# Essays on Microfinance under Weak Enforcement

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# Essays on Microfinance under Weak Enforcement

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# Abstract

This paper theoretically and empirically studies the optimal lending contracts for both non-profit and for-profit microcredit lenders. I begin by building a theoretical model, where both types of lenders use dynamic incentives mechanism to mitigate borrower strategic default due to two reasons. First, competition among lenders increases the borrower's outside options, thus lowering borrower's cost of default. Second, lacking traditional enforcement technologies, such as no credit history check or collateral, weakens borrower's incentive to repay. The model shows that, (i) as competition increases, both types of lenders ensure repayment by increasing ex ante threat to terminate loan renewal, and (ii) for-profit lenders are more likely to deny loan renewal than nonprofit lenders and charge higher interest rate. Furthermore, I find that borrower welfare under non-profit lending remains unchanged given any level of competition. But borrower welfare under for-profit is lower than under non-profit. I then provide empirical evidence on the implications (i) and (ii) derived from my model with a unique panel dataset from Bangladesh that contains itemized information on the lender's financial statements. Identifying the effects of competition and profit motives (non-profit or for-profit) is challenging due to difficulty of mapping the model variables into the empirical setting. I overcome this by introducing multiple innovative proxies, and utilize fixed effects strategies to account for unobserved heterogeneity. Consistent with the theory, I find that higher competition and profit-motive induce lenders to maintain higher loan loss reserves ratio, suggesting potential increase in loan termination. The results shed light on the importance of introducing credit bureaus in the microcredit market to improve information sharing among lenders, which limits borrower' outside options and reduces strategic default.

**Keywords:** Microfinance, Dynamic Incentives, Competition, Mission Drift, Optimal Contracts.

**JEL classification:** G21, O12, D82.

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# 1 Introduction

From the turn of the century, microfinance has been regarded as the most effective panacea to poverty alleviation. This eventually lead to the Nobel Peace prize being awarded to Muhammad Yunus and the Grameen bank in 2006 for their “text efforts to create economic and social development from below”.[1] Through microfinance, institutional financing was made available to parts of the population who were regarded unqualified for lending by traditional banks.[2] The microfinance industry is now worth $124B globally, serving 211M customers as of 2015, a 130M rise From 2003.[3]

These individuals lack proper collaterals to back the loan with, and there are presence of moral hazards and adverse selection in the market. The problem is exacerbated by the lack of information sharing technology—which can build credit histories and monitor double dipping—in most microfinance markets. To counter these problems, Microfinance institutions (MFIs)[4] came up with various innovative solutions—namely, joint liability, frequent payments, dynamic incentives and so on. Initial results of microfinance were astounding too, with Grammen bank posting repayment rates as high 96%-100% in the late 1990's.[5] Most economics literature has

[1] Prize, Nobel. "The Nobel Peace Prize 2006." Press Release, Oslo (2006).

[2] Informal village money lenders were present for centuries and are still present

[3] Microcredit Summit Campaign, 2015

[4] hereby to be referred as either MFI or bank or simply lender

[5] Muhammad Yunus, *The Grameen Bank* (Scientific American 281, no. 5, 1999), 114-119.

hailed joint liability loans as the driving factor behind the success of MFIs (Besley and Coates, 1995; Murdoch, 1999; Ghatak and Guinnane, 1999), but recent evidence suggests such phenomenon is in the decline (Cull et al., 2009; Ahlin and Suandi, 2018; de Quidt et al., 2018)[6]. Instead, other lending technologies, such as dynamic incentives mechanism is more identified behind the success of MFIs (Besley and Coates, 1995; Murdoch, 1999; Cull et al. 2009; Tedeschi, 2006; Galariotis et al., 2011).

## 1.1 Dynamic Incentives

Dynamic incentives mechanism promises the borrowers continual loan disbursement, often incremental, granted the borrowers repay the existing loan on time, with a threat of loan denial otherwise. Programs generally begin by offering small loans and then gradually increasing the loan size upon satisfactory repayment. This repeat nature of the interactions and the credible threat to cut off any future lending when loans are not repaid[7], can be exploited to overcome information problems and improve efficiency (Morduch, 1999).

Dynamic incentives, however, may result in adverse outcomes by encouraging strategic borrowing behavior, whereby borrowers repay a series of loans until they

[6]Along with high-profile MFIs like the Grameen Bank and BancoSol ceaasing the use of such

[7]This was not possible by the state-run banks, who were not able to exclude any borrower just because they failed a payment. Many believe that is one of the more prominent reasons behind the failure those state-banks

have reached the largest loan size and then run away with the money. Or, if the lending relationship is though of as a simple finite game, the the borrower always has to incentive to default in the ultimate stage of the game. Thus while the theoretical implications of dynamic incentives mechanism may be ambiguous, experimental studies found evidence that dynamic incentives both reduces risk taking and improves repayments (Gine et al. 2010a, Gine et al. 2010b), the later found improved repayments only for borrows with highest ex-ante default risk.

Lenders exploiting dynamic incentives mechanism face an increasing challenge to achieve high repayment rates with the rise in competition and the resulting overlapping borrowing. Competition will diminish the power of the dynamic incentives against the moral hazard problem of strategic default. As competition grows, the number of lenders from whom the borrowers can lend increases and hence, given the absence of traditional enforcement mechanisms, it becomes easier for them to default on existing loans and create new lending relations.

