day during Monga and zero if it consumes two or three meals.

Table 2.3 OLS Results

Impact of MFI Membership on:	(1)	(2)	(3)	(4)
Has 3 full meals per day during Monga (yes=1)	**0.009**	**0.007**	**0.009**	**0.010**
	(2.04)**	(1.78)*	(2.35)**	(2.87)***
	[9.69]***	[7.80]***	[10.07]***	[11.85]***
Has 1 full meal per day during Monga (yes=1)	**-0.042**	**-0.025**	**-0.026**	**-0.026**
	(-3.03)***	(-2.07)**	(-2.42)**	(-2.49)**
	[-15.89]***	[-9.31]***	[-10.02]***	[-9.31]***
Does not sell advanced labor (yes=1)	**0.016**	**0.015**	**0.002**	**0.002**
	(2.92)***	(2.46)**	(0.53)	(0.39)
	[14.41]***	[13.04]***	[2.16]**	[1.54]
Migrates in search of work (yes=1)	**0.010**	**0.011**	**0.008**	**0.017**
	(0.79)	(0.90)	(0.76)	(1.62)
	[3.94]***	[4.28]***	[3.20]***	[6.64]***
Control Variables	No	Yes	Yes	Yes
Fixed Effect	No	No	District	Upazilla
Number of observations	149,721	149,721	149,721	149,721

Table 2.4 Probit Marginal Effect Results

Impact of MFI Membership on:	(1)	(2)	(3)	(4)
Has 3 full meals per day during Monga (yes=1)	**0.009**	**0.006**	**0.008**	**0.006**
	(2.04)**	(1.94)*	(2.84)***	(3.23)***
	[9.69]***	[8.14]***	[11.83]***	[11.07]***
Has 1 full meal per day during Monga (yes=1)	**-0.042**	**-0.025**	**-0.027**	**-0.028**
	(-3.03)***	(-2.02)**	(-2.37)**	(-2.47)**
	[-15.89]***	[-9.06]***	[-9.76]***	[-9.75]***
Does not sell advanced labor (yes=1)	**0.016**	**0.014**	**0.002**	**0.001**
	(2.92)***	(2.84)***	(0.88)	(0.32)
	[14.41]***	[14.61]***	[2.98]***	[1.01]
Migrates in search of work (yes=1)	**0.010**	**0.011**	**0.009**	**0.019**
	(0.79)	(0.88)	(0.75)	(1.63)
	[3.94]***	[4.16]***	[3.15]***	[6.56]***
Control Variables	No	Yes	Yes	Yes
Fixed Effect	No	No	District	Upazilla
Number of observations	149,721	149,721	149,721	149,721

t-statistics clustered at village level in parenthesis

t-statistics robust to heteroskedasticity in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Model (1) regresses the outcome variable against microfinance membership.

Model (2) adds household and village control variables to Model (1)).

Model (3) adds District Fixed Effect to Model (2).

Model (4) adds Upazilla (sub-district) to Model (2).

See Table 2.1 for list of control variables.

As a reference, Table 2.6 OLS Full Regression Results

Table 2.5 MB and BC Results

Estimated Impact of MFI Membership on:	(1) MB	(2) MB-BC
Has 3 full meals per day during Monga (yes=1)	**0.010**	**0.159**
	[0.006, 0.016]	[0.111, 0.203]
Has 1 full meal per day during Monga (yes=1)	**-0.026**	**-0.650**
	[-0.034, -0.018]	[-0.804, -0.493]
Does not sell advanced labor (yes=1)	**0.003**	**0.188**
	[-0.001, 0.009]	[0.128, 0.241]
Migrates in search of work (yes=1)	**-0.029**	**-0.883**
	[-0.037, -0.021]	[-1.027, -0.734]
Number of observations: 149,721		

All models control for household and village characteristics (see Table 2.1) and include Upazilla fixed effect.
Model (1) reports the Minimum Bias (MB) estimate of the average treatment effect (ATE) of microfinance membership on the outcome variable. Model (2) reports the Bias Corrected (MB-BC) Estimate of the ATE. See Millimet and Tchernis (2012) for further detail.
Estimates of MB and MB-BC are estimated at a radius of 0.25.
The 90% confidence intervals, reported in brackets, are calculated by the bootstrap percentile method.

Table 2.6 OLS Full Regression Results

DEPENDENT VARIABLES	(1) Three Meals	(2) One meal	(3) No Advanced Labor Sale	(4) Migration
Is member of any MFI (yes=1)	0.0103***	-0.0259***	0.00169	0.0169***
	(0.000870)	(0.00262)	(0.00110)	(0.00254)
Age of household head (years)	-0.000134	0.00235***	0.000456**	-0.00665***
	(0.000168)	(0.000534)	(0.000231)	(0.000514)
Age Squared	1.21e-07	-1.13e-06	-2.65e-06	1.74e-05***
	(1.80e-06)	(5.73e-06)	(2.47e-06)	(5.51e-06)
Number of family members over 12 years	0.000610	-0.0112***	-0.00264***	0.0143***
	(0.000454)	(0.00137)	(0.000588)	(0.00135)
Total owned land	0.000196*	-0.00380***	0.000678***	-0.000933***
	(0.000110)	(0.000218)	(8.75e-05)	(0.000195)
Total cultivable land	0.000793***	-0.00134***	-1.55e-05	-0.000942***
	(9.85e-05)	(0.000157)	(7.48e-05)	(0.000144)
Self-employed in agriculture (family members)	-0.00990***	-0.0965***	-0.00285*	0.00597
	(0.00162)	(0.00406)	(0.00167)	(0.00397)
Employed as day laborer (family members)	0.00105	-0.0224***	-0.00925***	0.153***
	(0.000996)	(0.00250)	(0.00109)	(0.00250)
Has VGD card (yes=1)	-0.00692***	0.0258***	-0.00674**	0.0164***
	(0.00254)	(0.00628)	(0.00277)	(0.00633)
Percent of electric use in village	0.000202***	-0.000858***	-7.84e-05***	-0.00106***
	(1.43e-05)	(5.26e-05)	(2.13e-05)	(5.12e-05)
Average male agricultural wage (daily, taka)	-9.10e-05***	-0.00143***	0.000163***	-0.00184***
	(3.53e-05)	(4.60e-05)	(1.51e-05)	(9.19e-05)
Average female agricultural wage (daily, taka)	-4.61e-05*	0.00153***	0.000348***	-0.000793***
	(2.62e-05)	(8.61e-05)	(1.81e-05)	(9.65e-05)
Distance from bank (km)	-0.00136***	-0.00822***	0.00117***	-0.000720*
	(0.000104)	(0.000424)	(0.000205)	(0.000401)
Distance from business center (km)	0.000170	-0.00303***	0.00195***	0.00352***
	(0.000136)	(0.000477)	(0.000185)	(0.000468)
Distance from secondary school (km)	0.00106***	0.0141***	-0.00325***	0.00958***
	(0.000148)	(0.000595)	(0.000225)	(0.000610)
Moneylender interest rate (%)	0.000268***	0.000270***	0.000521***	0.000883***
	(2.69e-05)	(6.71e-05)	(2.06e-05)	(6.10e-05)

Table 2.6 (cont.)

DEPENDENT VARIABLES	(1) Three Meals	(2) One meal	(3) No Advanced Labor Sale	(4) Migration
Moneylender interest rate > mean (yes=1)	-0.0189***	-0.0903***	0.00824***	-0.217***
	(0.00261)	(0.00762)	(0.00262)	(0.00687)
Total owned land < mean (yes=1)	-0.00300*	0.0330***	0.00546***	-0.0249***
	(0.00172)	(0.00464)	(0.00180)	(0.00424)
Upazilla1	0.0253***	-0.0940***	0.0467***	-0.0573***
	(0.00120)	(0.00445)	(0.00166)	(0.00440)
Upazilla2	0.0102***	-0.0277***	0.0423***	-0.128***
	(0.000835)	(0.00437)	(0.00153)	(0.00430)
Upazilla3	0.00878***	0.163***	0.0283***	0.243***
	(0.00108)	(0.00531)	(0.00191)	(0.00511)
Upazilla4	0.0239***	-0.261***	0.0329***	-0.365***
	(0.00259)	(0.00759)	(0.00252)	(0.00705)
Upazilla5	0.122***	-0.205***	0.00335	-0.448***
	(0.00463)	(0.00734)	(0.00339)	(0.00632)
Upazilla6	0.148***	-0.216***	0.0391***	-0.478***
	(0.00690)	(0.00945)	(0.00338)	(0.00829)
Upazilla7	0.464***	-0.402***	-0.0252***	-0.435***
	(0.0110)	(0.00915)	(0.00632)	(0.0100)
Upazilla8	0.169***	-0.0488**	-0.153***	-0.533***
	(0.0151)	(0.0213)	(0.0160)	(0.0131)
Upazilla9	0.0459***	-0.0810***	-0.0684***	-0.0514***
	(0.00225)	(0.00688)	(0.00425)	(0.00678)
Upazilla10	0.0296***	0.0663***	-0.0707***	0.0301***
	(0.00157)	(0.00587)	(0.00340)	(0.00601)
Upazilla11	0.00667***	-0.0295***	-0.105***	-0.0288***
	(0.00117)	(0.00514)	(0.00322)	(0.00497)
Constant	-0.00105	0.600***	0.903***	0.831***
	(0.00442)	(0.0134)	(0.00569)	(0.0131)
Observations	149,721	149,721	149,721	149,721

t-statistics robust to heteroskedasticity in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%
This table reports the full results for column 4 of OLS results in Table 2.3 OLS Results.

Table 2.7 Household Characteristics for Main, Excluded, and Large Samples

	Main Sample		Excluded Sample		Difference in Mean	
	Obs.	Mean	Obs.	Mean	Diff.	t-stat
Outcome Variables						
Has 3 full meals per day during Monga (yes=1)	149,721	0.03	130,679	0.10	-0.07***	(-74.88)
Has 1 full meal per day during Monga (yes=1)	149,721	0.49	130,679	0.30	0.19***	(110.00)
Does not sell advanced labor (yes=1)	149,721	0.95	130,748	0.95	0.01***	(8.17)
Migrates in search of work (yes = 1)	149,721	0.49	130,748	0.34	0.15***	(81.71)
Treatment Variable						
Is member of any MFI (yes=1)	149,721	0.39	130,748	0.39	0.00	(0.24)
Household Characteristics						
Age of household head (years)	149,721	39.68	130,746	39.48	0.20***	(4.16)
Number of family members over 12 years	149,721	2.42	130,748	2.52	-0.10***	(-27.59)
Total owned land (decimal)	149,721	8.30	130,747	9.15	-0.85***	(-17.43)
Total cultivable land (decimal)	149,721	4.85	130,745	6.44	-1.59***	(-26.50)
Self-employed in agriculture (family members)	149,721	0.13	130,747	0.12	0.01***	(-7.38)
Employed as day laborer (family members)	149,721	0.61	130,747	0.90	-0.30***	(-134.74)
Has VGD card (yes=1)	149,721	0.04	130,748	0.10	-0.06***	(-64.92)

This Table Reports the household characteristics for the main sample used in the analysis, the excluded sample, and the large full sample.

3 Microfinance and Moneylenders: The Effects of MFIs on the Informal Credit Market in Bangladesh

3.1 Introduction

The rural poor have a long history of borrowing from moneylenders.[15] In contrast, microfinance—at least in its current form—is a relatively recent phenomenon. Since the debut of Grameen Bank in Bangladesh during the 1970s, microfinance has spread all over the world, across countries and continents. As opposed to private banks that shy away from lending to the rural poor, microfinance has focused on asset-poor rural households previously served only by informal financiers: friends, family, and the village moneylender. The number of poor served by microfinance institutions (MFIs) has mushroomed from 10,000 in 1980 to more than 100 million in 2009 worldwide (Microcredit Summit Campaign 2009). The expansion of microfinance was expected by many to free the poor from the usury terms of moneylenders. For example, Mohammed Yunus—founder of Grameen Bank—remarked that microfinance would deliver the poor "out of the clutches of the moneylenders" (Yunus 2009). The idea is that microfinance creates competition for moneylenders, reducing their market power, thus helping the poor by forcing down interest rates. Microfinance interest rates, after all, are on average lower than those charged by moneylenders. The implicit assumption that underlies this conventional view is that microfinance and moneylenders are substitutes in the village credit market and that as microfinance coverage increases, it should reduce the demand for informal loans, thereby lowering moneylender interest rates. This assumption

[15] 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 the story of Jesus "overthrew the tables of the moneychangers" (Matthew 21:12-13). Perhaps the most colorful example of a moneylender is that of Shakespeare's Shylock who demanded his pound of flesh in exchange for a late repayment (Merchant of Venice).

remains to be verified empirically: How in fact has the emergence and spread of microfinance impacted the existing informal credit markets in rural villages?

The theoretical literature on the interactions between formal and informal credit markets in rural villages tells us that the effect of microfinance on informal loans and interest rates is not unambiguous.[16] Microfinance and moneylenders may provide complementary services, in which case the expansion of microfinance may increase the demand for informal loans both at the *extensive margin* (new borrowers) and the *intensive margin* (larger loans for existing borrowers). For instance, when faced with a negative shock one may turn to the moneylender to meet the inflexible microfinance repayment schedule (an extensive margin effect). The demand for moneylender loans can also increase because of the indivisibility of investment projects as microfinance borrowers take additional informal loans to achieve economies of scale (which could have both extensive and intensive margin effects).[17]

There could also be a cream skimming effect whereby MFIs attract the safer borrowers from the moneylenders, leaving behind a riskier pool of informal borrowers, through adverse selection and moral hazard, leading moneylenders to raise their interest rates (see Bose 1998 for a formal analysis). A positive relationship between microfinance coverage and moneylender interest rates could also occur due to fixed costs of lending (Hoff and Stiglitz 1998). If there are significant fixed costs of screening

[16] Indeed, efforts by governments to drive out moneylenders by subsidizing credit have failed. In the early 1950s, the Reserve Bank of India (RBI) created a system of rural cooperatives in an effort to "provide a positive institutional alternative to the moneylender himself, something which will compete with him, remove him from the forefront and put him in his place." (RBI 1954, vol. 2, pp. 481-82, cited in Bell 1990). The Thai government expanded bank lending in the rural sector through the creation of an agricultural bank in 1966 and through the mandate that commercial banks lend to the rural sector in the mid-1970s. Despite this expansion of formal rural credit the informal credit market continued to flourish (Siamwalla et al 1993).

[17] This seems plausible given the recent evidence that the entrepreneurial MFI borrowers cut their consumption to undertake indivisible investments (Banerjee et al. 2010).

potential borrowers, competition from MFIs can force moneylenders to raise their interest rates to cover their fixed costs as the number of informal borrowers decline. It is thus an empirical question whether expanded microfinance coverage has increased or decreased moneylender interest rates and further how the demand for informal loans responds.

Surprisingly, there is little rigorous analysis of the effects of the spread of MFIs on the rural credit market equilibrium. The only study we are aware of is Mallick (2012) that uses an 89 village data set to estimate the impact of microfinance coverage on the moneylender interest rate. This paper finds a positive impact. Mallick's research is important as it provides the first analysis of this important policy question. However, his study has a number of limitations. First, the data set consists of a small sample (89-106 depending on the model estimated). One might worry about the external validity of the results and whether the results would hold when using a larger sample. Second, it does not attempt to uncover the underlying mechanism of the observed moneylender interest rate: is it due to higher demand, cream skimming, or fixed effects?

Our paper analyzes the impact of microfinance on the informal credit market by looking at both the impact on the moneylender interest rate and on informal borrowing by households. This enables us to differentiate between alternative hypotheses, e.g. increased demand, cream skimming, or fixed costs. We use two datasets: (i) a sub-set of the cross-section collected by the Institute of Microfinance (InM) in 2006-7 with more than 800 villages encompassing 65,000 ultrapoor households from the Northwestern region of Greater Rangpur; and (ii) a nationally representative panel of 1,599 households from 62 villages in 2000 and 2007, collected by Mahabub Hossain and his collaborators at the Bangladesh Institute of Development Studies (BIDS) and BRAC.

A central identification challenge is that location choices of the MFIs or the households' decision to join a MFI program are not random. As a result MFI coverage or membership is endogenous. Moneylender interest rates or household informal borrowing may be correlated with microfinance because they are driven by common unobserved factors. At the village level, MFIs may locate their branches in relatively better off villages to ensure repayment, which would help with donor funding. MFIs may instead be driven by poverty alleviation objectives in which case we would expect them to locate in poorer villages. At the household level, the decision to join an MFI and the decision to borrow informally may be driven by the same unobserved household characteristics such as entrepreneurial ability and degree of risk aversion. Participants in the informal credit market may be systematically different from non-participants, thus introducing a second layer of selection bias.

The standard approach to tackling such omitted variables bias is to employ an instrumental variables (IV) approach. However it is extremely difficult, if not impossible, to find a credible IV in this situation. Any variable that is correlated with our endogenous treatment, microfinance, is likely to also affect the outcome. In addition, there has been increasing skepticism about the validity of exclusion restrictions imposed in many different contexts.

In the absence of a credible exclusion restriction, we implement recently developed estimators to address the possible sources of selection bias. When working with the panel data, we partition the data using lower land ownership thresholds to create appropriate treatment and comparison groups. We focus on the subsample owning less

than an acre of land.[18] This is motivated by the fact that all the MFIs in Bangladesh use land ownership as a salient screening device. When the households at the right tail of the land distribution are excluded from the sample, the treatment and comparison groups become similar in terms of observable characteristics, mimicking the balancing properties of a successful randomized intervention. Working with both the cross-section and the panel, we implement a battery of recently developed econometric approaches that correct for biases due to omitted heterogeneity. We use heteroskedasticity-based identification methods, particularly those developed by Klein and Vella (2009a, 2009b, 2010). In cases where these are not appropriate, we employ the Minimum Biased (MB) matching estimator of Millimet and Tchernis (2012). With the panel, these estimators are used in addition to the household fixed effects in a sample with similar observables across treatment and comparison groups. Thus, we are confident that the biases due to non-experimental nature of the data are adequately addressed.

Our main findings are as follows. The penetration of microfinance in a village increases the equilibrium moneylender interest rate. The conventional wisdom that MFIs bring down the "exploitative" interest rates through competition thus seems to be contradicted. However, the welfare implication of the higher moneylender interest rate cannot be understood without additional evidence on the household demand for informal loans. For example, a higher moneylender interest rate may reflect higher demand for credit because of project indivisibility, or households may need more informal loans to repay the rigid MFI loans in the face of negative shocks or unsuccessful projects. The higher interest rate might instead reflect cream skimming by the MFIs in the rural credit

[18] Note that land cut-offs are unnecessary when working with the cross-section, as it focuses on the ultrapoor households, most of whom are functionally landless.

markets: as better borrowers become MFI members, the clientele pool of the moneylenders become worse (i.e. riskier) because of adverse selection. The higher moneylender interest rate in this case will be consistent with a lower demand for moneylender loans. Our estimates from the panel data show that there is a significant negative effect of MFI membership on the probability that a household borrows from a moneylender. The evidence thus contradicts the positive shift in demand explanation for the higher moneylender interest rate. The evidence is consistent with a cream skimming effect when MFI enters into a rural credit market. Thus, it can be argued that a majority of the households are in fact freed from the "clutches" of the moneylenders by the MFI interventions.

The rest of the paper is organized as follows: section 3.2 gives an overview of the informal credit market and related literature; section 3.3 discusses our two data sets; section 3.4 presents our empirical strategy; section 3.5 discusses our results; and section 3.6 concludes.