## 1.2 Competition

There is a growing evidence of rise in competition in the microfinance market (see Figure 3 & 4). Traditionally, the MFIs competed with the local money lenders. The local money lenders offer an imperfect substitute, their loans usually have much higher interest rates over short periods of time. Also, where as microloans are generally used for investment purpose, local short-term loans are usually used for consumption. But since the late 1990s there is a rise in the number of institutional microcredit lenders. For example, in the middle and late 1990s, Bangladesh saw the exponential growth of microfinance institutions like Grameen Bank, ASA, BRAC, and Proshika.

As the market becomes competitive MFIs face two central challenges; one of competing for borrowers—resulting in reduction of lending rates—the other of increase in incidence of strategic default as competition enhances the borrower's outside options which makes defaulting on the existing loans easier (see Figure 7), diminishing the lender's ability to extract repayments. While economists generally view competition as beneficial to the society, but strong competition can weaken dynamic incentives mechanism. If a lender is a monopolist, their threat to cut access to defaulters is the greatest since they are the only source of credit. Dynamic incentives can weaken when many lenders enter the market, because borrowers now have access to alternative source of finance which they can avail. Especially, since developing countries lack loan enforcement mechanisms, borrowers can default on existing loans and take up new loans.

### 1.3 Mission Drift

The trend in competition is accompanied by another phenomenon, often called *mission drift* in the literature, which suggests that MFIs, traditionally considered to be non-profits, are moving towards profit-seeking motives (see Figure 5 & also see the visual evidence provided in de Quidt et al., 2018). This rise in for profit entities is driven by two major factors:

- The previous success of the MFIs, which includes high repayment rates and net positive profits, attracted other institutions to enter the market to reap the excess profits.
- MFIs, once considered social institutions, were largely backed up by foreign donors, meaning many could operate at a loss, covering up losses with donor funds. But as the industry matured, donor funds dried up, forcing the MFIs to be financially self sufficient, which in turn meant rise of for-profit entities.

These two types of lenders are assumed to have different missions. Non-profits maximize borrower welfare or outreach, and for-profits maximize profits. In practice the objective functions of MFIs tend to be a mix of both. For example Salim (2013) finds that pure-profit motive cannot explain the branch selection decision of two of the largest MFIs in Bangladesh, but rather it is a mix of profit maximization and poverty alleviation. The term mission drift refers to the trade-off between maximizing profits and maximizing outreach/minimizing poverty. The results from empirical research remains ambiguous.

### 1.4 Research Question

To date there is little evidence, both theoretical and empirical, on the effect of competition and mission drift on the lender's optimal contract, when they use dynamic incentives as the primary mechanism to obtain repayment. This is important to study because on one hand– while competition in any market is generally welcomed in the economics literature–does it adversely affect the banks ability to collect repayments. If so, how does the lender react to such an adverse effect. If the lender denies defaulters the access to future loans, this will exacerbate the financial exclusion of the marginalized, because often the defaults are results of adverse income shocks due to natural disasters or poor harvest[8]. Also, given the rise in for-profits, which coincides with a call for financially sustainable MFIs, does maintaining for-profit motive scheme call for banks to be stricter in obtaining payment and hence resulting in further exclusion and eventually making the system unsustainable. The central question to be studied are:

- What are the alternative mechanisms MFIs use to ensure repayment from the

[8] According to Microfinance Barometer 2018, 62% of the mirocredits were invested in agricultural ventures.

borrowers? Why is dynamic incentives more preferred than others?

- What are the optimal lending contracts for lenders who use dynamic incentives to mitigate strategic default arising from competition?
- Is there a difference in decision making based on lender's type?
- Is there empirical support for the predictions from the theoretical model?

## 1.5 Objectives and Findings

To answer these questions, I build a theoretical model following Bhole and Ogden (2010), but I abstract from the joint liability aspects, since it is a fading phenomenon and instead include outside options and account for changes in the lender's mission. This allows me to examine the optimal loan contract for lenders maximizing borrower welfare and also lender's maximizing profits, when facing competition. The model consists of many risk neutral borrower and lenders. The penniless borrowers require a unit of capital each period to invest, there is no savings and information sharing technology in the market. The lenders, who either maximize borrower welfare or profits, provides a contract which specifies the interest rate and an ex-ante threat of contract non-renewal if borrower defaults. Competition enters the model as outside options available to the borrowers, following de Quidt et al. (2018). The contract obliges the borrower to pay the specified amount to the lender, it also specifies a penalty of default, modeled as a probability of future loan denial.

The model predicts that competition facilitates incidence of strategic default, consistent with the literature on weak enforcement, making it difficult for lenders to collect their due payment. Lenders counter this moral hazard problem by increasing the ex-ante threat of loan denial for the defaulters, this guarantees payment when the borrower is successful. The model also illustrates that profit-seeking MFIs, are prone to higher threats of termination to extract payment, then nonprofits.

I test these key predictions of the theoretical model using data from 363 MFI branches in Bangladesh. There are several challenges in empirically studying these issues. First, defining "profit-seeking motive" is difficult. Maintaining net positive income does not make a bank profit seeking, neither does having an NGO (Non-governmental organization) status make a bank non-profit.[9] Second, it's not possible for a direct measurement of the lenders threat of contract termination from the available data. Third, measuring the widely used competition indices like the Herfindahl Hirschman Index is difficult to compute for the microfinance market given the incomplete information of such markets because of underdeveloped financial systems.

[9]details in Section 8.2

To overcome these challenges, I first construct measures to capture MFI's profit-seeking motive. Following the literature on mission drift. I measure profit-seeking motive via average loan sizes. In particular, following Cull et al. (2009) I use the average loan as a percentage of National Income at the 20th percentile. Based on the area served by the MFIs, I divide the national income into rural, urban and national level, thus allowing to capture the dynamics better. Also, income at 20th percentile is used to capture the poor borrowers, who make up the bulk of microcredit customers. Probability of future loan denial is proxied by Loan Loss Reserve ratio, which according to the Microfinance Handbook measures "loan portfolio has been reserved for future loan losses". Among other factors, a key determinant of loan loss reserves is expected loss severity. The argument is that the if banks reserve more for future loan losses, suggesting they expect to lose money, they are more likely to deny future loans to defaulters. To measure competition, I construct two measures: i. Lerner Index, ii. Boone Indicator. Both are non-concentration indices, thus does not require full information on the market. Also both these measures are bank-specific and time-varying, which allows me study differences in competition across banks and time. Interest rates are constructed, following Dorfleitner et el. (2013), from the income statements and balance sheets of the banks. The mean estimates are close to the actual interest rates charged by Bangladeshi MFIs.

The panel data (FY2014-2016) comes from a 2016 survey conducted by Institute for Inclusive Finance and Development (InM), covering 363 MFI branches in 40 districts of Bangladesh. The data contains information from both income statements and balance sheets of the MFIs, along with general information and a section on the manager's perspective about various aspects.

To test the key predictions from the theoretical model, I start by regressing the indicator of loan denial on measures of profit-motive, competition and interest rates. The identifying assumption is that conditional on the included covariates, unobserved determinants of loan denying decisions are uncorrelated with measures of profit motive and competition. MFI fixed effects are included in all the models to capture the variation on key variables over time. The covariates include various measures of efficiency and productivity.

My results are consistent, to some extent, with the theoretical predictions. For-profits are more likely to deny loans to defaulters then non-profits. The results suggest that $(p-value = 0.0413)$ a ten-percent increase in average loan at the $20^{th}$ percentile income increases the Loan Loss Reserve ratio by about eight-percent, assuming interest rates at the 27%[10]. There is a slight evidence for the first hypothesis $(p-value = 0.1936)$, with a 10-percent decrease in the Lerner Index (suggesting a rise in competition), LLR ratio increases by around 14-percent, when interest rate is 27%.

[10] maximum possible interest rate in Bangladesh.

## 1.6 Contents

The rest of the paper proceeds as follows: Chapter 2 discusses the lending environment in which the MFIs operate in developing countries. It also provides detailed overview of the alternative lending techniques used by MFIs to solve the adverse selection and moral hazard problems. Chapter 3 gives an overview on competition in the microfinance market. Chapter 4 outlines the objectives of the MFIs and discusses the potential trade-off between profit maximization and outreach/welfare maximization. Chapter 5 develops a theoretical model that incorporates competition and dynamic incentives for a non-profit lender. The model is derived to use the optimal lending contracts for both with- and without competition. Borrower welfare is also compared under the two. Optimal contracts are also derived for for-profit lenders. Borrower welfare is compared. Chapter 6 provides empirical evidence of the assumptions used in the theoretical model. Chapter 7 provides empirical evidence for the assumptions used in the model and states the testable implications from the model. The institutional features of the Bangladeshi microfinance market and the unique panel dataset used for estimation are discussed here too. Further, the empirical strategy is explained and variables in the data are mapped to the parameters from the theoretical model Chapter 5. Key variables are then measured and the reduced form results are presented along with some heterogeneity and robustness checks. And finally Chapter 8 concludes and provides policy recommendations.

# 2 Alternative Microcredit Lending Methods

## 2.1 Lending Environment in Developing Countries

The environment where MFIs operate differs from the environment where traditional banks usually operate. Modern institutional microfinance began by operating in the 1970s, mostly in underdeveloped and developing countries characterized by high levels of poverty, undeveloped financial infrastructures, and incomplete markets or missing markets. Since then, many of these markets have developed, but financial infrastructure and female labor market still remains inadequate, especially in South Asia and Africa. Microfinance is now widely disbursed in more developed Western countries, but those markets will not be addressed in this dissertation.

MFIs, much akin to any other regular bank, have to design contracts which are incentive compatible and have to be modeled in a way to reduce problems arising from incomplete information, i.e. moral hazards and adverse selection problems, the former arising both due to hidden actions and hidden information. The hidden action problem concerned with the fact that borrowers might not put enough effort on their investments. Economics literature is rarely concerned with this problem and given that most of the borrowers are ultra-poor, borrowing to earn basic subsistence, this is not a major concern. Rather the literature is more concerned with the hidden information problem, both ex-ante and ex-post. Ex-ante moral hazard has been highlighted in the works of Boot, Thakor, and Udell (1991), where they show how collateral use, even though inefficient, rises as borrowers have more private information. Wydick (2001) shows that there may exist partial diversion of a loan from productive investment to present consumption. This dissertation is more concerned with ex-post moral hazard, which occurs when a borrower simply reneges on a promise to repay. This kind of strategic default, whereby a borrower only repays if the punishment from defaulting outweighs the reward, is the central problem in the models of Besley and Coates (1995), and Paulson and Townsend (2003).