3.2 Background: Informal Credit in Developing Countries

In order to better understand how the spread of microfinance impacts the moneylenders, one must first understand the informal credit market itself. The existence of the informal credit market has long been recognized as an important source of finance for the poor. "Informal moneylenders have been financing microentrepreneurs since commerce began" (Christen 1989, p. 10). Commercial banks typically shun the poor as too risky and expensive to lend to. Banks cannot distinguish between safe and risky investments and so require some form of assets as collateral, usually in the form of land which the poor do not have (Armendáriz and Morduch 2010). Before the arrival of

microfinance institutions (MFIs), the poor had little choice but to turn to the informal credit market if they wanted to get a loan.

The informal credit market in developing countries is characterized by: (i) small loans made by oral agreements with little or no collateral, (ii) segmented markets, with long-term exclusive relationships and repeat lending, (iii) interest rates typically higher than those charged by banks, (iv) frequent linkages with other markets (land, labor, crops, etc), and (v) significant credit rationing (Ghosh et al 2000).

Informal loans are provided by friends, family, and neighbors as well as by commercial moneylenders. These loans tend to be for consumption, emergencies, or special occasions (weddings, funerals, etc.). Though loans from friends, family, or neighbors typically carry low or no interest, these loans may have other strings attached such as the expectation of reciprocation, both financial and non-financial. Such loans are not a substitute for commercial credit, formal or informal (Robinson 2001).

Commercial moneylenders are those whose primary occupation is lending as well as those whose primary source of income comes from elsewhere, e.g. farming, trading, or fishing, etc. Some lend their own money at their own risk while others act as intermediaries between the poor and the commercial bank. Moneylenders typically advance very small loans, to be repaid within a short interval, and accompanied by very high interest rates. Moneylenders may or may not request collateral, depending on the size of the loan. A moneylender might ask for collateral such as land, but they accept a wider range of collateral than a bank would—watches, telephones, or antique shawls (Robinson 2001).

Moneylenders charge different interest rates to different clients depending on the size of the loan, the collateral offered, perceived risk, and the relationship with the client (Robinson 2001). The high interest rates charged by moneylenders can be explained by the opportunity cost of money, administrative transaction costs, the risk involved, in addition to a monopoly surcharge (Iqbal 1988). Bottomley (1983) explains that the opportunity cost of a moneylender's funds:

> may be the value to a rural saver of parting with liquidity, or of forgoing the opportunity to invest in his own farm, or fulfilling his social obligation to provide a lavish wedding for his daughter—that is, the supply price of money in the community. Alternatively, it may be the sum of what it costs a rural lender to get outside money to lend to a farmer—a national supply price. (Bottomley 1983, p. 243)

For example, when a moneylender acts as an intermediary between a rural borrower and a commercial bank, this cost incorporates the interest rate charged by a commercial bank.

"Transaction costs for lenders include the costs of collecting information about potential borrowers and updating information about repeat borrowers; assessing collateral when relevant; and extending, recording, and collecting loans." (Robinson 2001, p. 193). The moneylender's administrative cost is typically thought to be low, but this is only half true. Once a moneylender knows his clients, the costs involved in keeping tabs on them are relatively low. However, it takes time and effort to establish such a relationship. This is why borrowers typically do business with only one moneylender. Thus administrative or transaction costs are high for new clients, but become lower for repeat customers (Robinson 2001). Braverman and Guasch (1989) estimate that the administrative costs of handling small loans range from 15 to 40 percent of the loan size (cited in Armendáriz and Morduch 2010, p. 33.)

Lending to the poor can be a risky business, mostly due to the high risk of default. Outright default is rare, but payments are often delayed, only partially made, or terms are renegotiated (Bottomley 1983). Since the moneylender is not always able to recover all or even part of his loan, he must make up for it with higher interest charged to other borrowers (Singh 1983). In addition, moneylenders are often called upon to make consumption loans which by their very nature carry a higher risk than an investment loan would. The more assets a borrower has to fall back on, the lower his risk premium will be since the lender knows he can recover part of the loan by seizing assets. Determinants of the risk premium include land or other assets owned by the borrower, and his education. Also, the soil quality of the borrower's land and weather are factors which would influence the moneylender's perceived risk (Iqbal 1988).

Once the opportunity cost, administrative cost, and risk premium are accounted for, anything left over goes to the lender as profit. So while the moneylender may not be a monopolist, he may still have some small monopoly power. "In terms of components of the interest rate charged, opportunity cost accounted for more than 50 percent, risk cost some 25 percent, and distribution cost about 15 percent of the interest charged by the village moneylender on consumption loans. Monopoly profits accounted for only 6 percent of the interest." (Singh 1983, p. 254)

While the informal credit market does provide a useful service in meeting the credit needs of the poor, many of those needs continue to be unmet. There is evidence of widespread unmet demand for credit in the developing world. One might wonder why the interest rate does not simply rise to clear the market. The interest rate provides the lender a means of screening potential borrowers (Aleem 1993). The higher the interest

rate is set, the more risky the project which the borrower wishes to finance. Since the lender cannot identify who the safe borrowers are, the interest rate may be set lower in order to attract safer clients, even if doing so fails to clear the market. Through this adverse selection, credit is rationed (Stiglitz and Weiss 1981, Ghosh et al 1999).

> At very high interest rates, the only applicants are borrowers who could potentially generate very high returns (but presumably with small probability). Since lenders' preferences over project risk run counter to those of borrowers, they may hold interest rates at levels below market-clearing and ration borrowers in order to achieve a better composition and lower risk in their portfolio. Excess demand in the credit market may persist even in the face of competition and flexible interest rates. (Ghosh et al 1999 p. 3)

Moneylenders ration credit, which leaves a niche for microfinance to fill. There is evidence of widespread unmet demand for credit by the poor in rural communities. Microfinance has gone a long way towards meeting this demand. Even so, the poor continue to borrow from moneylenders. There is some evidence in the literature of households borrowing from moneylenders to repay MFIs and thereby maintain their credit rating (Robinson 2001).

Microfinance and moneylenders are really more complementary than substitutes. The services which moneylenders and microfinance institutions provide are different. Moneylenders provide small loans at short notice with flexible repayment. Microfinance institutions in contrast typically require forming a group to help guarantee the loan, offer one-year loans to be repaid weekly, and often require completion of a training course (Robinson 2001, Armendáriz and Morduch 2010, and Collins et al 2009). Also MFIs focus on women, since they are more likely than men to be credit constrained, are better borrowers, and lending to them has a greater impact on family welfare (Pitt et al 2006). Moneylenders are more concerned with being repaid than how a loan is spent (Robinson

2001). For example, if one's objective were to accumulate a dowry for your daughter's wedding one would turn to a moneylender instead of the MFI—dowries violate one of Grameen Bank's Sixteen Decisions (Yunus 2005, p. 136).

3.3 Data

This section details the two data sets, cross-section and panel data, used in this chapter.

3.3.1 Cross-Section Data

This is the same data set we used in chapter 2 (see Section 2.4), obtained by census of the ultrapoor households in the district of Lalmonirhat in 2006 and in the Districts of Gaibandha, Kurigram, Nilphamari, and Rangpur in 2007.[19] The household questionnaire used covered a broad range of topics including employment, family size, assets, food security, informal loans taken, and membership in any MFI. A separate questionnaire was used in Gaibandha, Lalmonirhat, and Nilphamari collecting village information from local NGO offices including: average moneylender interest rates, agricultural wages of men and women, and distances to the nearest bank, market, and secondary school. Unfortunately, these variables are missing for a large number of villages.

We focus on the village data in analyzing the impact of microfinance coverage on the average moneylender interest rate faced by the ultrapoor in a village. We define MFI coverage in a village as the percent of households in a village that are MFI members (where village size is taken to be the number of MFI members and nonmembers

[19] Data from all of the Upazillas in Lalmonirhat were collected, in Nilphamari from 3 of the 6 Upazillas, and in Gaibandha 4 of the 7 were included.

reported).[20] We find that villages have on average 42 percent MFI coverage. Similarly, we calculate the percent of households in a village owning less than 0.1 acre of land using the household variable total owned land, which accounts for 80 percent of the sample. After dropping villages with missing observations, we focus on 804 villages in Gaibandha, Lalmonirhat, and Nilphamari. Within these villages, the average moneylender interest rate is approximately 21 percent per month with a high degree of variation: ranging from 3 to 196 percent. See Table 3.1 for a list of summary statistics on the InM village data.

For our analysis of the impact of MFI membership on informal borrowing, we use both the cross-section and the panel. To make our household analysis comparable to our village one, we drop the same villages with missing observations. We also trim our data set to exclude observations which had unrealistic values for the age of the head of the household. [21] We drop those observations with recorded ages below 13 and above 70, about 1,490 observations.[22] Unfortunately, we do not have information on informal borrowing for much of the sample. In the end, we focus on 65,272 households in 389 villages. Among the 65,272 households for which we have data on informal borrowing, 7,256, or about 11 percent, borrow positive amounts (the rest borrowing zero). Among these, the average loan size is 3,018 taka. Within this group, 40 percent of households are MFI members, and the average household owns about 0.9 acre and cultivates 0.6 acre of land (see Table 3.2).

[20] Note that since our InM cross-section only covers the ultrapoor households in the village, we leave out the less-poor members of those villages. So a village with 100 percent MFI coverage only means that 100 percent of the ultrapoor households in that village are MFI members.
[21] It is unclear why the cross-section data set had so many observations with ages below 13 and over 70. One possible explanation is that in female-headed households, the numerator recorded the age of the male member of the household, whether he be an elder or a child.
[22] We found our results to be robust to different age cut-offs.

3.3.2 Panel Data

The collection of the panel data was led by Mahabub Hossain and his collaborators at the Bangladesh Institute of Development Studies (BIDS). The benchmark study was conducted in 1987-88, with the same villages resurveyed in 2000, 2004, and 2007. Intended to be nationally representative, a multi-stage random sampling method was used to select the villages to be studied. The survey technique is described in detail in Hossain and Bayes (2009). In brief, Bangladesh has 64 Districts so the team randomly selected 64 Unions (the smallest administrative unit) from across the country. Within each union, a village was selected such that it be representative of its Union. Households were randomly selected in each village to be given a detailed questionnaire. Data collected included information on age and education of the household head; number of agricultural workers living in the home; homestead and cultivable land, both owned and rented; household size; and informal loans taken. As we did with the InM cross-section, we exclude households from the panel which had unrealistic ages of the head of the household and drop 44 households with age above 70 years. In the end we focus on 1,555 households in 2000 and 2007.[23] Summary statistics are reported in Table 3.3**Error! Reference source not found.**. Note that between 2000 and 2007, the number of informal borrowers dropped from 187 to 132. Contrast this with the fact that over the same period MFI membership almost doubled, from 368 to 607 which accounts for an increase in the share of MFI membership from 24 to 39 percent. With regard to informal borrowing, the

[23] Though we have access to the 1988 dataset, it only includes 800 households and we chose to instead focus on the larger 2000 and 2007 panel. We do not have access to the 2004 data, nor do we have access to the village level variables which were part of the BIDS data collection.

average informal loan increased from 12,171 to 57,865 taka between 2000 and 2007 for the intensive margin, i.e. the positive amount borrowed from an informal source.

The main variables we focus on in the panel are the informal amount borrowed in 2007, and MFI membership in 2000 and 2007. There are four groups as defined by their MFI membership: *always members*—MFI members in 2000 and 2007; *new members*—MFI member in 2007, not in 2000; *dropouts*—MFI member in 2000, not in 2007; and *never member*—not a MFI member in either 2000 or 2007. As reported in Table 3.4, of the 1,555 households in the panel, most are never members (811) with the remainder divided among new members (376), always members (231), and dropouts (137). It is to be expected that those owning more than an acre of land be never members, since MFI membership is restricted to poorer households with less than half an acre of land. The fact that we have any households with more than an acre of land that are also MFI members suggests that there was some miss-targeting. If we focus on the 1,025 households owning less than an acre of land, the proportion of never members declines from 52 to 45 percent with increases in proportions of new and always members.

3.4 Empirical Strategy

In this section, we discuss the identification challenges involved and methodologies employed in estimating the impact of microfinance on the informal credit market. To this end, we estimate three models: (i) the impact of MFI coverage on the moneylender interest rate; (ii) the impact of a household's MFI membership on its decision to borrow from the informal credit market; and (iii) the impact of MFI membership on the size of informal loans taken by those households still borrowing informally. Using the two data sets, we employ a battery of econometric tests to identify

the causal impact of microfinance on each of these outcomes. Estimating each of these models is complicated by the presence of omitted variables. Below we elaborate on the identification challenges, the choice of controls, and our strategies for identifying each model individually.

3.4.1 Identification Challenges

The main identification challenge for our analysis is that the location choices of MFIs and the households' decision to join a microfinance program are not random; they are outcomes of optimizing choices. It is impossible to control for all the factors that affect these choices. When such omitted variables also affect the outcome of interest, OLS regressions would in general yield biased estimates. Consider trying to estimate the impact of microfinance coverage on the moneylender interest rate. If moneylenders have market power due to their informational advantage in segmented markets, as is commonly assumed, then the interest rate they charge would depend on the productivity of the village. If MFIs prefer to locate in villages with higher productive potential, so as to ensure higher repayment rates then we would observe a positive correlation between microfinance coverage and the moneylender interest rate even if the causal impact of microfinance were negative. If on the other hand, MFIs' location choices were primarily driven by poverty reduction goals, then they would target relatively poorer villages and the correlation between MFI coverage and the moneylender interest rate would be negative, implying that OLS estimates were biased downwards. Possible measurement error in MFI coverage rates would also bias the estimated effect toward zero due to attenuation.

Similar considerations apply when trying to estimate the impact of MFI participation on the incidence and amount of informal borrowing. A household's microfinance membership and informal borrowing decisions may both be driven by unobserved household characteristics: the households that participate in the informal credit market and those that do not may be systematically different. For example, a household with higher entrepreneurial ability may decide to join the MFI and also need more loans from the moneylender, especially if there is indivisibility in the investment projects. This can create a spurious positive effect of MFI membership on the incidence and size of moneylender loans. On the other hand, if high ability reduces the probability of joining an MFI, then there would be a negative bias.

3.4.2 Choice of Control Variables

As a first line of defense against omitted variables bias, we carefully choose the set of control variables in each regression to ensure that the "good controls" are included and "bad controls" are excluded (Angrist and Pischke 2009). In our analysis of the impact of microfinance coverage on the moneylender interest rate, we select a set of village variables which we expect would influence both the outcome and the treatment. The variables we control for in the Moneylender interest rate model are: male and female agricultural wage rate, percent of households in the village owning less than 0.1 acre of land, percent of households using modern technologies in cultivation, number of households in the village, and infrastructure variables.

The infrastructure variables we include are the percent of households in a village with a toilet and the distance to the nearest secondary school, bank, market, bus stop, and

paved road.[24] All of these variables serve as indicators of the village's level of development. The less poor a village is, the higher the moneylender interest rate and the higher microfinance coverage are expected to be. Although microfinance institutions target the poor, there is evidence that MFIs tend to locate in less poor villages with better infrastructure and that the ultrapoor have by and large not been reached (see Zeller et al. 2001 and Emran et al. 2012).

We control for the average male and female agricultural wages to capture the village's labor market opportunities and unobserved land productivity. The more opportunities available and the more productive the land is, the higher a moneylender interest rate one might expect people to be able to pay. Mallick (2012) also controls for agricultural wages, noting that they proxy for current poverty in a village. The lower the wages are, the poorer the village, and the less of a MFI presence there is expected to be. Another indicator of the level of poverty we control for is the percent of households in the village owning less than 0.1 acre of land. The more people who are functionally landless, the poorer the village is, the lower the moneylender interest rate and the lower the MFI coverage.

Iqbal (1988) studied the determinants of the moneylender interest rate in rural India. He found that farming areas which adopted new Green Revolution technologies faced lower interest rates. In an effort to capture this, we include percent of households in the village using modern technologies in agriculture. A village using such technologies is less poor, and we would expect it to have a lower moneylender interest rate and microfinance presence.

[24] There was some concern that distance to the nearest bank and market would be correlated, since they are often found in the same place, but the correlation between them is only 0.32. Therefore including them both is unlikely to bias the results.

The percent of households with a proper toilet serves as an indicator of that village's sanitation and health. The distance to the nearest secondary school gives us an idea of the village's access to education (we would have liked to include the literacy rate but our dataset lacked information on this). Distance to the nearest bank serves as an indicator of access to formal credit. Distance to the market captures the ease with which villagers can sell their produce. The distances to the bus stop or paved road indicate how remote a village is. MFIs tend to locate in villages with better infrastructure. The number of households in the village was included as an indication of the local demand for credit. Finally, we include Upazilla fixed effects to account for unobserved household heterogeneity.

In studying the impact that microfinance has on informal borrowing, we use both the InM cross-section and BIDS Panel data sets. In either case we chose control variables so as to minimize any potential bias. With regard to the InM cross-section, we include a rich set of household and village characteristics as control variables. We control for the same set of village characteristics as in the moneylender interest rate model, namely: the average agricultural wage for men and women, and the distance to the nearest secondary school, bank, and market. In addition, we include the moneylender interest rate which would logically play a role in determining how much one borrows informally. The household-level characteristics we control for are: the age of the household head, age squared, number of family members over the age of twelve, total owned land, total cultivable land, number of household members self-employed in agriculture, number of members employed as day laborers, and whether the household has a VGD card.

The age of the household head and its square are included as proxies for human and social capital which might be important for access to informal credit. MFIs might also target households with younger borrowers, since they tend to be more energetic. We control for the number of family members over age 12 as an indicator of the household's labor endowment. To capture the household's land endowment we include the total land owned. We control for the cultivable land so as to take into account the fact that households may lease land in or out. The number of household members self employed in agriculture and as day laborers reflect the household's labor market opportunities and sources of income, both of which are important when considering informal loans or MFI membership. We control for whether the household has a VGD card because most MFIs in Bangladesh use this as an exclusion criteria when screening for potential members.

We control for agricultural wages to capture labor market opportunities and unobserved land productivity. The moneylender interest rate is a determinant in a household's decision of whether and how much to borrow from informal sources, since some of this borrowing is from moneylenders. We control for the distance to the secondary school to capture the village's access to education.[25] The distance to the bank reflects access to formal credit. The distance to the market reflects how easy it is for villagers to sell their produce.

Working with the panel data set allows us to control for pre-treatment household characteristics, thereby eliminating unobserved time-invariant heterogeneity such as ability. The household characteristics we control for include age of the household head, education of the household head, number of agricultural workers living in the household,

[25] Our cross-section does not contain information regarding the education of the household head. We do have this variable in the panel though.

total owned land, total cultivated land, and household size. In addition we include Division fixed effects to account for unobserved heterogeneity. The choice of these variables was guided by the same rationale as before, namely to reduce omitted variables bias as much as possible. Age and education both serve as indicators of human and social capital of the household head. Including total owned land and total cultivable land serve to capture the household's land endowment and productivity. The household size serves as an indicator of the labor endowment.

3.4.3 Moneylender Interest Rate

To guide us in the analysis of the impact of microfinance coverage on the average moneylender interest rate in a village, consider the following model:

$$ML_j = \beta_0 + \beta_1 MF_j + X_j'\gamma + u_j \quad (3.1)$$

$$MF_j = \alpha_0 + X_j'\delta + v_j \quad (3.2)$$

Here, ML_j is the average moneylender interest rate in village j, MF_j is the percent of ultrapoor households in the village that are members of any MFI, and X_j is a set of household and village controls as well as regional fixed effects. We alternately include District and Upazilla (sub-District) fixed effects. The challenge is to overcome omitted variables bias and consistently estimate the causal impact of microfinance on the moneylender interest rate, β_1. In the absence of a credible instrumental variable, we turn to recently developed estimators that rely on heteroskedasticity in the data to achieve identification.