MFIs also have to deal with the problem of adverse selection. In the context of microfinance, adverse selection refers to the situation in which the MFIs lack proper information about the riskiness of the borrowers' projects, thus they are unable to discriminate between the borrowers. Stiglitz and Weiss (1981) describes the problem as there being two kind of borrowers in the market, one investing in high return risky investments, thus with more probability of default and the other investing in low return safe investments with low probability of default. But the bank does not have any ex-ante screening mechanism to differentiate between the two and hence ends up charging the same average interest rate to both the types.

This eventually drives out the less risky borrowers from the market, leaving only the risky ones.

MFIs have to solve these problems of adverse selection and moral hazard problems under conditions that are more difficult than those faced by traditional banks in both developing and developed countries. The reasons are:

1. The borrowers are often the poor and the ultra-poor. Banks use collaterals to reduce moral hazard arising from the hidden information problem, but due to the fact that these borrowers often lack any assets that could be collected as collaterals, the MFIs have to resort to other mechanisms.

2. Most developing countries have underdeveloped financial infrastructure. This means that information sharing technology, like central credit rating agencies are virtually non-existent. Meaning there is no information sharing among the MFIs about borrower default.

3. Due to the economic conditions, most MFIs in developing countries cannot impose bankruptcy on the borrowers. The cost of imposing bankruptcy often far outweighs the reward.

4. Physical infrastructure, like roads or internet are very limited. Thus, the cost of maintaining borrower relationships are very high. Often times loan officers

have to travel to remote parts of the country to establish and maintain relations with the borrowers.

The MFI clients mostly comprise of poor women, who take the loans to invest in some small investment. These ranges from small businesses, like vegetable vendors, to making handicrafts. Most of these households have at least one independent activity, which generates non-wage, self-employed income, usually through some informal activities. Usually for the MFI clients there is no distinguish between the household and the business, and the households simultaneously engage in investment and consumption decisions. This means that these clients are often subject to unlimited liability, the risk associated with their investments may directly affect their livelihoods. Thus, the MFIs, traditionally seen as social enterprises, do not enforce strict sanctions on defaulting clients. There are also political consequences on imposing sanctions, often times political or religious leaders will reprimand MFIs if they are too harsh. And on top of all these, there are the previously mentioned characteristics of microfinance markets which make it difficult for MFIs to implement traditional enforcement mechanisms. Thus they designed alternative lending mechanisms to ensure timely repayment from the borrowers. Three of the most prominent mechanisms mentioned in the literature are joint liability contracts, frequent payment schemes and dynamic incentives. In the following section I will discuss each of these mechanisms in detail, highlighting their strength and weaknesses.

## 2.2 Joint Liability Lending

The most highlighted feature of microfinance, particularly in the economics literature, is its use of joint liability (JL) loans. JL loans are disbursed in groups of 2-20, each member of the group receives an individual loan, but the group as a whole is responsible to repay the loan back. Meaning the liability of each member falls on every other member of the group. Group lending is a feature of JL lending, but group lending is possible without JL.

JL provides incentives to repay primary through one main channel. Peer pressure, expecting potential social sanctions from the group members if own share of liability is unpaid. Social sanctions may take both pecuniary and non-pecuniary forms, with the latter being more prevalent in practice. Non-pecuniary sanctions include physical and verbal punishments, social distancing and the cutting access to future group loans. Since, most microfinance clients have geographically limited mobility, they might not be able to form groups within the existing groups social network.

Many researches have been conducted on the effectiveness of joint liability on repayment rates, results are both for and against its use. But despite its success, in recent times, there has been a decline in the use of joint liability loans. High profile practitioners of JL loans, including Grameen Bank, has opt out from using JL loans. Early work includes Stiglitz (1990) and Varian (1990). The former shows that borrowers have strong incentives to form groups with individuals with similar risk characteristics, further the paper shows that group lending constitutes a welfare improvement for the borrowers through lower interest rates. The latter paper shows that the groups have an informational advantage over the bank and members of the group have incentives to take remedial action against a partner who defaults without cause.[11]

Besley and Coate (1995) looks at the willingness to repay under a joint liability contract. Their analysis of the problem of enforcement suggests that group lending may sometimes lead to better repayment rates, other times lead to worse repayment rates, depending on the partners success rates and return amounts. The positive effect results from the fact that successful borrowers may repay the loans of partners, who failed to earn enough returns tomake repayment profitable. On the other hand, the negative effect arises from the fact that there might be cases when some of the group members default. In fear of repaying the defaulted members loans, some members who would have otherwise repaid, had they not been saddled with the weight of liability for their partners' loans, choose to default too.

[11] Ghatak and Guinnane (1999) provides theoretical and empirical examples on how joint liability may solve problems of adverse selection, moral hazard and enforcement

More recently Rai and Sjostrom (2004) studied group lending under an innovative cross reporting mechanism. They showed that joint liability lending performs at least as good as individual lending under their mechanism, which involves the defaulting borrower reporting to the bank the successful borrower's information, in case later defaulted, even when they had the ability to pay. This paper was one of the first papers to model group lending without social sanctions. One drawback of the cross-reporting mechanism is that it is rarely seen in practice. [12]. Bhole and Ogden (2010) extended Rai and Sjostrom (2004) without the cross reporting mechanism. They showed that under a flexible group lending mechanism—where the successful borrower's transfer to the defaulting borrower is optimally determined—group lending perform better than individual lending even without social sanctions. This dissertation utilizes a similar framework to Bhole and Ogden (2010)—but with two key differences—inclusion of outside options the in lending model and introduction of heterogeneous bank types in the market.

Allen (2016) studies a similar model, called partial group liability. He shows that group lending performs better than individual lending if the transfer from successful to defaulting borrower is optimally determined. But if the transfer amount is greater than the optimal, then the successful borrowers strategically defaults. De Quidt et al. (2016) finds similar results, lower transfer costs encourages group lend-

[12]See Rutherford et al. (2004)

ing. They also find that individual lending may constitute a welfare improvement over group lending, as long as borrowers have a strong network to maintain mutual insurance. This dissertation extends these literature by incorporating the provision of outside options in the lending model, thus the results provides a deeper understanding of why borrowers may choose to default in the current microfinance setting. Guha and Chowdhury (2013) analyzes competition among lenders using the Salop circular city model. They show when lenders are relatively profit oriented, equilibrium involves double dipping, which eventually leads to default and inefficiency. Their paper does not make distinguish between joint and individual liability lending. And also, they do not assume presence of strategic default. Further, they focus on the problem of double dipping, rather than overlapping borrowing, where a borrower takes one loan for investment and one for consumption. De Quidt et al (2018) shows both theoretically and empirically that as the level of competition rises, lenders are more likely to offer individual liability loans rather than joint liability loans.

The focus of this dissertation is to see how repayment rates are effected when borrowers are allowed to loan from multiple lenders under both individual liability lending. In that sense, the paper is close to Besley and Coate (1995) in spirit. The novelty of the paper is the provision of outside options and modelling of MFIs into non-profit and for-profit institutions.

## 2.3 Frequent Payments

One of the most innovative, yet perhaps the least researched feature of most microfinance loan contract is that repayments must start almost immediately after disbursement. Gonzalez-Vega et al. (1997, 74) emphasizes the value of the early warning feature, asserting that "the most important tool for the monitoring of borrowers in these lending technologies is requiring frequent repayments followed by immediate reaction in the case of arrears." In a traditional loan contract, the borrower takes the loan then invests it and eventually repays the full amount with interest at the end of the term. But at most MFIs, terms for a yearlong loan are likely to be determined by adding up the principal and interest due in total, dividing by 50, and starting weekly collections a couple of weeks after the disbursement (Morduch, 1999). Some of the MFIs, mostly in east Asia and South America, where the loan structure is slightly different too, tend to be more flexible. But even then, they do not stray too far from the idea of collecting regular repayments in small amounts.

Regular repayment schedules may help screen out undisciplined borrowers. Most MFIs, especially those in South Asia, hold weekly meetings to collect payment from the clients. Loan officers usually visit a village every week, where all the client gather and submit their weekly repayments, they also discuss any problems they are facing during that time. By meeting weekly, the credit officers can get an up to date glimpse of their client's financial condition, they also get to build a relationship with the clients by knowing them personally and perhaps getting to know their overall situation better. This information can provide loan officers with early warning signs about potential problems and help them clamp down those more quickly and effectively.

This mechanism also ensures that the household has additional income sources on which they can rely on, at least for consumption purposes. Most clients are non-wage day laborers or have other income generated from self-employed informal activities. Therefore, collecting weekly repayments could mean that the bank is effectively lending partly against the household's steady income stream, not just the risky projects (Morduch, 1999).

Further, Rutherford (1998) suggests that by meeting regularly and collecting weekly payments the MFIs get to hold of cash flows before they are consumed or diverted to other channels. Because the absolute amount of cashflow is usually very low in the typical microfinance household, they are often faced with choices on where to spend the earnings on. Apart from consumption, the typical household may spend money on buying durables, paying dowries and so on.

Another advantage of the weekly payments, at least to the loan officers, is the consistency in collecting the payments. Any sort of flexibility will also bring in more variation, and that makes it more costly to keep track of the client's payment schedule. It is to be noted that most MFIs, at least up until the early 2010s utilized hand-written ledgers. Without digitization of the payment schemes, it becomes very difficult for the loan officers to keep track of the client's payments. Also, these frequent weekly payments help in enforcing discipline for the loan officers. It provides a leverage for to which helps them collect payments.

This confers advantages for the bank and for diversified households. But it means that microfinance has yet to make real inroads in areas focused sharply on highly seasonal occupations like agricultural cultivation. Seasonality thus poses one of the largest challenges to the spread of microfinance in areas centered on rainfed agriculture, areas that include some of the poorest regions of South Asia and Africa.

## 2.4 Dynamic Incentives

The third most widely studied mechanism for securing repayment, when traditional enforcement mechanisms are not available, is the exploitation of dynamic incentives. Besley and Coates (1995) was perhaps the first to recognize the concept of dynamic incentives in the economics literature.[13] Much of the literature on

[13] see footnote 8 of their paper

dynamic incentives has stemmed from their work.