Rigobon (2003) developed a methodology to identify models with an endogenous variable and no credible instruments. Extending the intuition of Wright (1928), Rigobon shows that heteroskedasticity of the shocks makes it possible to identify the relevant

parameters. The basic idea is that heteroskedasticity of the errors acts as a "*probabilistic* instrument". To illustrate this idea in the context of supply and demand curves, instead of shifting one of the curves, heteroskedasticity makes shifts more *probable*. These shifts trace out the causal relationship of interest.

Klein-Vella Control Function

Klein and Vella (2010) exploit heteroskedasticity to develop a control function estimator —henceforth KV-CF—for cases where both the outcome and endogenous treatment variables are continuous. This KV-CF estimator allows for general error structures and for heteroskedasticity in both equations to be functions of the same variables. To provide some insight into the KV-CF, consider our moneylender interest rate model, equations (3.1) and (3.2) above, and let $A(X_j)$ be the part of the error term u_j which is correlated with v_j, so that $u_j = A(X_j)v_j + \varepsilon_j$. Note that ε_j is independent of MF_j by construction. We can then rewrite equation (3.1) as follows:

$$ML_j = \beta_0 + \beta_1 MF_j + X_j'\gamma + A(X_j)v_j + \varepsilon_j \qquad (3.1')$$

Note that this model is only identified in the presence of heteroskedasticity, without it $A(.)$ is not a function of X_j and the matrix of controls is not of full rank. Given the presence of heteroskedasticity in the data, let $S_u(X_j)$ and $S_v(X_j)$ be the conditional standard deviations of the error terms u_j and v_j, respectively. Further assume that:

$$u_j = S_u(X_j)u_j^*$$

$$v_j = S_v(X_j)v_j^*$$

Where u_j^* and v_j^* are the underlying homoskedastic errors. The key assumption is that the correlation coefficient of these underlying homoskedastic errors is constant across the

equations, i.e. $\rho_0 = E[u_j^* v_j^*] = E[u_j^* v_j^* | X_j]$. Provided that this condition holds, Klein and Vella (2010) show that it is possible to consistently estimate $A(X_j)$, where $A(X_j) = \rho_0 \frac{S_u(X_j)}{S_v(X_j)}$ and $\rho_0 = \frac{cov(u_j v_j | X_j)}{S_u(X_j) S_v(X_j)}$. Once $A(X_j)$ is consistently estimated, equation (3.1') is identified and can be estimated by OLS.

Following Farré et al (2012), we assume that the conditional standard deviation has the following parametric form (due to Harvey 1976):

$$S_{ji} = \sqrt{exp(Z_{ji}\theta_j)} \qquad i = \{u, v\}$$

Here, S_{ji} is the conditional standard deviation, Z_{ji} is the vector of variables contributing to heteroskedasticity in both equations (3.1) and (3.2) and θ_j is a vector of unknown parameters to be estimated. Assuming the above parametric form, the estimation procedure of the KV-CF estimator is as follows:

- First, estimate equation (3.2) by OLS to obtain a consistent estimate of the residual: $\widehat{v_j} = MF_j - \alpha_0 - X_j^{'}\hat{\delta}$
- Estimate θ_v by Nonlinear Least Squares (NLS) using $\ln(\widehat{v_j}^2)$ as the dependent variable and use it to compute $\widehat{S_{vj}} = \sqrt{exp(Z_{vj}\widehat{\theta_v})}$
- The remaining parameters are estimated though a standard iterative process. Begin by estimating "candidate" values to use in the NLS procedure:
    - Estimate equation (3.1) by OLS to get candidate values for the parameters, and define $\widehat{u_{jc}} = ML_j - \beta_{0c} - \beta_{1c} MF_j - X_j^{'}\gamma_c$ (where subscript *c* denotes candidate)

- Use $\widehat{u_{jc}}$ to obtain candidate values for θ_u in a similar manner to how θ_v was estimated.
- Calculate $\widehat{S_{uJ}} = \sqrt{exp(Z_{vj}\widehat{\theta_{uc}})}$
- Use the above candidate parameters to estimate ρ_0 by NLS:

$$\rho_{0c} = min \sum_{i=1}^{N} \left[\widehat{u_{jc}} - \rho_{0c} \frac{\widehat{S_{uJ}}}{\widehat{S_{vJ}}} v_j \right]$$

- Continue this iterative process until the "final" parameter estimates are obtained.

Klein and Vella (2010) and Farré et al (2012) recommend finishing with one last step. Although the above procedure performs well, Monte Carlo simulations reveal that adding this last step improves results. Another advantage of this approach is that it separates the estimation of the parameters from the estimation of S_{uj}. We follow this advice and implement this "last step." Using the "final" estimates from the above iterative procedure, we define the residual $\widehat{u_{jf}} = ML_j - \beta_{0f} - \beta_{1f} MF_j - X_j'\gamma_f$ (where the subscript *f* denotes the final estimates). Use this to compute $\widehat{S_{uJ}}$. Finally, estimate the following augmented equation by OLS:

$$ML_j = \beta_0 + \beta_1 MF_j + X_j'\gamma + \rho \frac{\widehat{S_{uJ}}}{\widehat{S_{vJ}}} \hat{v}_j + \varepsilon_j$$

This yields consistent estimates of the parameters β_0, β_1, γ, and ρ, provided the key assumptions are met.

Klein and Vella (2010) provide Monte Carlo simulations to support the credibility of this control function estimator, and Klein and Vella (2009b) apply it to a return to schooling investigation. Schroeder (2010) implements the nonparametric KV-CF in an analysis of the impact of microcredit on household consumption in Bangladesh. Farré et

al. (2012) provide a helpful guide to implementing the KV-CF estimator parametrically (assuming a parametric form for the heteroskedastic functions). Monte Carlo simulations show that this performs similarly to the more computationally burdensome nonparametric version of Klein and Vella (2009b, 2010). In our paper, we employ the parametric KV-CF estimator presented in Farré et al. (2012) to our analysis of the moneylender interest rate.[26]

Lewbel Two-Stage Estimator

The second heteroskedasticity-based estimator we employ is the two-stage estimator developed by Lewbel (2010). Like the KV-CF, it identifies the above triangular model without any exclusion restriction. The key identifying assumptions are (i) that the error term from the selection equation is heteroskedastic and (ii) that there exist a vector of variables (Z_{vj}) such that $Cov\left(Z_{vj}, u_j v_j\right) = 0$. Under these conditions, an instrumental variable can be constructed which will satisfy the exclusion restriction, i.e. be uncorrelated with the error u_i. This IV is constructed as follows:

- First regress the endogenous variable on all the regressors and retrieve the residual: $\widehat{v_j} = MF_j - \alpha_0 - X_j^{'}\hat{\delta}$
- Using this residual, construct the instrumental variable: $\left(Z_{vj} - \bar{Z}\right)'\widehat{v_j}$ where $\bar{Z}$ is the mean of Z_{vj}.
- In the second stage, use this set of IVs to estimate the main equation in a Two-Stage Least Squares procedure.

[26] Note that Klein and Vella developed another estimator for cases with a continuous outcome and binary endogenous variable (Klein and Vella 2009). We will use this estimator, KV-IV, later in the paper. Though the KV-IV is based on related issues of heteroskedasticity, the two identification approaches are fundamentally different.

The variables in Z_{vj} are those that contribute to the heteroskedasticity in the selection equation, just as in the KV-CF estimator above. The heteroskedastic variables Z_{vj} can include all of or a subset of the exogenous variables, X_j. As noted by Emran and Shilpi (2009), variables which are "clearly exogenous" make especially good candidates.

3.4.4 Informal Loans

To understand the underlying mechanism behind the effect of microfinance presence on the moneylender interest rate, we examine how MFI membership impacts informal borrowing at the household level using both the cross-section and panel. We focus on the impact of microfinance on both the extensive margin (the impact on the probability that a household borrows informally) and on the intensive margin (the impact on the amount borrowed informally).

Extensive Margin

Beginning with the cross-section, we estimate the extensive margin guided by the following model:

$$dL_i = \sigma_0 + \sigma_1 dM_i + X_i'\Sigma + \xi_i \quad (3.3)$$

$$dM_i = \theta_0 + X_i'\Theta + \varepsilon_i \quad (3.4)$$

Here, dL_i is a dummy taking the value of one if household i has a current outstanding loan from an informal source and zero otherwise; dM_i is a dummy indicating whether household i is a member of any MFI; and X_i is a set of household and village characteristics and Upazilla fixed effects.

Once again we are faced with the challenge of overcoming omitted variables bias. We lack a credible exclusion restriction and the heteroskedastic based estimators are not consistent in cases like this one where both the outcome and endogenous treatment are

binary. We therefore turn to matching, specifically the Minimum Bias estimator developed by Millimet and Tchernis (2012). The MB estimator extends the normalized Inverse Propensity Weighting estimator of Hirano and Imbens (2001) by limiting observations to those within a radius around the bias minimizing propensity score, thereby minimizing the possible bias. We focus on a large radius (0.25) as Monte Carlo evidence presented in Millimet and Tchernis (2012) show that this successfully corrects for the bias. Since the bias minimizing propensity score is unknown, Millimet and Tchernis estimate it using Heckman's Bivariate Normal Selection Model.

Turning to the panel data set, we are able to get a clearer picture of how microfinance membership impacts the probability of informal borrowing. Consider the following model:

$$dL_{07,i} = \theta_0 + \theta_1 T_i + X'_{00,i}\Theta + e_i \qquad (3.5)$$

where $dL_{07,i}$ is a dummy taking the value of one if the household has a current outstanding informal loan in 2007 and zero otherwise. The dummy T_i takes the value of one if the household is "treated", in our case new MFI membership in 2007. The vector $X_{00,i}$ contains household characteristics from 2000, i.e. determined prior to the treatment. By controlling for these household fixed effects, we effectively account for time-invariant unobserved household heterogeneity (eg ability).

We focus on the treatment *new MFI membership*, i.e. a household that is a MFI member in 2007 but not in 2000, and compare to the control groups never members and dropouts, both separately and together. As mentioned above, there are four groups defined by microfinance membership: always member, new member, dropout, and never member. Given that we wish to assess how joining a MFI influences the probability of

that a household borrows informally, we focus on the treatment "new member". It was common in the literature when assessing the impact of new membership to compare to never members, but as Karlan (2001) argues these two groups are not very comparable. Karlan recommends adding dropouts to the comparison group because one would expect dropouts and new members to be more similar, after all both joined a MFI at some point. Therefore, the comparison groups we focus on are never members and dropouts, both separately and together.[27]

The difference-in-mean results are reported in Table 3.5. When looking at the sample as a whole, we see that several variables (age, education, agricultural workers, owned land, and cultivable land) are significantly different between new members and the combined group dropout and never members. The two groups become noticeably more similar when we restrict our attention to the subsample owning less than an acre of land, which is consistent with our prior expectation. Focusing on the subsample, we see that new members and dropouts are most similar; however the latter group is relatively small and by itself does not offer a convincing comparison. Consistent with theory, never members and new members are significantly different across several characteristics, especially age. However, in studying the differences in household head education and household owned land, we see that the magnitudes though significant are rather negligible. We are therefore confident in the similarity between our treatment and comparison groups.

Estimating equation (3.5) above by OLS should yield reasonably accurate estimates as controlling for the household and regional fixed effects should reduce

[27] We exclude the always-members, those who have been MFI members in both survey years because they lack pre-treatment observations.

potential bias from time-invariant heterogeneity. By going one step further and matching on pre-treatment characteristics in addition to differencing, we can improve the accuracy of our estimates. The difference-in-difference-matching estimator (DIDM) of Heckmen et al (1998) combines the methodologies of differencing, to purge time-invariant heterogeneity, with that of matching which takes care of selection bias due to unobservables. Like the OLS estimates with fixed effects, the DIDM estimates would still be biased if there were selection bias due to time-variant unobservables. To minimize this potential bias, we estimate the model with MB.

Intensive Margin

Continuing with the panel, we shift our focus to the intensive margin, i.e. the impact of microfinance membership on the amount of informal borrowing. The panel set has too few informal borrowers (134 in 2007) for us to identify the causal impact of MFI membership on the intensive margin. We therefore estimate the impact on both the extensive and intensive margins together by looking at the impact of microfinance on two other outcomes (i) a dummy indicating whether informal borrowing increased between 2000 and 2007 and (ii) a dummy whether a household borrowing from an informal source in 2007 but not in 2000. The first dummy captures both the extensive margin (new borrowers) and the intensive margin (larger loans for existing borrowers). The second dummy is a subset of the first, i.e. focusing only on new informal borrowers' loan sizes.

Turning back to the cross-section which has over 7,000 informal borrowers, we are able to look at the intensive margin directly. Consider the model:

$$L_i = \gamma_0 + \gamma_1 dM_i + X_i'\Gamma + \eta_i \quad (3.6)$$

$$dM_i = \omega_0 + X_i'\Omega + \upsilon_i \quad (3.7)$$

Here, L_i is the amount borrowed informally (if positive), dM_i is a binary variable indicating whether a household is a member in any MFI, and X_i is a matrix of household and village controls as well as Upazilla fixed effects. We use the same control variables as in the calculation of the extensive margin, namely: age, age squared, number of family members over the age of 12, total owned land, total cultivable land, number self-employed in agriculture, number employed as day laborers, average village agricultural wage for men and women, moneylender interest rate, and distances to the nearest secondary school, bank, and market.

Here there are two sources of bias to contend with: (i) sample selection bias stemming from the fact that informal borrowers are likely to be different from non-borrowers in unobserved ways and (ii) omitted variables bias from unobserved characteristics influencing both informal borrowing amounts and microfinance membership choices. To control for potential sample selection bias we implement the Heckit procedure of Heckman (1979), that is we augment the above model including the inverse mills ratio (λ_i) as an additional control. The inverse Mills ratio is calculated as:

$$\lambda_i = \frac{\phi(K_i)}{\Phi(K_i)}$$

Where, $\phi(.)$ is the standard normal density function, $\Phi(.)$ is the standard normal distribution function, and K_i is the predicted probability that household *i* borrows from an informal source. We obtain this predicted probability by estimating equation (3.4) above by heteroskedastic probit. By controlling for the inverse Mills ratio we get the following augmented equation:

$$L_i = \gamma_0 + \gamma_1 dM_i + \gamma_2 \lambda_i + X_i'\Gamma + \eta_i \qquad (3.8)$$

To tackle the omitted variables bias, we estimate the above augmented equation with the Klein and Vella IV estimator, KV-IV (Klein and Vella 2009a). Klein and Vella (2009a) show that heteroskedasticity in the selection equation is sufficient to provide an exclusion restriction. Their paper provides Monte Carlo simulations which support the strength of their estimator and apply it to the question of whether or not attending a state funded school in Australia is a determinant of that individual's total educational level. Millimet and Tchernis (2012) apply a parametric version of the Klein-Vella IV estimator, making the additional assumptions of normally distributed errors and a parametric form for the heteroskedastic variance of the errors. The parametric form they assume is the same as was used in Farré et al (2012), namely that

$$S_{vi} = \sqrt{exp(Z_{vi}\theta_v)} \qquad (3.9)$$

Monte Carlo simulations in Millimet and Tchernis (2012) demonstrate that their parametric form works nearly as well as the original semiparametric version. We apply the parametric KV-IV to estimate the impact of microfinance membership on informal borrowing by households. First, we estimate equation (3.7) by heteroskedastic probit. From this we obtain fitted values, i.e. the probability of treatment. Finally, we use this probability of treatment as an IV in a two-stage least squares procedure.[28]

3.5 Empirical Results

In this section, we outline the main findings from our econometric analysis of the impact microfinance has on the informal credit market. First, we consider the impact of MFI coverage on the moneylender interest rate relying on the InM village cross-section. Second, we focus on the impact of microfinance membership on a household's decision

[28] For another example of combining Heckit and KV-IV, see Bentancor and Robano (2012). For other recent empirical applications of this KV-IV estimator see Emran et al. (2012), Emran and Sun (2011), and Wang (2012).

to borrow or not from the informal credit market using both the InM household cross-section and the BIDS panel. Finally, we consider the impact on the intensive margin relying on the InM cross-section.

3.5.1 Impact of MFI coverage on the Moneylender Interest Rate

The picture that begins to emerge from preliminary OLS results reported in Table 3.6 is that microfinance coverage seems to have a significant positive impact on the moneylender interest rate. We estimate four specifications: beginning with a bivariate regression, we progressively add first village characteristics then District fixed effects, and finally including Upazilla fixed effects (instead of District). What we find is that as we add controls to the model, the estimated impact doubles from 0.13 to 0.26 (significant at the one percent level). This would suggest that the endogeneity bias is negative. As discussed above in section 3.4.1, this negative bias could be explained by omitted variables or measurement error. To correct for the bias, we turn to the heteroskedastic-based estimator KV-CF.

First, though, we must establish the presence of heteroskedasticity in the data and second we must select the set of variables to be included in the heteroskedastic index (Z_v and Z_u). As discussed in section 3.4.3, we follow Farré et al (2012) in assuming the heteroskedastic functional form due to Harvey (1976). It is common in the literature to proceed with the "kitchen sink approach" and include all the exogenous variables (X_j) in Z_{ji} (see for example Klein and Vella 2009b, 2010, Farré et al 2012). We tried this approach but ran into non-convergence issues, perhaps as a result of our large number of controls. Instead, we selected the variables guided by both empirical results and economic theory. Table 3.7 and Table 3.8 report the OLS regression results from

regressing the squared errors ${u_j}^2$ and ${v_j}^2$ from equations (3.1) and (3.2) on all the explanatory variables (village controls and Upazilla fixed effects X_j). The Breusch-Pagan/Cook-Weisberg test rejects the null hypothesis of homoskedasticity in both cases.

We focus on those exogenous variables which have a significant impact on the squared residual. We find that average female agricultural wage, percent of households with less than 0.1 acre of land, and the number of households in a village all had a statistically significant impact (at the 1 percent level) on the squared residual from the selection equation (3.2) as reported in Table 3.7.[29] The percent of functionally landless households (owning less than 0.1 acre of land) is an indicator of the poverty level in the village. As discussed above, the poorer the village, the less likely it is to have a MFI locate there. This should decrease the variance in microfinance coverage. The average female agricultural wage is also an indicator of the village level poverty. A low female wage, might indicate less access to microfinance and thus have a positive impact on microfinance variance (v_j^2), which is confirmed by our test results. The male wage does not have much of an impact on the microfinance variance. This might be because MFIs lend almost exclusively to women and so the female wage would be more of a factor. The larger a village is, the more likely it might be for a MFI to locate there. More households mean more potential clients, and those clients might find it easier to form required groups to take out loans. This greater access to microcredit suggests a lower variance in microfinance coverage.

[29] Some of the Upazilla dummies were also significant, but we did not include them since there was no clear economic reason to do so and because including them caused convergence problems of the KV-CF estimator.

The squared residual test for the moneylender interest rate outcome equation, reported in Table 3.8, reveal that use of modern technology in agriculture, distance to market, and the number of households in the village are significant determinants of the variance in informal loans (u_j^2). As mentioned above, Iqbal (1988) found that areas adopting new technologies faced lower interest rates. So the greater the percent of households in a village using developed technologies, the less risky they are to lend to, and the lower the interest rate they would be charged. This would lower the spread in the interest rates, so there would be a negative impact on the variance. The farther a village is from the market (the more remote it is) the poorer it is. As such, the poor villagers present more of a risk to the moneylender which might induce her to raise her interest rates. Those who are already better off can more easily access the market (if they owned a car for example) and could negotiate a lower interest rate (using the car as collateral maybe). The difference among villagers increases the variance of the interest rate errors. The more households within a village, the more likely it is that villagers are heterogeneous. Moneylenders charge different interest rates to different clients so this should increase the spread in moneylender interest rates. With these variables included in Z_{vj} and Z_{uj} we proceed to estimate the model with KV-CF.