MFIs typically begin by lending just small amounts and then gradually increasing loan size upon satisfactory repayment, hence the name dynamic incentives. This mechanism provides the MFIs with two distinct tactics to sort and retain regular, less risky clients. Firstly, by starting with a very low loan amount, the MFIs screen out the impatient, who are often the risky borrowers, since they are less likely to be interested in such small loans. Kraus (2013), has shown that in fact borrower can be used as a screening device for default risk. Secondly, the repeated nature of the interactions-and the credible threat to terminate future lending if loans remain unpaid acts as a means to gather private information about borrower's repayment behavior and improve efficiency. Incentives to repay are further improved if the borrowers expect a gradual increase in the size of the loan.

Experimental studies found evidence that dynamic incentives both reduces risk taking and improves repayments (Gine et al. 2010a, Gine et al. 2010b), the later found improved repayments only for borrows with highest ex-ante default risk.

This dissertation is mainly concerned with this strand of the alternative mechanism literature. It contributes to a body of research that studies how dynamic incentives are provided to reduce the incidence strategic default and extract payment. In recent literature, more focus has been given on dynamic incentives as a key lending technology to mitigate strategic default. The existing studies mostly show game theoretically that dynamic incentives can be a viable lending technology to extract repayment. Morduch (1999) provides extensive overview of the mechanism.

Some papers have utilized dynamic incentives in their model to reduce incidence of strategic default in the context of joint liability lending (Armendariz 1999 and Bhole and Ogden 2010). Most of these papers model dynamic incentives as a threat to non-renewal of future loans if borrowers' default on the existing loan. Tedeschi (2006) shows that infinite exclusion as a punishment to default may not be necessary if the borrower gains from the lending relation.

However, there are several drawbacks in utilizing the dynamic incentives mechanism. Firstly, the repeated nature of the dynamic incentives' mechanism means that it also runs into the common problem of all finite repeated games. That is, if the lending period has an end, the borrowers always have an incentive to default in the last period. Thus, the lender might choose not to lend in the final period, ending the relation at the penultimate period. Anticipating that, the borrower will default in the penultimate and hence eventually the entire mechanism will stop even before the first period. Shapiro (2009) has shown the limitations of dynamic incentives using the usual finite repeated games argument, that if the lending relation has a clear end, even the most patient borrower default in all but one equilibrium.

Shapiro then extends the model to show that in presence of double dipping loans have to be more favorable to outweigh increased gains from default.

But in practice, is there a certain graduation date? Or do the poor borrower really possess such economic vision? Financial access under the microscope has shown that borrowers to graduate from microfinance to commercial bank loans without defaulting on the MFI loans. Thus, unless there is a clear end date or if graduation from one program does not depend on past performance; this theoretical inconsistency might not hold in practice.

Rather, the real problem facing the lenders exploiting dynamic incentives mechanism is the rise in competition. Competition will diminish the power of the dynamic incentives against the moral hazard problem of strategic default. As competition grows, the number of lenders from whom the borrowers can lend increases and hence, given the absence of traditional enforcement mechanisms, it becomes easier for them to default on existing loans and create new lending relations. This is often named as the overlapping borrowing phenomenon. Chaudhury and Matin (2002), Mcintosh et al. (2005) and Faruqee and Khalily (2011) found overlapping promotes default. Thus competition, doubled with the increased mobility of the borrowers are deemed to be the greatest threat to exploiting dynamic incentives as a mean to achieve high repayment rates.

# 3 Competition in the Microfinance Sector

There is a growing evidence of rise in competition in the microfinance market (see Figure 3 & 4). Since the late 1990s there is a rise in the number of institutional microcredit lenders. While traditionally, the MFIs competed with the local money lenders, who often offers a rather imperfect substitute, loans with much higher interest rates lent over short periods of time and mostly taken to smooth out consumption, rather than invest to earn returns. Also, microloans, while still disbursed over short period, tend to be longer than local money lender's term.

As the market becomes competitive MFIs face two central challenges.

1. Competing for borrowers. This results in a reduction of lending rates as the lenders compete for borrowers and offers the lowest possible interest rates to attract them.

2. Incidence of strategic default. Competition enhances the borrower's outside options which makes defaulting on the existing loans easier (see Figure 6), diminishing the lender's ability to extract repayments.

While economists generally view competition as beneficial to the society, but strong competition can weaken dynamic incentives mechanism. If a lender is a monopolist, their threat to cut access to defaulters is the greatest since they are the only source of credit. Dynamic incentives can weaken when many lenders enter the market, because borrowers now have access to alternative source of finance which they can avail. Especially, since developing countries lack loan enforcement mechanisms, borrowers can default on existing loans and take up new loans from the competing lenders, a phenomenon known as overlapping borrowing. For instance, 25% of borrowers have been reported taking loans from six or more different MFIs in India in 2009 (Srinivasan, 2009). In Morocco, the figure is as high as 40 percent, which along with other factors, lead to the eventual repayment crisis in the microfinance industry (Chen et al., 2010). In Bangladesh, from the 33,346 loan incidents from the Pathrail Union in the district of Tangail, 21.8% of those loans were found to have been overlapping (Rabbani and Khalily, 2012).

Besley and Coate (1995) looks at the willingness to repay under a joint liability contract. Their analysis of the problem of enforcement suggests that group lending may sometimes lead to better repayment rates, other times lead to worse repayment rates, depending on the partners success rates and return amounts. The implication is that since competition lowers the screening ability of the bank (Marquez, 2002), repayment rates may be adversely affected. There are two channels at work here. One of the weakened lending relations and the other of lower borrower selection criteria. The latter channel is simple, as the banks compete for borrowers, they have to relax the selection criteria to attract more borrowers. This means that the chance that the banks end up lending to potential risky borrowers, who otherwise would have been screened out, increases. The first channel is a bit less intuitive. The idea is that the more clients the MFI has, the less regularly they can meet up with them and hence the lending relation might be deteriorated. This is specially a concern for the MFIs is developing countries, where frequent meet-ups, as mentioned in the previous chapter, is a technique to achieve high repayment rates McIntosh and Wydick (2005), following the weak enforcement argument, show that impatient borrowers are more prone to take multiple loans and thus leads to a decrease in the expected repayment rates on all transactions in the Bertrand equilibrium.

Guha and Chowdhury (2013) analyzes competition among lenders using the Salop circular city model. They show when lenders are relatively profit oriented, equilibrium involves double dipping, which eventually leads to default and inefficiency. Their paper does not assume the presence of strategic default and they study borrower's behavior instead of lender's. Further, they focus on the problem of double dipping, rather than increase in outside options due to competition, where a borrower takes one loan for investment and one for consumption. De Quidt et el (2018) shows both theoretically and empirically that as the level of competition rises, lenders are more likely to offer individual liability loans rather than joint liability loans.

There are conflicting results on the effect of competition in the empirical literature. Krishnaswamy (2007), Lakhar and Pingali (2014) found overlapping to have a positive effect on repayment rates. While Chaudhury and Matin (2002), Mcintosh et al. (2005) and Faruqee and Khalily (2011) found overlapping promotes default. This paper primarily provides theoretical evidence to the later findings, although the results provides some support to the former findings too.

# 4 Vision of Microfinance Institutions

This paper is also concerned with a strand of literature on mission drift in microfinance, which is intertwined with the literature on microfinance profitability and outreach. To fully understand the mission and vision of microfinance institutions, we need a brief glimpse at the evolution of microfinance institutions.

## 4.1 Evolution of Microfinance Institutions

The earliest concept of microcredit can be traced back to the 1800s with likes of Jonathon Swift, who inspired the Irish Loan Fund in an effort to empower families in poverty through microloans or Friedrich Wilhelm Raiffeisen, who started the cooperative movement in Germany, were the earliest examples of modern microcredit pioneers. While they had the theoretical concept right, the system was flawed and the eventual goal of achieving access to financial services for the rural poor was not achieved.

Over a century later, in 1959, Akhtar Hameed Khan started another cooperative movement through the Comilla Model in modern day Bangladesh. The cooperatives collected savings from the members and disbursed loans among the members who want to utilize them. But over-involvement of the government and malevolent political hierarchy eventually led to the collapse of the cooperative model.

Two decades later, Dr. Muhammad Yunus provided a small amount from his savings to some poor rural women in the village next to Chittagong University in Bangladesh. The poor, thought by many as untrustworthy, returned his money back with interest in due time. This success prompted him to expand the lending, initially with govt. support. Grameen Bank was followed by organizations like BRAC and ASA in in Bnagladesh. Microcredit reached Latin America with the establishment of PRODEM in Bolivia in 1986. The 1990s saw a sharp rise in the number of microcredit lenders and 'microcredit' eventually graduated to 'microfinance.' Microfinance offered a broader suite of products such as savings, insurance and pensions to the members. The Microcredit Summit in Washington (1997) legitimized the concept and aimed to build upon the success of the previous three decades in order to alleviate poverty. The initial idea of microfinance was financially sustainable poverty alleviation. Years of experience have shown that government intervention was not successful in alleviating poverty and perhaps more importantly not sustainable due to corrupt political hierarchy and mismanagement. Morduch (1999) writes ". . . many now believe that government assistance to the poor often creates dependency despite decades of aid, communities and families appear to be increasingly fractured, offering a fragile foundation on which to build … amid the dispiriting news, excitement is building about a set of unusual financial institutions prospering in distant corners of the world the hope is that much poverty can be alleviated and that economic and social structures can be transformed fundamentally by providing financial services to low-income households under the banner of microfinance . . .". In 2006, the Nobel Peace Prize was awarded to Muhammad Yunus and the Grameen Bank for helping to alleviate poverty, the microfinance movement reached it's peak.

However, in recent years, microfinance is being seen less and less as the most efficient panacea to poverty. There are growing concerns about the financial sustainability of the MFIs, which traditionally depended on large donor funds. This is coupled with a rise in for profit institutions, who encouraged by the earlier success of pioneering institutions, entered the market to reap the excess profits. These have, as many call it, caused a mission drift among the microfinance institutions. Institutes once thought to have maximized outreach, minimized poverty, are now seen as profit seekers. Questions have been raised whether both these can be achieved simultaneously. This dissertation accounts for both for-profits and non-profits, in an attempt to see the difference in their approach.