The KV-CF estimates, reported in Table 3.9, indicate that a one percent increase in microfinance coverage increases the average moneylender interest rate by 0.5 percent (recall that both treatment and outcome are in percentage terms). Twice as large as the OLS estimate, this is further evidence that the endogeneity bias is negative. If anything, we are underestimating the impact.

As a robustness check, we estimated the model using the Lewbel two-stage estimator (Lewbel 2012). Though both KV-CF and Lewbel estimators are identified through heteroskedasticity, they are not very comparable as they estimate different local average treatment effects. We find that both estimators yield positive significant impact. We estimate four models using the Lewbel-IV Estimator, controlling for village characteristics and Upazilla fixed effects, results reported in Table 3.10 below. In column (1) we use instrumental variables constructed from all the village variables and find that microfinance has a positive impact on the moneylender interest rate of 0.50, the same as we found with the KV-CF estimator (see column (1) of Table 3.9). It too is statistically significant at the 1 percent level. However, the Hansen's J P statistic is zero, telling us that these IVs do not satisfy the exclusion restriction.

In column (2) of Table 3.10 we employ IVs constructed from the female agricultural wage, percent of households that are functionally landless, and the number of households in the village. These three variables were found to have a statistically significant impact on the squared residual from the selection equation, as revealed in the heteroskedasticity regressions in Table 3.7. Here, we find that an increase in microfinance presence has about a one-for-one increase in the moneylender interest rate, and is statistically significant with a t-statistic of 3.99. The Hansen's J P statistic in this model is 0.26, evidence that these IVs satisfy the exclusion restriction. The AP F statistic is 10.89 which is greater than the Stock-Yogo 5 percent critical value for one endogenous variable and three instruments is 9.08 (Stock-Yogo 2003).

The IV constructed from the percent of functionally landless was not significant in the first stage of column (2) (t-statistic is -1.08). So in column (3), we only include the

IVs constructed from female wage and the number of households. Here we find that the impact of microfinance on the moneylender interest rate increases only slightly, and is similarly significant. Both remaining IVs are significant in the first stage, Hansen's J P statistic increases to 0.39, and the AP F statistic is 15.50, evidence that these IVs are strong and exogenous.

In column (4) we report the Lewbel estimates when using distance to bank as the only variable in the heteroskedastic index. Here we find that microfinance is positive, though not significant. The AP F Statistic is small, suggesting that the IV constructed from the distance to bank is weak. So while distance to bank works well in the informal loan model, it does not work well in the moneylender interest rate model. This is consistent with the findings of the squared residual test. (Table 3.7 and Table 3.8).

Although the magnitudes of the microfinance impact changes between the different estimators and across various specifications, the impact is consistently positive and statistically significant. These findings are consistent with those of Mallick (2011) and with our larger sample, we add credibility to the assertion that a wider microfinance presence leads to a higher moneylender interest rate.

As an additional robustness check, we estimate the model excluding the agricultural wage variables from the controls. There is some concern that the wage variables may be endogenous, that is they may be outcome variables themselves, see Chapter 4. As Angrist and Pischke (2009) point out, this would make them "bad controls". However, the reason we chose to include the wages in the main analysis is because wages play an important role in the participation decision of households in MFIs (see for example Emran et al (2011) for a discussion of this point). Excluding the wages

from the analysis could bias the results. Here we briefly discuss the results obtained when excluding the two agricultural wage variables.

Table 3.17 below presents the OLS estimates of the impact of MFI coverage on the moneylender interest rate, excluding the agricultural wages from the controls. Comparing these estimates to those from Table 3.6, we see that the estimates for columns (2) through (4) are remarkably similar.[30] Excluding the wage variables from the regression yields marginally larger estimates. This provides an added justification for including them in the main analysis.

We estimated the model excluding the wage variables using both the KV-CF and Lewbel-IV estimators. Without the wage variables, the variables which contribute to the heteroskedasticity in the selection equation are percent of landless households and the number of households in the village. In the outcome equation the variables contributing to heteroskedasticity are the same as previously. The KV-CF estimator, which is sensitive to changes in the model's specification, yields insignificant results.

The Lewbel-IV estimates are reported in Table 3.18 and show that consistent with earlier findings in Table 3.10. We estimate three specifications: in column (1) we use all remaining control variables to construct the Lewbel-IVs; in column (2) we focus on the percent of landless households and the number of households as sources of heteroskedasticity in the selection equation; and in column (3) we assume that the number of households accounts for the heteroskedasticity. All three models include strong IVs, according to the AP F Statistic which exceeds the critical value of 10. Note

[30] Note that column (1) estimates the exact same bivariate regression in both tables.

that column (2) is very comparable between Table 3.10 and Table 3.18, the only difference is that in Table 3.18 the wages are excluded from the controls.

Given all the available data, we are confident in our analysis that microfinance coverage has a positive impact on the moneylender interest rate. The question is why? For this we turn our attention to the impact on informal borrowing.

3.5.2 Extensive Margin: Impact of microfinance membership on a household's decision to borrow or not from the informal credit market

In estimating the impact of a household's microfinance membership status on its decision to borrow from an informal source or not, we use both the cross-section and the BIDS panel.

Table 3.11 reports the OLS estimated impact using the InM cross-section. Here we find a weakly positive impact of microfinance on the extensive margin. As we progressively add household and village controls, we find the estimated impact declines. With the inclusion of Upazilla fixed effects, the estimated impact becomes negligible. Here it would seem that the endogeneity bias is positive. Turning to the MB estimates in Table 3.12, we find a weakly negative impact.

Thus far, the evidence based on the cross-section is inconclusive. To pin down the impact of microfinance on the extensive margin, we turn to the BIDS panel. Table 3.13 reports the estimates from DIDM and MB, as well as OLS with fixed effects (OLS-FE) for reference. The OLS-FE estimates the impact that being a new MFI member has on whether or not the household borrowed informally in 2007. From these estimates we see that new membership seems to have a significant negative impact on the probability

of borrowing informally. Being a new MFI member decreased the probability of informal borrowing in 2007 by about 5 percent. These estimates may still be biased by omitted time variant heterogeneity. To account for this we turn to matching techniques. The DIDM and OLS-FE estimates prove very similar and significant. The MB estimate is less negative, -0.04 and significant. These estimated impacts are not insubstantial, considering that roughly 7 percent of the sample borrows informally. In sum, the panel data provides evidence that microfinance membership decreases the likelihood of informal borrowing.

3.5.3 Intensive Margin: Impact of microfinance membership on the amount households borrow informally

Informal borrowers make up a small share of both InM and BIDS data sets, about 10 percent. In the InM data, we have 7,256 informal borrowers while the BIDS panel reports 187 in 2000 and 132 in 2007.

Table 3.14 reports the OLS estimated impact of microfinance membership on the intensive margin, using the InM data. The results suggest that MFI membership increases the average size of informal loan (3,019 taka) by about 1,800 taka for those still turning to informal lenders. As we progressively include household and village controls, as well as regional fixed effects, we find that the estimated impact declines, suggesting that the omitted variables bias may be positive.

To address the endogeneity bias potentially plaguing our OLS estimates, we employ the KV-IV estimator to correct for omitted variables bias, augmented with Heckit's inverse mills ratio to account for selection bias, as discussed above in section 3.4.4 (see Table 3.15). Correcting for both omitted variables and selection bias yields a

larger estimate of roughly 6,000. This impact is robust to alternative inverse mills ratios. Our constructed IV does not seem to suffer any problem of weak instrument: the AP F statistic, 29, is larger than the rule of thumb critical value of 10.[31]

The BIDS panel does not have enough informal borrowers for us to estimate any convincing regression models. There were 176 informal borrowers in 2000 and 99 in 2007. During the same interval, the number of MFI members increased from 285 to 465. Hossain and Bayes (2009) report that the percent of households borrowing from moneylenders decreased from 14.6 percent in 1988 to 4.6 in 2007, with the average loan size increasing from 155 to 537 US dollars (4,799 and 37,817 taka respectively).[32]

Though we cannot estimate the impact on the intensive margin directly using the panel, we can gain some insight by looking at the question indirectly. Table 3.16 reports the estimates of the impact of new MFI membership on the probability that informal borrowing increased. By looking at this outcome, equal to one if informal borrowing increased between 2000 and 2007 and zero otherwise, we can assess the impact on both the extensive margin (new informal borrowers) and intensive margin (larger loans for existing informal borrowers). Here we find negative impacts, similar in magnitude to that on the extensive margin alone (Table 3.13) this would suggest that most of the impact is at the extensive margin.

3.6 Conclusions

There are two broadly held hypotheses of the effect of MFIs on the informal credit market. First, the MFI view, borne out by conventional wisdom: an increase in

[31] The Stock-Yogo 5 percent critical value for one endogenous variable and three instruments is 9.08 (no critical values for less than three instruments were reported). We expect the critical value for our case of one instrument to be smaller (Stock and Yogo 2003).

[32] Daily wages converted from taka into dollars at the average 1988 and 2007 exchange rates of 0.0323 (World Bank 1988) and 0.0142 dollars/taka (http://www.oanda.com/currency/historical-rates/) respectively.

MFI credit leads to a decrease in the demand for informal loans, which in turn leads to a decrease in borrowing from moneylenders, thereby to a decrease in interest rates. Second, the "alternative view": an increase in MFI credit leads to an increase in demand for credit from moneylenders due to the rigid microfinance repayment schedule, the small size of MFI loans relative to indivisible investment projects. This increase in demand for moneylender credit in turn leads to increased moneylender interest rate. Our analysis shows that our results are fully consistent with neither hypothesis. On the one hand, moneylender interest increased which is consistent with the alternative view. On the other hand, the number of informal borrowers and the volume of informal loans have decreased which is consistent with the MFI view.

Indeed, making use of the InM cross-section of more than 800 villages, our study finds evidence that as microfinance spreads the moneylender interest rates rise. This finding is robust to different specifications and estimators and is consistent with the findings of Mallick 2012. Further results suggest that microfinance membership is accompanied by a fall in the number of informal borrowers, i.e. extensive margin. In the cross-section, only about 11 percent of the households borrow positive amounts from informal sources. In the panel, informal borrowers made up 12 percent of the sample in 2000, falling to 8 percent in 2007. Using a more complete dataset, Hossain and Bayes (2009) find that the percent of households borrowing from moneylenders fell from 14.6 percent in 1988 to 4.6 percent in 2007, with a similar decline for borrowing from friends and family. Thus overall, microfinance has been seen to decrease the number of poor turning to informal sources of finance.

To explain these unexpected results, we searched for alternative explanations, cream skimming (Bose 1998) and fixed costs (Hoff and Stiglitz, 1998). Under cream skimming, MFIs attract the better borrowers, leaving relatively risky borrowers in the credit market. Hoff and Stiglitz (1998) present a model in which screening costs are fixed, enforcement costs are endogenous, and under certain conditions a subsidy of formal credit could lead to an increase in informal interest rates.

With regard to the cream skimming argument, it seems reasonable to imagine that those still borrowing from the informal sector are riskier than their MFI member counterparts. Consider a microentrepreneur seeking credit. To join an MFI, she must first form a five-member group. Suppose she is unable to do so because no one is willing to join her. That would suggest that she is relatively risky. Further, Microfinance Institutions typically target women precisely because they are more creditworthy than men (Armendáriz and Morduch 2010). So probably men make up a greater share of the informal borrowers after the arrival of microfinance, making it a riskier pool.

An interesting finding in the cross-section is that among those still borrowing from the informal sources, microfinance membership increases the average size of the loan, i.e. the intensive margin. It is unclear why the average informal loan size is increasing with MFI membership. One possible explanation is that if the number of borrowers per moneylender falls with microfinance, then moneylenders may have more funds available to lend to each individual borrower they retain. Although we do not have information on the number of moneylenders in the market, we can reasonably argue that there is likely to be a decline in borrowers per moneylender as more switch to microfinance.

Typically though, larger loans carry lower interest rates, since interest rates are determined by administrative costs, opportunity cost of money, risk premium, and monopoly profit (Bottomley 1983). Given that the administrative costs are a smaller share of these larger loans, this would suggest that larger average loan size should be accompanied by a lower interest rate.

The administrative costs of the loan include screening expenses. As discussed in Hoff and Stiglitz (1998), these are fixed in the sense that once the moneylender has exerted time and effort to evaluate a potential client, then this process does not need to be repeated each time the same client comes for a loan. Hoff and Stiglitz present a model in which this fixed screening cost helps explain why informal interest rates rise in spite of subsidized government credit. In the model, government subsidized credit attracts landlords into the moneylender market. With these new entrants, the number of borrowers per moneylender declines. Enforcement costs increase because as borrowers have more options for finance, the threat of being cut off from future lending from a given moneylender has less meaning. This is consistent with a riskier pool of borrowers. With higher enforcement costs, moneylenders will increase their interest rates accordingly. In the Hoff and Stiglitz model, the government subsidized credit has a *direct* effect on the moneylender by lowering the cost of capital (which lowers the interest rate) and an *indirect* effect through the number of moneylenders (which raises the interest rate). Government subsidized credit is seen to raise the moneylender interest rate if the direct effect is dominated by the indirect effect.

The main difference between our situation and the one presented by Hoff and Stiglitz is that microfinance should not have any effect on the moneylender's opportunity

cost of capital. Moneylenders are often large landowners, relatively wealthier villagers and should not have access to microfinance which targets the poor. What our cases do have in common is that we believe the moneylender's risk premium and enforcement costs increase as a consequence of the new entry of microfinance.

The remaining piece of the puzzle is what happens to those individuals who continue to borrow from moneylenders. We find that there are fewer informal borrowers, that they are borrowing on average larger amounts, and that the moneylender interest rate is on average higher. What we cannot determine, given the limitations of our data, is whether those still borrowing informally are made worse off by the arrival of microfinance? In other words, are they facing a higher interest rate than they would have otherwise? Among the limitations of our data is the fact that we cannot observe the interest rate paid by individual informal borrowers. Instead we only see the average interest rate in the village. In addition, we are relying on a cross-section in our analysis of the moneylender interest rate. Thus, we cannot truly see from our data whether individual informal borrowers are paying higher interest rates or not. Still, we feel we have enough evidence to tell a convincing story.

Increased interest rates do not in themselves suggest a negative welfare effect for those who continue to borrow from moneylenders. As MFIs arrived on the scene, they attract the safer borrowers, consistent with the cream skimming theory presented by Bose (1998). This changes the composition of informal borrowers; those still borrowing informally would be riskier on average. Thus, we would argue, those who still borrow informally would be paying the same high interest rate regardless of the entrance of MFIs or not. The cream skimming model presented in Bose (1998) assumed initially a constant

interest rate charged by moneylenders to all their clients and then extended it to allow for interest rates to vary with the size of the loan. As discussed above, however, moneylenders are known to charge different interest rates to different clients (Robinson 2001). The fact that the less risky borrowers moved on does not worsen the situation of those who continue to borrow informally, in fact they may even have easier access to informal credit as suggested by the larger average loan size.

To conclude, as microfinance made its entrance on the informal credit scene, many expected it to drive informal interest rates down through competition. As it turns out, we are seeing an increase in moneylender interest rates in villages with high concentration of microfinance. Indeed, with the arrival of MFIs, more and more people are turning away from informal finance in favor of microfinance. As the low risk/high ability borrowers are picked up by MFIs, this leaves high risk/low ability borrowers in the moneylender segment of the market. Average informal interest rates are high to compensate for high risk. In sum, our results are best explained by the cream skimming theory.

Table 3.1 Summary Statistics, Cross-Section Village-level Data

Variable	Mean	Std. Dev.	Min	Max
Dependent Variable				
Moneylender Interest Rate (%)	21.42	32.83	3	196
Treatment Variable				
Microfinance Presence (%)	41.82	22.59	0	100
Control Variables				
Average male agricultural daily wage (taka)	62.52	21.58	7	350
Average female agricultural daily wage (taka)	38.39	16.27	0	170
Houses in village with less than 0.1 acre land (%)	79.96	12.49	8	100
Houses in village using modern technology in cultivation (%)	61.94	29.86	0	100
Distance to secondary school (km)	1.96	2.81	0	30
Distance to bank (km)	4.55	3.96	0	30
Distance to market (km)	3.82	3.21	0	26
Distance to bus stop (km)	4.25	4.03	0	32
Distance to nearest paved road (km)	2.71	20.04	0	400
Houses in village with toilet (%)	13.57	13.83	0	100
Number of Households in Village	209.62	205.14	3	2,698
Number of Villages = 804				

(1) Source: InM Cross-Section, village data
(2) Data consists of ultrapoor households in selected villages in the districts of Gaibandha, Lalmonirhat, and Nilphamari

Table 3.2 Summary Statistics, Cross-Section Household-Level Data

Variable	Mean	Std. Dev.	Min	Max	Obs.
OVERALL					
Dependent Variable:					
Current outstanding loan from informal lender	335.59	1,776.01	0	75,000	65,272
Informal Loan, Intensive Margin[33]	3,018.82	4,502.91	30	75,000	7,256
Household Variables:					
Member of any MFI (yes=1)	0.3	0.46	0	1	65,272
Age of the head of the household	39.3	11.77	13	70	65,272
Number of family members over 12 years	2.48	0.99	1	11	65,272
Total owned land (decimal)	8.52	12.57	0	363	65,272
Total cultivable land (decimal)	5.57	16.51	0	850	65,272
Household members self-employed in agriculture	0.08	0.29	0	6	65,272
Household members employed as day laborers	0.78	0.59	0	17	65,272
Have VGD card (yes=1)	0.06	0.23	0	1	65,272
Village Variables:					
Average male agricultural daily wage (taka)	52.65	12.22	7.5	100	65,272
Average female agricultural daily wage (taka)	34.18	9.35	0	80	65,272
Moneylender interest rate (%)	34.15	53.94	3	196	65,272
Distance to secondary school (km)	1.69	2.18	0	30	65,272
Distance to bank (km)	5.07	3.83	0	26	65,272
Distance to market (km)	3.54	2.96	0	26	65,272

(1) Source: InM Cross-section data
(2) We exclude observations with unrealistic values for the age of the head of the household, dropping those with values less than 13 or greater than 70 years.

[33] Average positive loan amount borrowed informally (i.e. excluding zero).

Table 3.3 Summary Statistics, Panel Data

Variable	Year	Mean	Std. Dev.	Min	Max	Obs.
Dependent Variable:						
Informal Loan Amount (taka)	2000	736.18	3,661.63	0	50,000	1,516
	2007	876.12	5,390.01	0	80,000	1,516
Informal Loan Amount, Intensive Margin (taka)[34]	2000	6,341.19	8,962.45	200	50,000	176
	2007	13,416.16	16,708.30	800	80,000	99
Treatment Status:						
MFI Member (yes = 1)	2000	0.24	0.42	0	1	1,516
	2007	0.40	0.49	0	1	1,516
Household Level Controls:						1,516
Age of the household head (years)	2000	0.24	0.42	0	1	1,516
	2007	0.40	0.49	0	1	1,516
Education of the head	2000	42.71	11.88	16	70	1,516
	2007	48.72	12.98	19	95	1,516
Agricultural worker (number in hh working as)	2000	3.98	4.34	0	16	1,516
	2007	3.95	4.35	0	16	1,516
Total owned land (ha)	2000	0.78	0.79	0	4	1,516
	2007	0.88	0.87	0	6	1,516
Total cultivated land (ha)	2000	0.49	0.85	0	10	1,516
	2007	0.48	0.83	0	13	1,516
Household size	2000	0.37	0.61	0	7	1,516
	2007	0.34	0.57	0	10	1,516

(1) Source: BIDS Panel Data

(2) We exclude observations with unrealistic values for the age of the head of the household, dropping those with values greater than 70 years.

(3) We exclude observations with unrealistic values for the size of the informal loan (i.e. those borrowing more than 80,000 taka).

[34] Average positive loan amount borrowed informally (i.e. excluding zero).

Table 3.4 Treatment and Comparison Groups, Panel Data

Panel A: Overall Sample

		MFI member in 2007?		
		No	**Yes**	**Total**
MFI member in 2000?	**No**	Never Member 785	New Member 373	1,158
	Yes	Dropout 131	Always Member 227	358
	Total	916	600	1,516

Panel B: Subsample Owning less than an acre of land

		MFI member in 2007?		
		No	**Yes**	**Total**
MFI member in 2000?	**No**	Never Member 450	New Member 267	717
	Yes	Dropout 87	Always Member 198	285
	Total	537	465	1,002

(1) Source: BIDS Panel Data
(2) We exclude observations with unrealistic values for the age of the head of the household, dropping those with values greater than 70 years.
(3) We exclude observations with unrealistic values for informal loan, excluding those borrowing more than 80,000 taka.

Table 3.5 Difference-in-Means Test, Panel Data

	New – (Dropout & Never)	New – Never	New – Dropout
Panel A: Overall Sample			
Age	3.92***	-3.94***	-3.79***
	(5.29)	(-5.19)	(-3.27)
Education	1.08***	-1.35***	0.48
	(4.01)	(-4.81)	(1.20)
Agricultural workers	0.11**	-0.10**	-0.14*
	(2.27)	(-2.13)	(1.85)
Owned land	0.21***	-0.24***	-0.02
	(3.72)	(-4.09)	(-0.23)
Cultivable land	0.10***	-0.12***	-0.02
	(2.70)	(-2.92)	(-0.32)
Household size	0.18	-0.19	-0.11
	(1.35)	(-1.38)	(-0.59)
Number of observations	1,289	1,158	504
Panel B: Subsample owning less than an acre of land			
Age	3.00***	-2.87***	-3.63***
	(3.41)	(-3.16)	(-2.71)
Education	0.79***	-0.97***	0.16
	(2.76)	(-3.26)	(0.41)
Agricultural workers	0.06	-0.07	-0.05
	(1.17)	(-1.20)	(-0.56)
Owned land	0.04***	-0.04***	-0.02
	(4.54)	(-4.80)	(-1.57)
Cultivable land	0.01	-0.01	0.02
	(0.25)	(-0.47)	(0.64)
Household size	0.05	-0.05	-0.05
	(0.31)	(-0.28)	(-0.24)
Number of observations	804	717	354

(1) Source: BIDS Panel Data

(2) Robust t-statistic in parentheses. Significance levels are denoted as *** 1%, ** 5%, and *10%.

(3) We exclude observations with the head older than 70 and informal loans above 80,000 taka.

Table 3.6 OLS Estimates of the Impact of Microfinance Coverage on the Moneylender Interest Rate, Cross-Section Data

Dependent Variable: Moneylender Interest Rate				
	(1)	**(2)**	**(3)**	**(4)**
Microfinance Coverage (%)	0.13*	0.22***	0.27***	0.26***
	(1.88)	(3.39)	(4.87)	(5.09)
Village Controls	No	Yes	Yes	Yes
Fixed Effects	No	No	District	Upazilla
Number of Observations = 804				

(1) Source: InM Cross-Section Data

(2) Robust t-statistic in parentheses. Significance levels are denoted as *** 1%, ** 5%, and *10%.

(3) Village controls are: average agricultural wages for men and women in the village, percent of households in the village that are functionally landless (owning less than 0.1 acre of land), percent of houses using modern technology in cultivation, percent of households with a proper toilet, number of ultrapoor houses in a village, and distance to the nearest secondary school, bank, market, bus stop, and paved road.

Table 3.7 Heteroskedasticity Contributing Variables in the Selection Equation of Microfinance Coverage

Dependent Variable: Squared Residual of Microfinance Coverage Selection Equation	
Average male agricultural wage	-1.012
	(-1.04)
Average female agricultural wage	3.890***
	(3.19)
Percent of houses in village with less than 0.1 acre	-3.364**
	(-2.28)
Percent of houses in village using modern technology in cultivation	-0.817
	(-1.26)
Distance to secondary school	-12.360*
	(-1.70)
Distance to bank	6.482
	(1.22)
Distance to market	-5.515
	(-0.86)
Distance to bus stop	-2.483
	(-0.44)
Distance to nearest paved road	-1.146
	(-1.35)
Percent of houses in village with toilet	0.881
	(0.68)
Number of Households in Village	-0.400***
	(-4.20)
Upazilla1	327.600***
	(5.56)
Upazilla2	-55.050
	(-1.08)
Upazilla3	-91.680
	(-1.09)
Upazilla4	-135.600
	(-1.41)
Upazilla5	-204.300
	(-1.59)
Upazilla6	-256.500**
	(-2.54)
Upazilla7	-141.50
	(-0.89)
Upazilla8	-56.290
	(-0.37)

Upazilla9		-71.800
		(-0.63)
Upazilla10		-198.600**
		(-2.02)
Upazilla11		-65.770
		(-0.67)
Constant		705.50***
		(4.54)
Breusch-Pagan / Cook-Weisberg test	chi2(1) =	4.37
for heteroskedasticity	Prob > chi2	0.0365
Observations		804

(1) Source: InM Cross-section

Table 3.8 Variables Contributing to Heteroskedasticity in the Outcome Equation of Moneylender Interest Rate

Dependent Variable: Squared Residual of Moneylender Interest Rate Outcome Equation	
Average male agricultural wage	8.010*
	(1.689)
Average female agricultural wage	8.737
	(1.465)
Percent of houses in village with less than 0.1 acre	-8.995
	(-1.247)
Percent of houses in village using modern technology in cultivation	-9.455***
	(-2.969)
Distance to secondary school	47.33
	(1.335)
Distance to bank	-39.49
	(-1.525)
Distance to market	110.3***
	(3.531)
Distance to bus stop	-21.31
	(-0.770)
Distance to nearest paved road	1.680
	(0.406)
Percent of houses in village with toilet	-3.349
	(-0.528)
Number of Households in Village	2.119***
	(4.556)
Upazilla1	-108.9
	(-0.378)
Upazilla2	701.3***
	(2.823)
Upazilla3	1,370***
	(3.328)
Upazilla4	88.65
	(0.189)
Upazilla5	451.8
	(0.721)
Upazilla6	-172.2
	(-0.349)
Upazilla7	-428.4
	(-0.550)
Upazilla8	-733.0
	(-0.990)

Upazilla9		1,663***
		(2.985)
Upazilla10		5,006***
		(10.39)
Upazilla11		21.01
		(0.0439)
Constant		84.76
		(0.112)
Breusch-Pagan / Cook-Weisberg test	chi2(1) =	1,616.06
for heteroskedasticity	Prob > chi2 =	0.0000
Observations		804

(1) Source: InM Cross-section, village data

Table 3.9 KV-CF Estimates of the Impact of Microfinance Coverage on the Moneylender Interest Rate, Cross-Section Data

Dependent Variable: Moneylender Interest Rate	
Microfinance Coverage (%)	0.499***
	(2.64)
rho	-0.096***
	(-3.18)
Z_v variables	Female agricultural wage
	% in village owning < 0.1 acre land
	Number of households in village
Z_u variables	% using modern technology in cultivation
	Distance to market
	Number of households
Number of replications	300

(1) Source: InM Cross-section data

(2) Robust t-statistics in parentheses. Significance levels are denoted as *** 1%,** 5%, and *10%.

(3) The parameter rho indicates the correlation between the error terms.

(4) Village controls are: average agricultural wages for men and women in the village, percent of households in the village that are functionally landless (owning less than 0.1 acre of land), percent of houses using modern technology in cultivation, percent of households with a proper toilet, number of ultrapoor houses in a village, and distance to the nearest secondary school, bank, market, bus stop, and paved road.

(5) The Zv vector contains variables contributing to heteroskedasticity in the selection equation and Zu contains the variables contributing to the heteroskedasticity in the outcome equation.

Table 3.10 Lewbel IV Results

Dependent Variable: Moneylender Interest Rate	**(1)**	**(2)**	**(3)**	**(4)**
MFI coverage (%)	0.50 (3.79)***	1.11 (3.99)***	1.17 (4.08)***	1.33 (0.72)
IVs included constructed from:				
Average male agricultural wage	Yes			
Average female agri. wage	Yes	Yes	Yes	
% of households with less than 0.1 acre	Yes	Yes		
% using modern technology in cultivation	Yes			
Distance to secondary school	Yes			
Distance to bank	Yes			Yes
Distance to market	Yes			
Distance to bus stop	Yes			
Distance to nearest paved road	Yes			
Use of proper toilet	Yes			
No. of Households in Village	Yes	Yes	Yes	
AP F Statistic	15.51	10.86	0.39	0.74
Hansen's J P Statistic	0.00	0.26	0.39	N/A
Number of Observations	804	804	804	804

Table 3.11 OLS Estimates of the Effect of MFI membership on the Decision to Borrow Informally, Cross-Section Data

Dependent Variable: Borrowed Informally in 2007 (yes=1)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Member in any MFI? (yes=1)	0.053***	0.044***	0.038***	0.010***	0.002
	(18.31)	(15.21)	(13.25)	(4.10)	(1.08)
Household Variables	No	Yes	Yes	Yes	Yes
Village Variables	No	No	Yes	Yes	Yes
Fixed Effects	No	No	No	District	Upazilla
Number of Observations	65,272	65,272	65,272	65,272	65,272

(1) Source: InM Cross-section Data

(2) Robust t-statistics in parentheses. Significance levels are denoted as *** 1%, ** 5%, and *10%.

(3) Household controls are: age of the head of the household, age squared, number of household members over the age of 12, total owned land, total cultivable land, number of household members self-employed in agriculture, number employed as day laborers, and whether the household has a vulnerable group development card (VGD).

(4) Village controls are: average agricultural wages for men and women in the village, percent of households in the village that are functionally landless (owning less than 0.1 acre of land), percent of houses using modern technology in cultivation, percent of households with a proper toilet, number of ultrapoor houses in a village, and distance to the nearest secondary school, bank, market, bus stop, and paved road.

Table 3.12 Minimum Bias (MB) Estimates of the Impact of MFI Membership on the Decision to Borrow Informally (Extensive Margin), Cross-section data

Dependent Variable: Borrowed Informally in 2007 (yes=1)		
	ATE	**ATT**
New MFI member in 2007 (yes = 1)		
MB	-0.001	-0.001
	[-0.007, 0.005]	[-0.007, 0.004]
Number of Observations = 65,272		

(1) Source: InM Cross-section Data

(2) Minimum Bias (MB) and Bias Minimizing Propensity Score (P*) is calculated using Millimet and Tchernis (2012) Stata code. The 90% Confidence Intervals are displayed in square brackets.

(3) The MB is estimated using a large radius (0.25). See Millimet and Tchernis (2012) for further details.

(4) Each model is calculated with household and village controls along with upazilla fixed effects. Household controls are: age of the head of the household, age squared, number of household members over the age of 12, total owned land, total cultivable land, number of household members self-employed in agriculture, number employed as day laborers, and whether the household has a vulnerable group development card (VGD). Village controls are: average agricultural wages for men and women in the village, percent of households in the village that are functionally landless (owning less than 0.1 acre of land), percent of houses using modern technology in cultivation, percent of households with a proper toilet, number of ultrapoor houses in a village, and distance to the nearest secondary school, bank, market, bus stop, and paved road.

(5) Estimates are average treatment effects (ATE) and average treatment effects on the treated (ATT).

Table 3.13 Effect of New MFI Membership on Informal Borrowing, Panel Data

Dependent Variable: Borrowed Informally in 2007 (yes=1)						
Control Group:	**Never Member & Dropouts**			**Never Member**		
	(1) OLS	(2) DIDM	(3) MB	(4) OLS	(5) DIDM	(6) MB
FULL SAMPLE						
New MFI Member in 2007 (yes=1)	-0.045***	-0.044***	-0.044	-0.053***	-0.054***	-0.056
	(-3.24)	(-3.14)	[-0.080, 0.003]	(-3.53)	(-3.61)	[-0.104, -0.008]
Number of Observations	1,289	1,289	1,289	1,158	1,158	1,158
SUBSAMPLE OWNING LESS THAN AN ACRE OF LAND						
New MFI Member in 2007 (yes=1)	-0.059***	-0.059***	-0.055	-0.066***	-0.066***	-0.075
	(3.15)	(-3.18)	[-0.143, -0.012]	(3.27)	(-3.31)	[-0.146, -0.015]
Number of Observations	804	804	804	717	717	717

Table 3.13 (cont.)

Dependent Variable: Borrowed Informally in 2007 (yes=1)			
Control Group:		**Dropout**	
	(7) OLS	(8) DIDM	(9) MB
FULL SAMPLE			
New MFI Member in 2007 (yes=1)	-0.009	-0.017***	-0.008
	(-0.44)	(-3.03)	[-0.096, 0.036]
Number of Observations	504	504	504
SUBSAMPLE OWNING LESS THAN AN ACRE OF LAND			
New MFI Member in 2007 (yes=1)	-0.026	-0.017	-0.057
	(-0.85)	(0.55)	[-0.129, 0.059]
Number of Observations	354	354	354

(1) Robust t-statistics in parentheses in columns 1, 2, 3, 4, 5, 7, and 8. Significance levels are denoted as *** 1%, ** 5%, and *10%.
(2) Each model is calculated with the household controls (age, age squared education, total owned land, total cultivated land, and household size from year 2000) and Division fixed effects.
(3) 90% confidence intervals are given in brackets for MB estimates in columns (3), (6), and (9).
(4) Estimates are for average treatment effect on the treated (ATT).
(5) Columns 1, 4, and 7 report estimates from OLS with household fixed effects. Columns 2, 5, and 8 report estimates from difference-in-difference-matching (DIDM). Columns 3, 6, and 9 report Minimum Bias (MB) estimates for a large radius (0.25).
(6) Estimates exclude households whose head is older than 70 and households that borrowed more than 80,000 taka from an informal source.

Table 3.14 OLS Estimates of the Impact of MFI Membership on the Amount Borrowed Informally (Intensive Margin), Cross-Section Data

Dependent Variable: current outstanding loan from informal lender (if positive)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Member in any MFI? (yes=1)	1,849.86***	1,708.28***	1,653.06***	1,604.89***	1,377.06***
	(15.53)	(14.78)	(14.04)	(13.67)	(12.00)
Household Variables	No	Yes	Yes	Yes	Yes
Village Variables	No	No	Yes	Yes	Yes
Fixed Effects	No	No	No	District	Upazilla
Number of Observations	7,256	7,256	7,256	7,256	7,256

(1) Robust t-statistics in parentheses.

(2) Significance levels are denoted as *** 1%, ** 5%, and *10%.

Table 3.15 KV-IV with Heckit Estimates of MFI Membership on the Amount Borrowed Informally (Intensive Margin), Cross-Section

Dependent Variable: current outstanding loan from informal lender (if positive)		
	(1)	**(2)**
Member of any MFI (yes=1)	6,160***	6,052***
	(2.95)	(2.94)
Inverse Mills Ratio	-6,319**	-6,211**
	(-2.43)	(-2.41)
First Stage Results:		
IV	0.50***	0.51***
	(5.42)	(5.47)
AP F Statistic	29.39	29.87
Heteroskedastic variables to get IV:	"IV1"	"IV2"
Age of the head of the household	Yes	
Age squared	Yes	Yes
Number of family members over 12 years	Yes	Yes
Total owned land	Yes	
Total cultivable land	Yes	
Household members self-employed in agriculture	Yes	Yes
Household members employed as day laborers	Yes	
Have VGD card (yes=1)	Yes	Yes
Average male agricultural wage	Yes	Yes
average female agricultural wage	Yes	Yes
Moneylender interest rate	Yes	Yes
Distance to secondary school	Yes	
Distance to bank	Yes	Yes
Distance to market	Yes	Yes
N = 7,256		

(1) Source: Cross-section Data
(2) Each model is calculated with household and village controls along with upazilla fixed effects. Household controls are: age of the head of the household, age squared, number of household members over the age of 12, total owned land, total cultivable land, number of household members self-employed in agriculture, number employed as day laborers, and whether the household has a vulnerable group development card (VGD). Village controls are: average agricultural wages for men and women in the village, percent of households in the village that are functionally landless (owning less than 0.1 acre of land), percent of houses using modern technology in cultivation, percent of households with a proper toilet, number of ultrapoor houses in a village, and distance to the nearest secondary school, bank, market, bus stop, and paved road.
(3) Robust t-statistics in parentheses. Significance levels are denoted as *** 1%, ** 5%, and *10%.
(4) Both columns control for the same inverse Mills ratio (IMR). The IMR was calculated by estimating, using heteroskedastic probit, the propensity to borrow informally. The heteroskedastic variables included were: total cultivable land, number of household members working as day laborers, average female agricultural wage, distance to the bank, and distance to the market.

Table 3.16 Effect of New MFI Membership on Informal Borrowing, Panel Data

Dependent Variable: Increased Informal Borrowing (yes=1)						
Control Group:	**Never Member & Dropouts**			**Never Member**		
	(1) OLS	(2) DIDM	(3) MB	(4) OLS	(5) DIDM	(6) MB
FULL SAMPLE						
New MFI Member in 2007 (yes=1)	-0.040***	-0.039***	-0.037	-0.046***	-0.047***	-0.047
	(-2.91)	(-2.81)	[-0.080, 0.010]	(-3.17)	(-3.23)	[-0.090, 0.004]
Number of Observations	1,289	1,289	1,289	1,158	1,158	1,158
SUBSAMPLE OWNING LESS THAN AN ACRE OF LAND						
New MFI Member in 2007 (yes=1)	-0.052***	-0.051***	-0.055	-0.057***	-0.057***	-0.061
	(-2.82)	(-2.82)	[-0.134, -0.010]	(-2.91)	(-2.92)	[-0.122, 0.005]
Number of Observations	804	804	804	717	717	717

Table 3.16 (cont.)

Dependent Variable: Increased Informal Borrowing (yes=1)			
Control Group:		**Dropout**	
	(7) OLS	(7) OLS	(7) OLS
FULL SAMPLE			
New MFI Member in 2007 (yes=1)	-0.009	-0.009	-0.009
	(-0.44)	(-0.44)	(-0.44)
Number of Observations	504	504	504
SUBSAMPLE OWNING LESS THAN AN ACRE OF LAND			
New MFI Member in 2007 (yes=1)	-0.026	-0.017	-0.056
	(-0.85)	(-0.55)	[-0.116, 0.051]
Number of Observations	354	354	354

(1) Robust t-statistics in parentheses in columns 1, 2, 3, 4, 5, 7, and 8. Significance levels are denoted as *** 1%, ** 5%, and *10%.
(2) Each model is calculated with the household controls (age, age squared, education, total owned land, total cultivated land, and household size from year 2000) and Division fixed effects.
(3) 90% confidence intervals are given in brackets for MB estimates in columns (3), (6), and (9).
(4) Estimates are for average treatment effect on the treated (ATT).
(5) Columns 1, 4, and 7 report estimates from OLS with household fixed effects. Columns 2, 5, and 8 report estimates from difference-in-difference-matching (DIDM). Columns 3, 6, and 9 report Minimum Bias (MB) estimates for a large radius (0.25).

Table 3.17 Robustness check—OLS Estimates of the Impact of Microfinance Coverage on the Moneylender Interest Rate, excluding the average agricultural wages, Cross-Section Data

Dependent Variable: Moneylender Interest Rate				
	(1)	**(2)**	**(3)**	**(4)**
Microfinance Coverage (%)	0.13*	0.25***	0.30***	0.27***
	(1.88)	(3.61)	(4.90)	(5.07)
Village Controls	No	Yes	Yes	Yes
Fixed Effects	No	No	District	Upazilla
Number of Observations = 804				

(1) Robust t-statistic in parentheses.
(2) Significance levels are denoted as ***
1%, ** 5%, and *10%.
(3) Village controls are: percent of households in the village that are functionally landless (owning less than 0.1 acre of land), percent of houses using modern technology in cultivation, percent of households with a proper toilet, number of ultrapoor houses in a village, and distance to the nearest secondary school, bank, market, bus stop, and paved road.

Table 3.18 Robustness Check—Lewbel-IV Estimates of the impact of MFI Coverage on the Moneylender Interest Rate, excluding wage controls

Dependent Variable: Moneylender Interest Rate	(1)	(2)	(3)
MFI coverage (%)	0.53***	1.00***	1.07***
	(4.02)	(3.42)	(3.48)
IVs included constructed from:			
% of households with less than 0.1 acre	Yes	Yes	
% using modern technology in cultivation	Yes		
Distance to secondary school	Yes		
Distance to bank	Yes		
Distance to market	Yes		
Distance to bus stop	Yes		
Distance to nearest paved road	Yes		
Use of proper toilet	Yes		
No. of Households in Village	Yes	Yes	Yes
AP F Statistic	16.91	11.87	20.62
Hansen's J P Statistic	0.0000	0.215	NA
Number of Observations	804	804	804

Village controls included are: percent of households in the village that are functionally landless (owning less than 0.1 acre of land), percent of houses using modern technology in cultivation, percent of households with a proper toilet, number of ultrapoor houses in a village, and distance to the nearest secondary school, bank, market, bus stop, and paved road.

4 Microfinance and the Labor Market: How the Spread of Microfinance Impacts Agricultural Wages

4.1 Introduction

Microfinance institutions (MFIs) overwhelmingly target women who are perceived to be better credit risks, and whose empowerment has a large impact on poverty alleviation.[35] While there is a substantial economic literature on the impact of microfinance on the consumption or welfare of women and their families, the same cannot be said of its impact on wages in the labor market.[36] This empirical study addresses this issue by investigating the impact of MFIs on women's agricultural wages, taking Bangladesh as a case study. We investigate both the impact on the general, "Normal", agricultural wage rate and the wage prevailing during the slack season "*Monga*". The Monga season (mid-September through mid-November) strikes parts of Northwestern Bangladesh annually, and is characterized by few jobs, lower wages, and extreme hunger. In addition to the seasonal wage gap, we consider the gender-wage gap.

As women receive microfinance, they leave the agricultural labor force in favor of self-employment. Theory would predict a rise in agricultural wages since the shift of labor from agriculture to microenterprises causes a left-ward shift of the supply curve for agricultural labor, increasing the wage rate at the village level for those villages where labor market is segmented.

Using the data set of over 900 villages shared by the Institute of Microfinance (InM), we estimate the impact of microfinance coverage on the village daily agricultural

[35] See for example Armendáriz and Morduch (2010) for a review.
[36] By labor market, we mean the market for trading one's labor in exchange for a wage. This definition excludes self-employment.

wage earned by women in Northwestern Bangladesh.[37] The challenge in identifying this impact is overcoming the endogeneity bias from the non-random placement of MFIs. We cannot control for every variable that would determine the location choices of MFIs. When such omitted variables also influence the outcome of interest, then OLS will yield biased estimates. We take two approaches to address the endogeneity. First, we employ the Minimum Bias estimator due to Millimet and Tchernis (2012). Second, we exploit heteroskedasticity in the data to achieve identification, specifically we employ the Klein-Vella IV estimator (Klein and Vella 2009a).

We find that microfinance expansion tends to increase the average wages earned by women working in agriculture, both during the Monga and Normal seasons. As MFIs lend to poor women, they will substitute their time away from agricultural wage work in favor of their new or expanding microenterprise. As fewer women participate in the agricultural labor market, i.e. the supply curve of labor shifts to the left, it can be expected that the wage rate increases in response. Those still working in the agricultural wage market, including men, would then benefit from this higher wage. Also, with an alternate source of income, women's bargaining position in the agricultural labor market is improved (Joshi et al 2011).

These results are consistent with findings in the literature as well as with prior expectations. See for example Pitt (2000) which finds that male program credit should induce men to substitute away from supplying agricultural labor to nonagricultural labor, and self-employment financed by MFIs. Binswanger and Khandker (1995) find that credit expansion in rural India has a positive effect on both non-agricultural and (more

[37] This is a larger sub-sample of villages of the InM cross-section, than was used in Chapter 2.

modestly on) agricultural wages. The authors further find a net gain to non-agricultural jobs.

The estimated impact of microfinance on the wages of men is found to be similar in percentage terms (though higher in absolute value) than the impact on women's wages. This is somewhat surprising as MFIs tend to specifically target women. As women leave the labor force, though, it is the men who continue to work in the wage market who would benefit with a higher wage resulting from the decreased labor supply. The wage gap seems to widen significantly during the Monga season, but not during the Normal season. So while increased MFI coverage increases the wages earned by both men and women, the impact on the men's wages is greater which would cause the gap to widen during Monga. Note that by reducing distressed advanced sale of labor during the Monga season, typically at much reduced wage (see Section 2.2), microfinance can be expected to have a positive impact on wages during the Normal season.

The rest of this paper is organized as follows. Section 4.2 briefly reviews the literature and available evidence relating to women working in agriculture. Section 4.3 presents the theoretical framework. Section 4.4 discusses the data set we analyze. Section 4.5 presents our empirical strategy and Section 4.6 analyzes the empirical results. Finally, Section 4.7 concludes.

4.2 Background

Agriculture remains an important sector in Bangladesh. It accounts for almost half of employment and 30 percent of income in 2005 (World Bank 2008). In Bangladesh, the female share of the agricultural labor force, including both self-employed and wage labor, appears to exceed 50 percent (FAO 2011); but wage labor is a

small share of the total as will be shown. In this section, we review the background literature relating to women working in agriculture and how the expansion of credit access is expected to impact the female wage market. We document the segmented nature of credit and labor markets, and address the female labor market, the seasonal wage gap, and the gender wage gap.

4.2.1 Market Imperfections

If markets functioned perfectly and all cleared, then there should not be any significant variation in wages between villages, beyond what can be explained by the cost of migration. Markets however are rarely perfect, with market imperfections often reinforcing one another. As Emran et al (2011) explain, if only one market fails then the remaining markets are able to compensate. However when more than one market fails, inefficiencies arise. Here we consider in turn the imperfections of the rural credit and labor markets.

The credit market is often segmented in developing countries, and this segmentation is largely due to informational asymmetries. Until relatively recently, the only source of credit available to the poor came from the informal sector: friends, family, and moneylenders. These sources are typically better informed of credit risks than a commercial bank would be. Friends and family may extend interest free loans but expect reciprocation or other favors. Moneylenders charge different clients different rates of interest depending on the perceived risk, collateral offered, and relationship with the borrower (Robinson 2001). As such, vastly different interest rates can prevail within the same village. Further, there is evidence of credit rationing. The interest rate serves as a screening mechanism, as only the most risky borrowers are willing to pay the highest

interest rates (Aleem 1993). Lenders prefer less-risky borrowers, so due to adverse selection they may lower the interest rate to attract safer borrowers. At rates below equilibrium, credit is rationed (Stiglitz and Weiss 1981; Ghosh et al 1999).[38]

Like the credit market, the labor market can be fragmented. Basic microeconomic theory would predict that movements of labor between villages in search of higher wages would naturally bring wages for similar work into alignment, as wages are expected to reflect the marginal product of labor. "The price of labor in a perfectly competitive market, like other prices in that impossible place, would be determined by its marginal value product." (Gittinger 1982, p. 258) However, wages vary significantly among the various villages in our data from Northwestern Bangladesh. There is similar wage variation among villages in Northeast rural India (Bardhan 2003a, b). Bardhan (2003a) analyzed a random sample of 110 villages in West Bengal, India, in 1979 and found that wages for casual workers were surprisingly uniform within a village, yet surprisingly different across villages. Even neighboring villages had different wages for the same work with little movement of casual labor between these villages (Bardhan 2003b). Surveying 80 villages in West Bengal in 1981-82, Bardhan (2003b) notes that: "there are sometimes considerable wage differentials on similar work across even neighboring villages; and yet laborers often do not walk across to the next village to take advantage of higher wages." (Bardhan 2003b, p. 238) Bardhan goes on to note that: "The boundaries of labor mobility across neighboring villages are sometimes significantly defined by territorial affinities and the relationship of trust and credit between laborers and their employers." (ibid.) Workers are often more concerned with maintaining a long-term relationship with the employer of their village, rather than a short-term higher wage in the

[38] See Chapter 3 for an analysis of the impact of Microfinance coverage on the informal credit market.

neighboring village. Further, employers are reluctant to hire laborers from neighboring villages because they do not know them well enough, i.e. their trustworthiness and whether they are hard workers.

This is not to suggest that there is no movement of workers between villages, there is, but not in the manner one would expect. There is evidence in India of workers migrating in "perverse" directions, from a high-wage to low-wage village. Workers may also travel greater distances than one would expect. For example, Bardhan (2003b) writes that employers might bring in a worker from a greater distance, barring the costs of transport, housing, and food, etc. Thus, migrant workers may cost the employer more than the local workers would. This might be worthwhile to the employer if the worker possesses certain skills or is easier to control (Bardhan 2003b).

Another explanation of the inter-village wage variation suggested by the literature is the linkage of labor and credit markets practiced in the region. Known as *dadan*, it is common for employers to pay their workers in the lean season in exchange for the promise of their labor during the peak harvesting season. In other words, the worker receives an "advance" on his future wage, and must either work for free or at wage considerably lower than the market rate during the harvest season. This practice has the effect of "tying" workers to their employers, limiting their ability to seek alternative employment. An employer is unlikely to grant a loan to a worker from a neighboring village. It is both harder to trust the neighboring villager and difficult to enforce the repayment of the loan through labor once the peak season arrives (Bardhan 2003b).

The practice of dadan could also explain the finding that wages are only weakly related to how advanced a village is. One would expect that villages using more

developed technology in agriculture (e.g. irrigation, tube wells, pumps, etc.), and therefore more productive, would pay higher wages. Bardhan (2003a) finds that the incidence of loan repayment with labor is significantly higher in more advanced villages. Further, Bardhan (2003a) sites that there is "weak evidence" suggesting that this system of repayment lowers the overall market rate for labor. This finding echoes that of Bhakta (1980), which studied the Northwest part of the Indian State of Bihar, finding only "a weak positive relationship between the wage rate and productivity of labor" (Bhakta 1980, p. 54). He too explains it by the feudal system of tied labor. When labor is not free to move between employers, they cannot negotiate higher wages. It was only in villages that had moved into a "post-feudal capitalist productive relations" that Bhakta found a positive relationship between workers' wages and their productivity.

Economists have long puzzled over the seeming paradox of a downwardly inflexible wage rate, and large numbers of unemployed poor. One thought that these unemployed would jump at any opportunity to work, no matter how low the wage. However, early work by Leibenstein (1957) built on the link between nutrition and work efficiency, and concluded that at too low a wage, workers would not be able to consume enough food to be productive. Stiglitz (1976) extended this efficiency wage hypothesis in the context of developing countries. Dasgupta and Ray (1986) advanced the idea that those without other sources of income (say from owned land or help from relatives) have a higher reservation wage. Those with a small amount of land, though not enough to fully support themselves, would be able to supplement their income by accepting a low wage for work done on another farm. This idea of farming households being both demanders and suppliers of their labor is illustrated by the Agricultural Household Model

(Singh et al 1986). Thus the landless would need a higher wage than the landed to make wage work worthwhile. (See Bardhan and Udry 1999 for a survey of this literature.)

Emran et al (2011) examine the implications of imperfections in the credit and labor markets on poor women. Their paper argues that the lack of credit alternatives can be extended to other missing markets, such as the labor market. When women lack access to the labor market, they will value self-employment opportunities even more (Emran et al 2011; Armendáriz and Morduch 2010). Banerjee and Newman (1993) develop a theoretical model to explain occupational choices of people at different stages of development. Access to the credit market can mean the difference for the marginal poor between being self-employed, being a wage laborer, or unemployed.

4.2.2 Female Labor in Agriculture

In this study, we focus on the labor market for women because MFIs specifically target them. There are several reasons for this, women are more likely than men to be credit constrained, have restricted access to the labor market, and have an unequal share of decision-making power within the household (Pitt et al 2006). Also women are better borrowers, with higher repayment rates and credit to women is more beneficial to the family as a whole (Armendáriz and Morduch 2010). The impact of microcredit is widely acknowledged to depend on the gender of the borrower (see for example, Pitt and Khandker 1998, Pitt et al 1999, Pitt 2000, and Pitt et al 2003). Pitt and Khankder (1998) find that for every 100 taka borrowed by women, consumption expenditures increases by 18 taka (compared to 11 taka in the case of men). Pitt et al (2003) find that loans to

women improve health and nutrition for the children, while finding no significant effect on these outcomes for loans to men.[39]

In rural Bangladesh, it is only the poorest women who turn to the agricultural labor market in search of income.[40] FAO (2011) found that in 2000 in Bangladesh, 3 percent of women participated in the rural wage labor market compared to 24 percent of men. Hossain et al (2004) find that only 12 percent of women (compared to 35 percent of men) participate in the labor force. Goldin (1995) shows that there is evidence to support the idea that women's participation in the labor force over the course of economic development is U-shaped. At low levels of development, women are forced by economic necessity to take unskilled jobs in the wage labor market. Once their husband (or other supporting family member) earns enough to support them, women tend to drop out of the labor force and devote most of their time to domestic work. At higher levels of development, once women have achieved higher education, they opt towards skilled jobs. The case of rural northwest Bangladesh is clearly towards the low end of the development spectrum, where women only participate in the wage market in order to survive.[41]

Working as an agricultural day laborer is physically demanding and poorly paid. There is also often a negative stigma attached to such work. For example, Garikipati (2012) observes that in rural India, wage work is not only physically demanding, badly

[39] On the other hand, loans to men have higher returns to investment (Emran et al 2011). This is likely to be the result of men's better access to market. So there may be a tradeoff between poverty reduction and profit maximization.

[40] Interestingly, one of the inclusion criteria employed by BRAC's TUP (Targeting the Ultrapoor) program was whether the household was dependent upon female domestic work outside the household (Robano and Smith 2013), evidence that women working outside the home is a sign of poverty.

[41] Bangladesh as a whole has seen greater labor market participation by more educated women: participation doubled between 2000 and 2005. In contrast there has been almost no growth in labor market participation among uneducated women. (World Bank 2008)

paid, but is also considered socially demeaning. Working outside the home is thus a signal of one's poverty. Amin (1997) explains that in Bangladesh women working outside the home for a wage is a violation of *purdha* (the practice of social seclusion of women) and is thus associated with a loss of social status.

4.2.3 Gender-Wage Gap

Even worse, women are typically paid less than their male counterparts. Worldwide, "women's participation in rural labor markets varies considerably across regions, but invariably women are over represented in unpaid, seasonal and part-time work, and the available evidence suggests that women are often paid less than men" (FAO 2011). In South Asia, the wage gap is on average between 20 and 40 percent (World Bank 2008). Emran (2011) quotes estimates presented by Hossain and Bose (2004): "women's average wage in agriculture was 58 percent of men's in 2000" (p. 5). Given the situation, it would be preferable for women to either work on their own land or in their own microenterprise, thereby more fully benefiting from their labor. In our data set, the general (non-Monga) average wage earned by women in agriculture is 44 taka (US$0.62) compared to 70 taka ($0.98) earned by men, i.e. women earn 0.62 taka for every taka earned by men. The gender wage gap is similar during Monga, with women earning 35 taka ($0.49) compared to the 54 taka ($0.77) earned by men.[42] These wages are all extremely low by any measure.

4.2.4 Seasonal Wage Gap

Another question to consider is whether microfinance helps to narrow the wage gap between Monga and Normal seasons in Bangladesh. To recall, the Monga season

[42] Daily wages converted from taka into dollars at the average 2006 exchange rate 0.0142 dollars/taka (http://www.oanda.com/currency/historical-rates/).

(mid-September through mid-November) strikes parts of Northwestern Bangladesh annually, is a period of few jobs, shortfall in income, and extreme hunger. Agriculture is by its very nature seasonal, so some variation in income is to be expected. The situation in Greater Rangpur, which encompasses the Districts of Gaibandha, Kurigram, Lalmonirhat, Nilphamari, and Rangpur, however, is arguably extreme. To put this into context, while normally only 2 percent of households reported being without work for 4-7 days a week in Bangladesh overall, during the Monga season this figure leaps to 62 percent (Rahman and Hossain 1995).

In the Monga of October 1991, Greater Rangpur experienced an average 50 percent drop in the daily wage rate compared to the rest of the year (Rahman 1995). The existing evidence shows that the inhabitants of this region are poorer than the rest of the country in terms of a variety of indicators including income. Extreme poverty in Greater Rangpur is 42 percent compared to the national rural average of 27 percent. Also, the daily wage rate for male agricultural worker in Greater Rangpur is 46 taka compared to 64 taka found elsewhere (Khandker et al. 2010b).

With lower demand for labor during the slack season of Monga, the agricultural wage is much lower than it normally is throughout the year. As reported in Table 4.1, the average daily women's agricultural wage in the three Districts we focus on in this study (Gaibandha, Lalmonirhat, and Nilphamari) is 34 taka during Monga as compared to 42 taka generally, a 19 percent drop. For Bangladesh as whole, in 1991 there was an average drop of 30 percent in October compared to the rest of the year with Greater Rangpur experiencing a 50 percent decline (Rahman and Hossain 1995).

4.3 Theoretical Framework

To illustrate the theoretical implications of MFI expansion on agricultural wages, consider the Bardhan (1983) model of labor-tying in a poor agrarian economy. Suppose there are two seasons: a lean season (i.e. Monga) during which there is no agricultural work and a peak season (i.e. Normal) with a random labor demand. Labor demand during the peak season depends on the agricultural yield to be harvested which is uncertain due to weather and other potential shocks. There are two types of agents in this model: landed employers and functionally landless workers. For simplicity, assume that there are *N* workers and one employer.

To ensure a reliable supply of labor during the peak season, the employer hires workers during the lean season. These workers are "tied labor", i.e. they are effectively selling their labor in advance. The tied workers receive some compensation in advance during the lean season, and agree to work during the peak season at rate lower than the spot market wage. Tied workers earn the same amount during both the lean and peak season. If the employer needs more workers during the peak season than he has already hired, then he turns to the casual labor market. Casual workers are paid at the spot market wage rate. Tied workers are unable to sell their labor at the going spot wage, having already entered into a tied arrangement. The model assumes that workers cannot split their time between tied labor and casual wage work. The employer decides how many tied workers to hire in the lean season so as to maximize his expected profit.

The worker decides whether or not to enter into a tied arrangement so as to maximize his utility. A worker who does not enter into a tied contract expects to receive y_0 during the lean season and $y > y_0$ during the peak season. In other words, y_0 and y

are the worker's opportunity cost of accepting a tied labor contract. This income could come, for example, from self-employment. Workers are assumed to all have the same y_0 during the lean season, but differ in the value of the outside option y they can expect during the peak season.

If the casual wage is greater than the outside option, then the worker enters into the casual labor market during the harvest period. All those workers with expected outside income below a certain threshold ($y \leq \bar{y}$) will enter into the tied contract and those with expected income above that threshold ($y > \bar{y}$) will either be self-employed or enter the casual labor market.

The expansion of microfinance in the village has the effect of increasing the values of both y_0 and y. The model implies that this expansion should both reduce the amount of tied labor supplied and increase the wage offered in the casual labor market. Gulesci (2010) considers the same theoretical framework to analyze the implications of an increase in the outside options on poor women's participation in tied labor and similarly finds that the wages in the labor market increase through two channels: (i) because workers are switching from tied to casual labor and (ii) through general equilibrium effects in the village labor market.

The introduction of microfinance can be thought of as a proxy raising the outside option of women, or introducing a new option that was not previously available. Before the introduction of microfinance, the ultrapoor had limited options: either work for a casual wage or as a tied laborer. The option of self-employment simply did not exist for most of the poorest of the poor. With the availability of microcredit, poor women were

able to use these loans to start microenterprises, opening up the possibility of earning income from an outside source.

In our particular case, the evidence shows that relatively few workers enter into formal tying arrangements (see Table 2.1). Nonetheless, even if workers and employers are not formally tied, similar to the Bardhan (1983) findings, labor mobility across neighboring villages is likely limited by territorial affinities and the relationship of trust and credit between laborers and their employers, among other factors.

Under these circumstances, a more appropriate theoretical model may be the missing market model of Emran et al (2011). This model deals more comprehensively with the sources of segmentation in the labor market, and while the focus is on the female labor market, the authors point out that "the main conclusions are gender-neutral, as long as the labor market is 'missing' or characterized by significant transaction costs." (p. 2). The authors demonstrate that where the market for female labor exists, the selling price (i.e. the effective rate after netting out transaction costs defined as the monetary and non-monetary costs of participating in the outside labor market) is, in general, much lower than the buying price (i.e. the wage paid by the employer). The model applies to the "missing" labor market at the household level, but the same logic can be applied to the village level.

There are many transaction costs. On the demand side, the transaction costs of employing hired labor reflect the cost of controlling for moral hazard. Consistent with Bardhan (1983) employers favor well-known workers over new recruits because the latter's productivity is more uncertain and requires more supervision, meaning that the shadow wage they are willing to pay is $W_d = W - T_d$ (where W is the zero transaction

cost competitive labor market wage rate and T_d is the transaction cost incurred by the employer).

On the supply side, the transaction costs include the costs of information and job search in the labor market. Also, there are well-documented large social costs for women working outside the family, and cultural norms limit women's access to paid employment (see Section 4.2.2). Furthermore, jobs outside the family are not easily compatible with raising children, creating additional costs of working outside the home. Finally, in our analysis of wages across villages, there are transportation costs associated with moving to the broader labor market and for most women, a quasi-impossibility in seeking work outside the village. This means that the shadow wage rate laborers are willing to accept is $W_s = W + T_s$ (where T_s is the transaction cost incurred by the laborer).

Due to the transaction costs, there is a wedge between the buying and selling price of labor equal to $T_d + T_s$. In the missing market model, the analysis simplifies the transaction costs by only considering T_s. With a positive T_s, the net wage faced by a worker who is a net seller of labor is lower compared to the neoclassical labor market with zero transaction costs. Note that the effective wage faced by the laborer is a negative function of the transaction costs.

In any case, Emran et al (2011) models transaction cost in terms of a "band" that reflects the wedge between the wage paid by the employer and the labor price received by the worker. In effect, the paper shows that when the participation costs are high, which is likely to be the case for our village laborers in Northwestern Bangladesh (especially for the poor women), there is a transaction costs band and the households (in our case villages) that fall in the band effectively face a closed internal market. When an

MFI reaches such a village, it increases the equilibrium wage. As women receive microfinance, they have the option to leave the agricultural labor force in favor of self-employment. This causes a leftward shift of the supply curve of labor, thus increasing the wage rate.

However, there is an upper bound: if the effect of the MFI is so strong as to push the wage beyond the top of the band, then the village labor market becomes integrated with the broader labor market. That is, as the wage rises it will reach a point when it overcomes the transaction costs of worker movement between villages. In brief, when labor markets are integrated across villages, MFI coverage will make no difference to the determination of wages. However, as long as the village falls within the transaction band, its labor market is isolated and microfinance will have a wage effect. How much of an effect will depend on the transaction costs across villages. Our analysis of the literature has shown that transaction costs are likely to be significant in Northwestern Bangladesh village labor markets. Therefore we can expect an effect of MFI on wages. Below, we attempt to quantify that effect.

4.4 Data

In analyzing the impact of MFI coverage on wages, we use the InM cross-section data set (Section 2.4). The questionnaire used in Gaibandha, Lalmonirhat, and Nilphamari collected village information from local NGO offices including: agricultural wages of men and women broken down by season, average moneylender interest rates, and distances to the nearest bank, market and school. Unfortunately, these are missing for a large number of villages. We drop outliers and observations with zero as the

recorded agricultural wage. Further, we trim unrealistically high observations for wages. In the end we limit the analysis to a sample of 942 villages.

Our focus variable, MFI coverage, is defined as the percent of households in a village that are members of any MFI (where village size is taken to be the number of MFI members and nonmembers reported).[43] We find that the villages we study have on average 43 percent MFI coverage. The outcome variables we concentrate on are the daily agricultural wage earned by women during the Monga season and Normal times. For comparison, we also consider the wages of men.

4.5 Empirical Strategy

To guide us in our analysis of the causal impact of microfinance coverage on agricultural wages, consider the following triangular model:

$$W_{ijk} = \beta_0 + \beta_1 MF_j + X_j\gamma + u_j \quad (4.1)$$

$$MF_j = \alpha_0 + X_j\delta + v_j \quad (4.2)$$

Here, equation (4.1) is the outcome equation depicting how agricultural wages (W_{ijk}) during season *i* (Monga or Normal) in village *j* and gender *k* (Women or Men) depend on microfinance coverage (MF_j), village characteristics and regional fixed effects (X_j). We define microfinance coverage as the percent of households in the village that are members of any MFI. Equation (4.2) is the selection equation, showing how microfinance coverage depends on the same set of control variables. Identification of the parameter of interest, β_1, i.e. the causal impact of microfinance coverage on wages, is complicated by the endogeneity of microfinance coverage.

[43] Recall that only ultrapoor households are included in the sample. So a village with 100 percent MFI coverage only means that 100 percent of the ultrapoor households in that village are MFI members.

4.5.1 Identification challenge

The challenge in identifying the impact of microfinance coverage on average agricultural wages is overcoming the endogeneity bias from the non-random placement of MFIs. We cannot control for all the factors which determine the location choices of MFIs, and when these unobserved variables also determine the agricultural wages, the OLS regression would in general yield biased results. The direction of the bias would depend on the impact of these omitted variables on both microfinance coverage and agricultural wages.

It seems reasonable to assume that the more productive (less poor) a village is, the higher their agricultural wage should be. Findings in the literature suggest that MFIs' location choices are influenced by villages' economic potential (see for example Armendáriz and Morduch 2010, Zeller et al 2001, and Sharma and Zeller 1999). An MFI may choose to locate in a relatively less-poor village so as to ensure repayment of loans, which aids in attracting donor funding. Zeller et al (2001) find that MFIs choose to locate in less poor villages and target the poorer members of those villages. Some of this may be driven by infrastructure considerations, it is easier to set up in a better connected village. In this case, the omitted indicators of the village's potential would bias the OLS results upwards. If on the other hand, MFIs are guided by poverty reduction goals, they may be more likely to target poorer villages. In this situation, the OLS estimates would be biased downwards. Measurement error could also bias OLS towards zero.

4.5.2 Choice of Village Controls in X_j

As a starting point, it is important to select a set of controls which would serve to minimize any potential bias. To this end, we include a set of variables which serve to

indicate a village's level of economic development. Also, we focus on variables which shed light on the extent to which a village is integrated with the market. The village characteristics we control for are the percent of landless households in the village, percent of households in a village that use modern technology in cultivation, the distance to the nearest bank, the distance to the nearest market, the average amount of land a household owns in the village, and the total number of villagers over 12 years old in the village.

The percent of landless households in a village serves as an indicator of a village's level of poverty. The more landless households in the village the poorer it is. Since it is the poor who turn to the agricultural wage market, the percent of landless also serves as an indicator of the labor supply. Villages using modern technology in agriculture, e.g. irrigation, are expected to be more productive which would influence both agricultural wages and microfinance coverage. The distance to the nearest market indicates how integrated the village is with the local market, the closer the village is to the local market the easier it is for farmers and craftsmen to sell their produce. The distance to the nearest bank similarly indicates how integrated a village is to other services such as credit. Banks provide credit to the landed households in the village, i.e. those who demand labor. We include average landholding to capture the direct effect of land on the wage. The larger the average landholding is in the village, the more landed households there are and so there is a greater demand for labor. Including the total number of people in the village over the age of 12 gives us an idea of the labor supply.

4.5.3 Minimum Bias and KV-IV Estimators

The traditional approach to omitted variables bias is to employ an instrumental variable (IV) in a two-stage least squares model. However, to be credible an IV must

have both a direct effect on the endogenous treatment (microfinance coverage) and be independent of the outcome (wages). Given the current context, it is extremely difficult if not impossible to find a valid IV. Anything that influences microfinance coverage is likely to also influence wages. For example, distance to the nearest bank certainly influences microfinance coverage, since MFIs tend to locate near banks. However, landed villagers who hire labor are also likely to borrow from these commercial banks, which would influence wages. Other candidate IVs were considered and rejected as they failed either the exclusion restriction or the weak identification tests.

In the absence of a traditional IV, we turn to recent developments in econometrics to achieve identification. In particular, we employ the methods developed by Klein and Vella (2009a) and Millimet and Tchernis (2012). In order to implement these techniques, we must first transform our endogenous variable, MFI coverage, into a binary treatment. That is, we define a dummy equal to one if the MFI coverage is greater than the average of 40 percent and equal to zero if coverage is less than the average.

As an intermediate step, we employ the Minimum Bias (MB) estimator of Millimet and Tchernis (2012). The MB estimator builds on the Inverse Propensity Weighting (IPW) estimator of Hirano and Imbens (2001), which weighs the treatment observations by the inverse of the propensity score; and then the MB trims the sample so as to minimize any potential bias arising from omitted variables. Millimet and Tchernis (2012) report Monte Carlo evidence supporting their MB estimator.

Klein and Vella (2009a) show that heteroskedasticity in the selection equation is sufficient to provide an exclusion restriction. Their paper provides Monte Carlo simulations supporting the strength of their estimator. Millimet and Tchernis (2012)

apply a parametric version of the Klein and Vella estimator (KV-IV), making the additional assumption of normally distributed errors and parametric form for the heteroskedasticity of the variance of MFI coverage. That is, they assume the parametric form:

$$S_{vj}^2 = \exp(Z_j\theta_v)$$

Where $S_{vj}^2$is the variance of the errors of the selection equation v_j, and Z_j is a set of exogenous variables which could either equal the set of controls, X_j, or a subset of it. Note that this parametric form for heteroskedasticity, originally due to Harvey (1976) is the same as the form assumed in Farré et al (2013). Millimet and Tchernis (2012) report Monte Carlo simulations supporting the strength of this parametric version of the KV-IV.

To employ the parametric KV-IV, one first estimates the following equation by heteroskedastic probit:

$$dMF_j = 1(\phi_0 + X_j\psi + \mu_j > 0) \qquad (4.3)$$

Where dMF_j is the dummy indicating high MFI coverage (i.e. greater than the average). From this, we predict fitted values for high MFI Coverage and use it as an IV.

4.6 Empirical Results

4.6.1 Preliminary Results

We begin our analysis with simple OLS regressions, reported in Table 4.2. For each of the outcomes (women's wage during Monga, women's wage normally, men's wage during Monga, and men's wage normally), we estimate three specifications. Panel A reports the estimates for women's wages, and Panel B reports the estimates for men's wages.

First, we estimate a bivariate model of wage on the percent of MFI coverage in the village. For each outcome, we find that MFI coverage is positively correlated with the wage, and significantly so. Second, we add village level variables (see section 4.5.2 above). As we add these village characteristics to the model, the estimated correlation decreases slightly but remains significant. These control variables provide further insight to wage determination. As expected, increased use of modern technology in cultivation is significantly and positively correlated with the wage rate. Distance to the bank is negatively correlated. Surprisingly, distance to market is positively correlated with the wage rate. This is intriguing, as we expect that the farther away a village is from the market, the poorer it is, and so the lower its agricultural wages are expected to be (see for example Emran and Hou, forthcoming). Interestingly, Barua (2010) includes distance to town as a control variable determining agricultural wages, expecting to find a negative impact. Instead, the effect is not statistically significant. So perhaps it is not a given that remote villages pay higher wages. Third, we include District fixed effects to account unobserved heterogeneity. The inclusion of these fixed effects leads to a fall in both the magnitude and significance of the estimated impact. The correlation with women's wages remains significant at the 10 percent level. Here we find that an increase in MFI coverage by 1 percentage point is estimated to increase the average wage rate by 0.0400 taka during Monga (Table 4.2, column (3)) and by 0.0466 taka in normal times (Table 4.2, column (6)). In the case of men, we find that an increase in MFI coverage increases men's wage during Monga by 0.0610, significant at the 5 percent level (Table 4.3, column (3)) and by 0.1180 during the normal season, not statistically significant (Table 4.3, column (6)).

It is interesting to note that the impact on men's wages is larger—in absolute value—than that for women, and significantly so during the Monga season. Relative to the average though, given that the men are already earning higher wages to begin with, the impact is comparable. OLS estimates reported in Table 4.7 show that as MFI coverage increases, the wage gap seems to widen significantly during the Monga season, but not during the Normal season. It is comforting though, that the wage gap is widening as a result of men's wages increasing by a larger margin than those of women rather than if women's wages were to decrease. So while increased MFI coverage increases the wages earned by both men and women, the impact on the men's wages is greater, which cause the gap to widen during Monga. These OLS results may still be biased due to unobserved village heterogeneity. Below we present estimated results from alternate estimators, Minimum Bias, and KV-IV.

4.6.2 Minimum Bias

As discussed above in section 4.5.3, to take advantage of the Minimum Bias estimator we must first transform the continuous endogenous variable (MFI Coverage) into a binary treatment indicator, where treatment is "high" MFI Coverage. We define the binary treatment as equal to one if MFI Coverage is greater than the average (40 percent) and zero if it is less. Table 4.5 presents the estimated Average Treatment Effect on the Treated (ATT) of High MFI Coverage on agricultural wages using the MB estimator (columns 2 and 4). As a reference, we include OLS estimates (columns 1 and 2). All the estimates control for village characteristics and District Fixed Effects.

Comparing the estimated impact of high MFI coverage from the two estimators, we find that the MB estimates are systematically higher than the OLS. For each

outcome, MB predicts similar impacts, high MFI coverage is associated with about a 6 taka increase in the average wage. The 90 percent confidence interval is significant for the impact on women's wages (Panel A). The MB estimate is not significant in the case of men's wages. When considering the gender wage gap, we do not find a significant impact (Table 4.7).

While the preliminary OLS results (section 4.6.1) showed that the estimated impact of MFI coverage decreased and weakened as one added controls suggesting that the bias was positive, the MB estimator seems to be minimizing a negative bias. This negative bias can be from omitted village productivity. As discussed above in section 4.5.1, if MFIs are guided by poverty reduction goals, they would be more likely to target poorer villages, and so OLS estimates would be biased downwards. Measurement error could also bias OLS towards zero.

4.6.3 KV-IV Estimates

We turn now to the estimated results using the Klein-Vella IV strategy (Klein and Vella 2009a). We estimate two specifications: first we assume that all the exogenous variables contribute to heteroskedasticity in the selection equation and define IV1; and second we use only the percent of modern technology use in cultivation and the distance to bank as sources of heteroskedasticity to define IV2. As discussed above in section 4.5.1, one would expect that MFI coverage to be lower in poorer villages, i.e. those that are further away from the nearest bank and those with a lower percent of modern technology use, given that MFIs are less likely to locate there. This would suggest that the error term in the MFI coverage equation would have a lower variance the farther the village is from the bank and a higher variance when the percent of modern technology

use is lower. When estimating equation (4.3) by heteroskedastic probit, both use of modern technology in cultivation and distance to the bank are found to be significant contributors to the heteroskedasticity. The LR Test also firmly rejects the null that the errors are homoskedastic, thus it is appropriate to proceed with KV-IV. The Angrist-Pischke F test of excluded instruments is far greater than 10, the rule of thumb critical value needed for strong instruments. The KV-IV estimates using IV1 and IV2 are reported in Table 4.8, Table 4.9, and Table 4.10.

Consider first the impact of high MFI coverage on women's agricultural wage during Monga. Using both IV1 and IV2 we find a positive impact of about 7 and 9 respectively, significant at the 10 percent level. In other words, as MFI coverage becomes high (i.e. the dummy switches from zero to one), the agricultural wage of women increases by about 8 taka relative to the average. The case of women's wages during normal times is interesting, we find a similar positive impact in both cases but it is only significant when using IV1 and not when we use IV2. Turning to the results for men, we find even higher estimated impacts of high MFI coverage on the agricultural wages. The KV-IV estimates are more than double those of MB for men's wages. It is interesting to find that high MFI coverage should have such a high impact on men's wages, considering that MFI typically target women. The KV-IV finds some evidence that the gender gap is widened during Monga, but only when using IV1 and not with IV2, so the finding is not very robust.

Across the board, the KV-IV estimate of the impact of high MFI coverage is considerably greater than the corresponding OLS and MB estimates. The difference between these sets of estimates could be explained in part because the MB and KV are

estimating two different things. The MB estimates the average treatment effect while the KV-IV estimates the local average treatment effect (see Angrist and Pischke 2009). Further, the KV-IV suffers from large variance so the point estimate should be treated with caution. It is possible that the KV-IV is overestimating the impact of microfinance coverage on the agricultural wages. Nonetheless, the KV-IV provides further evidence that the impact on wages is positive and significant. Considering the magnitude of the estimated impacts, we find that OLS < MB < KV-IV. This adds credibility to the notion that the bias is downward, and by first minimizing it with MB and then correction for it with KV-IV, we get closer to the actual estimated impact. Overall, we are confident that MFI coverage has a positive impact on wages, especially during the Monga season.

4.7 Conclusions

In this study, we considered the impact of microfinance coverage on women's agricultural wages during both the Monga and Normal seasons. We also considered the impact on men's agricultural wages. Overall, we find that increased microfinance coverage is associated with higher agricultural wages on average across villages for both women and men, during both the Monga and Normal seasons. The significant positive impact on women's agricultural wages is found in each of the different estimators used: OLS, MB, and KV-IV. As discussed above, OLS underestimates the impact of microfinance on wages due to the selection bias. Given the magnitude of its estimates, KV-IV likely overestimates the impact due to the large variance of IV estimators. MB, one could argue, provides the most reliable estimates in this instance. MB estimates the ATT of high MFI coverage to be 5 taka during Monga, this finding is significant as the 90 percent confidence interval does not cross zero. High MFI coverage is expected to

increase the male wage during Monga by four taka. Given that MFIs target women, we would expect a larger impact on the wages of woman as compared to men. As a percentage of the average wage in the village, the impacts on men and women's wages are comparable for each of the estimators.

These findings are consistent with the theory that as women receive microfinance, they leave the agricultural labor force in favor of self-employment. This causes a left-ward shift of the supply curve of agricultural labor, increasing the wage rate at the village level for those villages that fall within a transaction band. Past a certain point, the increase in wages will overcome the transaction costs of movement between villages and labor markets will become integrated.

In the limited instances of dadan in our case—receiving pay during Monga for the promise of labor during the harvest—the Monga determines in part the non-Monga average wage. Similar logic may well apply to those more frequent instances of bonded labor due to territorial affinities and the relationship of trust between laborers and their employers. We pointed to some evidence in the literature that the practice of advanced sale of labor decreases the average wage outside of the lean season. Chapter 2 of this dissertation showed that microfinance significantly reduced the advanced sale of labor in Northwestern Bangladesh. With access to credit, women are better able to feed their families; so that they and other members of the household can better avoid advanced sale of their labor. This could explain in part why the impact of MFI coverage is stronger during the normal season than during the Monga season. By improving the situation during Monga microfinance has an even greater impact during the non-Monga season,

when some laborers, both men and women, are available to work at going wage, instead of discounted wages previously.

These findings could also be an indication of women's increased bargaining power. As microfinance offers women an alternative source of income—namely from self-employment in a microenterprise—they are in a stronger position to negotiate higher wages for themselves, with some impact on the average labor market wage. Joshi et al (2011) develop a theoretical model in which an alternative employment opportunity leads to employees' increased bargaining power. The examples given in the paper include that of BRAC, which through its microfinance and other programs increased the bargaining power of laborers. In sum, we find evidence that not only women borrowers, but also women laborers have been empowered by the spread of microfinance.

Table 4.1 Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Women's Daily Wage, Monga (Taka)	34.56	12.78	10	80
Women's Daily Wage, Normal (Taka)	43.70	13.99	15	100
Men's Daily Wage, Monga (Taka)	54.34	15.97	15	100
Men's Daily Wage, Normal (Taka)	69.62	30.72	20	650
MFI Coverage (%)	40.32	22.55	0	100
Functionally Landless Households in Village (%)	77.85	12.33	8.33	100
Households with Irrigation (%)	61.23	30.01	0	100
Distance to commercial bank (km)	4.74	4.09	0	30
Distance to market (km)	4.04	3.55	0	30
Population Density	0.28	0.14	0.06	1.57
Number of observations = 942				

Table 4.2 OLS Estimated Impact of MFI Coverage on Women's Agricultural Wages

Dependent Variable	(1) Women's Monga Wage	(2) Women's Monga Wage	(3) Women's Monga Wage	(4) Women's Normal Wage	(5) Women's Normal Wage	(6) Women's Normal Wage
MFI Coverage (%)	0.0825***	0.0694***	0.0402*	0.0917***	0.0777***	0.0469**
	(4.181)	(3.342)	(1.884)	(4.299)	(3.460)	(2.053)
Functionally Landless Households in Village (%)		0.0695	0.00542		0.134***	0.0403
		(1.576)	(0.122)		(2.712)	(0.838)
Households with Irrigation (%)		0.0457***	0.0389***		0.0687***	0.0654***
		(3.402)	(2.998)		(4.581)	(4.568)
Distance to Bank (km)		-0.253**	-0.317***		-0.145	-0.268*
		(-2.090)	(-2.601)		(-1.056)	(-1.936)
Distance to Market (km)		0.637***	0.555***		0.676***	0.587***
		(4.116)	(3.694)		(3.909)	(3.501)
Population Density		-0.385	1.039		-5.117	-4.263
		(-0.0796)	(0.224)		(-1.106)	(-0.995)
District = Lalmonirhat (yes=1)			-6.423***			-8.898***
			(-7.361)			(-9.142)
District = Nilphamari (yes = 1)			-4.107***			-2.301*
			(-3.423)			(-1.721)
Constant	31.23***	22.28***	30.97***	40.00***	25.28***	36.90***
	(35.99)	(7.306)	(9.326)	(42.88)	(7.094)	(9.867)
Observations	942	942	942	942	942	942

* Significant at 10%; ** Significant at 5%; *** Significant at 1%
Robust t-statistics are in parenthesis.

Table 4.3 OLS Estimated Impact of MFI Coverage on Men's Agricultural Wages

Dependent Variable	(1) Men's Monga Wage	(2) Men's Monga Wage	(3) Men's Monga Wage	(4) Men's Normal Wage	(5) Men's Normal Wage	(6) Men's Normal Wage
MFI Coverage (%)	0.134***	0.125***	0.0616**	0.206***	0.189**	0.119*
	(5.154)	(4.872)	(2.501)	-2.798	(2.572)	(1.680)
Functionally Landless		0.179***	0.0317		0.281***	0.0705
Households in Village (%)		(3.114)	(0.597)		(2.956)	(0.714)
Households with Irrigation (%)		0.0618***	0.0480***		0.0895***	0.0818***
		(3.561)	(2.959)		(4.559)	(4.479)
Distance to Bank (km)		-0.238	-0.394***		-0.259	-0.533***
		(-1.612)	(-2.713)		(-1.525)	(-3.148)
Distance to Market (km)		1.190***	1.010***		1.135***	0.934***
		(6.057)	(5.491)		(5.187)	(4.495)
Population Density		-10.11*	-7.189		-16.68***	-14.71***
		(-1.867)	(-1.503)		(-2.746)	(-2.754)
District = Lalmonirhat (yes=1)			-14.66***			-19.95***
			(-13.79)			(-11.94)
District = Nilphamari (yes = 1)			-8.387***			-5.302***
			(-6.443)			(-3.269)
Constant	48.93***	30.64***	50.35***	61.32***	35.92***	61.98***
	(43.79)	(7.240)	(12.18)	(26.35)	(5.217)	(8.588)
Observations	942	942	942	942	942	942

* Significant at 10%; ** Significant at 5%; *** Significant at 1%
Robust t-statistics are in parenthesis.

Table 4.4 OLS Estimated Impact of MFI Coverage on the Gender Gap[44]

Dependent Variable	(1) Gender Gap, Monga	(2) Gender Gap, Monga	(3) Gender Gap, Monga	(4) Gender Gap, Normal	(5) Gender Gap, Normal	(6) Gender Gap, Normal
MFI Coverage (%)	0.0517***	0.0560***	0.0214	0.114	0.111	0.0723
	(3.281)	(3.629)	(1.349)	(1.573)	(1.537)	(1.025)
Functionally Landless Households in Village (%)		0.110***	0.0263		0.147*	0.0302
		(2.671)	(0.661)		(1.722)	(0.324)
Households with Irrigation (%)		0.0161	0.00910		0.0208	0.0164
		(1.415)	(0.818)		(1.423)	(1.117)
Distance to Bank (km)		0.0153	-0.0769		-0.115	-0.266**
		(0.182)	(-0.903)		(-1.047)	(-2.368)
Distance to Market (km)		0.553***	0.455***		0.458***	0.347***
		(5.559)	(4.761)		(3.444)	(2.609)
Population Density		-9.730***	-8.228**		-11.56***	-10.45**
		(-2.715)	(-2.309)		(-2.660)	(-2.392)
District = Lalmonirhat (yes=1)			-8.236***			-11.05***
			(-10.20)			(-7.742)
District = Nilphamari (yes = 1)			-4.280***			-3.002**
			(-4.173)			(-2.193)
Constant	17.70***	8.360***	19.38***	21.31***	10.64*	25.09***
	(24.63)	(2.981)	(6.884)	(9.649)	(1.797)	(3.858)
Observations	942	942	942	942	942	942

* Significant at 10%; ** Significant at 5%; *** Significant at 1%
Robust t-statistics are in parenthesis.

[44] The gender gap is calculated as the difference between the male and female wage for each season.

Table 4.5 Women's Agricultural Wage, OLS and MB Results

Dependent Variable	(1) Women's Monga Wage	(2) Women's Monga Wage	(3) Women's Normal Wage	(4) Women's Normal Wage
	OLS	MB	OLS	MB
Dummy for High MFI Coverage	1.479	5.493	1.785	5.719
	[-0.169, 3.105]	[0.607, 7.965]	[0.142, 3.328]	[0.745, 8.327]
Observations	942	942	942	942

Table 4.6 Men's Agricultural Wage, OLS and MB Results

Dependent Variable	(1) Men's Monga Wage	(2) Men's Monga Wage	(3) Men's Normal Wage	(4) Men's Normal Wage
	OLS	MB	OLS	MB
Dummy for High MFI Coverage	2.736	4.180	3.796	3.080
	[1.214, 4.231]	[-0.668, 6.965]	[1.430, 6.818]	[-1.240, 7.328]
Observations	942	942	942	942

Minimum Bias (MB) estimated using the Stata code of Millimet and Tchernis (2012). The MB estimate of the average treatment effect on the treated (ATT) is presented in columns (2) and (4) with the 90% Confidence intervals are given in brackets.
The dummy for high MFI coverage is equal to one if MFI coverage is greater than the average (40%) and zero if it is less.
Each specification controls for village characteristics variables (percent of landless households, percent of households using modern technology in cultivation, distance to the bank, distance to the market, and villagers over age 12) and includes District Fixed Effects.

Table 4.7 Gender Wage Gap,[45] OLS and MB Results

Dependent Variable	(1) **Gender Gap, Monga**	(2) **Gender Gap, Monga**	(3) **Gender Gap, Normal**	(4) **Gender Gap, Normal**
	OLS	MB	OLS	MB
Dummy for High MFI Coverage	1.257	-1.312	2.012	-2.639
	[0.191, 2.479]	[-3.141, 1.297]	[-0.455, 4.612]	[-4.893, 1.406]
Number of Observations	942	942	942	942

Minimum Bias (MB) estimated using the Stata code of Millimet and Tchernis (2012), bmte.ado. The MB estimate of the average treatment effect on the treated (ATT) is presented in columns (2) and (4) with the 90% Confidence intervals are given in brackets.
The dummy for high MFI coverage is equal to one if MFI coverage is greater than the average (40%) and zero if it is less.
Each specification controls for village characteristics variables (percent of landless households, percent of households using modern technology in cultivation, distance to the bank, distance to the market, and villagers over age 12) and includes District Fixed Effects.

[45] The gender gap is calculated as the difference between the male and female wage for each season.

Table 4.8 Women's Wages, KV-IV

Dependant Variable	(1)	(2)	(3)	(4)
	Women's Monga Wage		Women's Normal Wage	
	IV1	IV2	IV1	IV2
Dummy for High MFI Coverage in a Village	11.021**	10.470**	14.967***	10.207*
	(2.45)	(1.93)	(3.02)	(1.77)
Functionally Landless Households in Village (%)	-0.011	-0.010	0.019	0.024
	(-0.25)	(-0.23)	(0.38)	(0.50)
Using modern technology in cultivation (%)	0.022	0.023	0.042**	0.051***
	(1.48)	(1.46)	(2.50)	(3.02)
Distance to Bank (km)	-0.181	-0.190	-0.074	-0.152
	(-1.30)	(-1.29)	(-0.48)	(-0.95)
Distance to Market (km)	0.614***	0.611***	0.667***	0.641***
	(4.02)**	(3.99)	(3.92)	(3.79)
Village Population over 12 years old	1.977	1.935	-3.008	-3.370
	(0.43)	(0.43)	(-0.69)	(-0.80)
District = Lalmonirhat (yes=1)	-5.002***	-5.095***	-6.886***	-7.686***
	(-3.93)	(-3.73)	(-4.81)	(-5.39)
District = Nilphamari (yes = 1)	-1.332	-1.502	1.589	0.119
	(-0.64)	(-0.65)	(0.71)	(0.05)
Constant	27.529***	27.804***	31.830***	34.203***
	(6.90)	(6.50)	(6.97)	(7.33)
LR Test of Homoskedasticity				
χ^2	29.56	17.84	29.56	17.84
p-value	0.0001	0.0001	0.0001	0.0001
First State of IV Regression				
Angrist-Pischke F Statistic	41.23	29.88	41.23	29.88
p-value	0.0000	0.0000	0.0000	0.0000
Observations	942	942	942	942

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.
Robust t-statistics are in parenthesis.

Table 4.9 Men's Wages, KV-IV

Dependant Variable	(1) Men's Monga Wage IV1	(2) Men's Monga Wage IV2	(3) Men's Normal Wage IV1	(4) Men's Normal Wage IV2
Dummy for High MFI Coverage in a village	20.860***	15.238**	19.269**	15.471*
	(3.67)	(2.33)	(2.24)	(1.72)
Functionally Landless Households in Village (%)	0.002	0.009	0.037	0.041
	(0.04)	(0.16)	(0.36)	(0.40)
Using modern technology in cultivation (%)	0.014	0.025	0.057**	0.064**
	(0.70)	(1.26)	(2.03)	(2.43)
Distance to Bank (km)	-0.120	-0.213	-0.351	-0.413*
	(-0.68)	(-1.19)	(-1.33)	(-1.62)
Distance to Market (km)	1.121***	1.091***	1.035***	1.014***
	(6.13)	(6.10)	(4.77)	(4.81)
Village Population over 12 years old	-5.450	-5.877	-12.950**	-13.239**
	(-1.12)	(-1.25)	(-2.41)	(-2.52)
District = Lalmonirhat (yes=1)	-11.815***	-12.759***	-17.990***	-18.628***
	(-7.00)	(-7.59)	(-5.84)	(-6.35)
District = Nilphamari (yes = 1)	-2.908	-4.644*	-1.214	-2.386
	(-1.20)	(-1.79)	(-0.33)	(-0.63)
Constant	43.094***	45.897***	58.468***	60.361***
	(8.14)	(8.54)	(5.89)	(6.34)
LR Test of Homoskedasticity				
χ^2	29.56	17.84	29.56	17.84
p-value	0.0001	0.0001	0.0001	0.0001
First State of IV Regression				
Angrist-Pischke F Statistic	41.23	29.88	41.23	29.88
p-value	0.0000	0.0000	0.0000	0.0000
Observations	942	942	942	942

* Significant at 10%; ** Significant at 5%; *** Significant at 1%
Robust t-statistics are in parenthesis.

Table 4.10 Gender Gap, KV-IV

Dependant Variable	(1) Gender Gap, Monga IV1	(2) Gender Gap, Monga IV2	(3) Gender Gap, Normal IV1	(4) Gender Gap, Normal IV2
Dummy for High MFI Coverage in a village	9.839**	4.768	4.302	5.264
	(2.29)	(1.03)	(0.56)	(0.69)
Functionally Landless Households in Village (%)	0.013	0.019	0.018	0.017
	(0.30)	(0.47)	(0.19)	(0.18)
Using modern technology in cultivation (%)	-0.007	0.002	0.015	0.013
	(-0.57)	(0.17)	(0.63)	(0.60)
Distance to Bank (km)	0.061	-0.023	-0.277	-0.261
	(0.54)	(-0.20)	(-1.25)	(-1.22)
Distance to Market (km)	0.508***	0.480***	0.368**	0.373***
	(5.17)	(5.04)	(2.51)	(2.62)
Village Population over 12 years old	-7.427**	-7.813**	-9.942**	-9.869**
	(-2.04)	(-2.24)	(-2.28)	(-2.27)
District = Lalmonirhat (yes=1)	-6.812***	-7.664***	-11.104***	-10.943***
	(-6.18)	(-7.08)	(-3.94)	(-4.14)
District = Nilphamari (yes = 1)	-1.576	-3.142*	-2.802	-2.505
	(-0.95)	(-1.89)	(-0.85)	(-0.78)
Constant	15.565***	18.093***	26.638***	26.159***
	(4.19)	(4.90)	(2.89)	(3.02)
LR Test of Homoskedasticity				
χ^2	29.56	17.84	29.56	17.84
p-value	0.0001	0.0001	0.0001	0.0001
Angrist-Pischke F Statistic	41.23	29.88	41.23	29.88
p-value	0.0000	0.0000	0.0000	0.0000
Observations	942	942	942	942

* Significant at 10%; ** Significant at 5%; *** Significant at 1%
Robust t-statistics are in parenthesis.

5 Conclusion: Policy Implications

The findings of this dissertation clarify some of the outstanding issues that surround the debate over the effects of microfinance on alleviating the plight of the poor, in particular its impact on seasonal hunger, on the informal credit market, and on the market for poor women working in agriculture. In doing so, our results could help inform policy decision making.

Concerning the hungry season, our results have shown unambiguously that microfinance has a positive impact on the food security of the poor. The rural poor who can only eat twice per day—and therefore are underfed—are more likely to consume three meals per day thanks to microfinance membership, thus receiving a more adequate calorie count. The ultrapoor who only eat one meal per day on average during the Monga—and thus are on the brink of starvation—are more likely to eat at least twice per day, thus moving from a situation of quasi-starvation to one of being better fed. This was not obvious a priori because the seasonal decline in demand for labor and thus income may affect the sales of goods and services from microenterprises, and potentially reduce earnings from these activities. Given our findings, it seems that the non-seasonal employment in off-farm activities ultimately contributes to smoothing incomes throughout the year, and thereby has a stabilizing effect on food consumption. Our findings in Bangladesh may be of interest to other countries that are similarly plagued by seasonal hunger caused by the agriculture cycle.

Microfinance can be a useful tool to implement if the policy objective is to reduce recurring seasonal hunger in Bangladesh. However, it may not be a sufficient measure to help the starving move to a fully sufficient diet. First, although microfinance institutions

target the poor, there is evidence that MFIs tend to locate in less poor villages with better infrastructure and that the ultrapoor have by and large not been reached (see Zeller et al. 2001 and Emran et al. 2012). Also as noted by Emran et al (forthcoming), ultrapoverty—with its multiply reinforcing poverty traps, malnutrition, illiteracy, and poor health—will require more than merely access to microfinance. Given the multiple reinforcing poverty traps often faced by the ultrapoor, a multidimentional program incorporating both livelihood protection together with microfinance may be appropriate. BRAC's TUP program is an example of such a program, providing microloans, microenterprise training, health services, and education (Emran et al forthcoming).

If instead the objective is to reduce the reliance of the poor on informal sources of finance, then microfinance is an effective intervention. Our findings are that microfinance increases the average perceived moneylender interest rate in the village, while reducing the likelihood that households borrow informally. It is important to note that while the average moneylender interest rate within the village has increased, this does not necessarily mean that those continuing to borrow from moneylenders see any increase in their individual interest rates. Instead, since moneylenders charge interest rates to individuals based on their perceived riskiness, it is likely that the higher observed average interest rate reflects the riskiness of the *residual* pool of informal borrowers. So in sum, the evidence suggests that microfinance reduces reliance on informal lenders without penalizing those who continue to borrow informally.

For policy purposes, it should be highlighted that microfinance has a positive impact on the village labor market for poor agricultural laborers. Indeed our findings indicate that microfinance expansion has a positive impact on wages both during the

Monga and normal seasons and also for both men and women. From a poverty alleviation perspective, this is an interesting result since agricultural laborers are the most underprivileged working class. In particular, it is only the most destitute women who work as agricultural laborers because of the social stigma attached to such work.

In sum, despite misgivings expressed in the literature concerning the impact of microfinance, our findings add credibility to microfinance as an effective poverty alleviation tool. While microfinance cannot solve all the problems faced by the poor, it is an effective measure to improve their livelihoods. When combined with alternative measures, microfinance can go a long way towards reducing the level of poverty.

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