## 4.2 Mission Drift

Cull et al. (2007, 2009, 2011) utilizes average loan sizes to determine profit motive, their method is consistent with findings that MFI ownership is not relevant in determining profit-seeking motive (Mersland and Strøm 2008b). The idea is challenged by Armendariz and Szafarz (2011). They also find that relatively profit oriented MFI's charge lower interest rate than NGO's owning to the fact that smaller loan sizes carry larger operating costs. The argument is put forth by Conning (1999), Hulme and Mosley (1996), Lapenu and Zeller (2002) and Paxton and Cuevas (2002), which is that the smaller the size of the loans, the higher per unit transaction costs and therefore greater outreach would have a negative impact on efficiency, implying a trade-off between outreach and sustainability. Finding a counter to Roberts (2013). The later study also finds that for-profit MFIs provide similar loan sizes and shows tendency to avoid targeting rural clients, however the paper uses legal profit status to proxy for for-profit motive. Mcintosh and Wydick (2005) modeled a non-standard client maximizing non-profit. Mersland and Strøm (2008, 2009, 2010) find no significant difference in performance and client outreach between non-profit organizations and share-holder organizations. But recent studies show that for-profit MFIs are more likely to provide individual liability loans than non-profits (de Quidt 2018b) and that market structure effects borrower welfare, suggesting that non-profit provides maximum welfare, while competition in the market delivers similar borrower welfare to non-profit lending (de Quidt 2018a). Studies have shown that greater outreach is positively correlated with better performance (Quayes 2012, 2015).

This paper studies the effect on dynamic incentives when the market is competitive and there exists mission drift. The idea is similar to that mentioned in Morduch (1999) and methodologically similar to Armendariz and Bhole. In the empirical part, this paper attempts to estimate that effect using a unique panel data.

# 5 A Model of Microcredit Lending with Strategic Default and Outside Options

## 5.1 Borrowers

This is a model of microcredit under ex-post competition. The economy consists of many borrowers— assumed to be risk neutral[14] [15] and penniless—requires a unit of capital to invest in a risky project at period $t_0$, which yields a return $Y_i = \{0, y^h\}$ at period $t_1$. The success probability of the project is $p_i = Pr(Y_i = y^h)$.[16] The borrower needs to repay the MFI $R_i$, inclusive of interest rate, at end of the loan period, $t_2$.[17] I assume $0 < R \leq y^h$, therefore after observing the low outcome 0, the borrower is forced to default as she cannot be compelled to repay more than her maximum project return. Thus, repayment is an all or nothing decision, hence the borrower either repays the full amount due or defaults on the total amount. Thus the borrower defaults whenever the punishment of defaulting is lower than the gains from

[14] A risk neutral agent's decisions is not affected by the degree of uncertainty in a set of outcomes, so a risk neutral agent is indifferent between choices with equal expected payoffs even if one choice is riskier. Thus it is imperative that the borrower's be risk neutral, so that they are willing to undertake the risky projects.

[15] Economists have long argued that agents are risk neutral over smaller stakes (see Arrow, 1971), Rabin (2000) argues that, within the expected-utility model, anything but virtual risk neutrality over modest stakes implies unrealistic risk aversion over large stakes

[16] As noted in Banarjee et al. (2015) the usual microcredit borrower does not engage in high risk activities. But nonetheless, this all or nothing framework is simpler to analyze, while keeping the spirit of investment uncertainty.

[17] In practice the loan is repaid over time instead of being a one-time lump-sum repayment. But this assumption should not hurt our flow of argument.

default. But if a contract makes her better off paying than defaulting, then she pays for each successful venture, thus $\pi = 1$. If the loan is successfully repaid, the borrower may secure a refinancing from the MFI. This mechanism, known as dynamic incentives, is a implicit promise by the lender to continuously provide access to capital to the borrower as a reward for loan repayment.[18] And since the borrower does not have access to a savings technology, they require a loan at the start of each investment period to finance their projects. This refinancing yields a benefit to the borrower, which reflects the potential future earnings for the borrower from the refinancing. Borrowers discount exponentially with discount factor $\delta$.

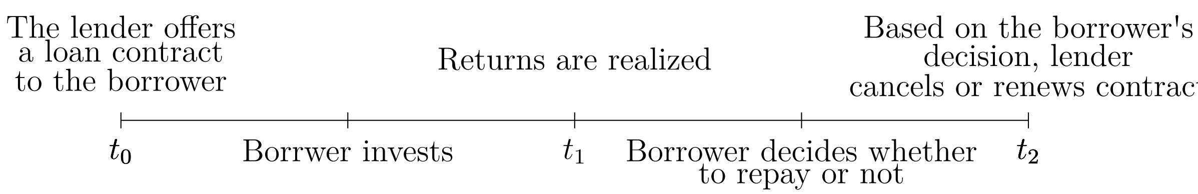


Figure 1: Timeline of the individual liability lending model.

## 5.2 Lenders

There are many banks in the economy—assumed to be either non-profit social enterprise or for profit banks—extending loans to borrowers if they expect non-negative profits, i.e., if they expect a return at least equal to the opportunity cost of capital $\rho$. Non-profits banks maximize the borrowers welfare, while for-profit

[18] In practice each successive loan is usually larger than the previous. But assuming non-increasing incentives serves the purpose without loss of generality.

banks are profit maximizers. Our assumption on non-profit banks follows that of Rai and Sjostrom (2004) and Bhole and Ogden (2010).[19] Further De Quidt et al. (2018) showed that borrower welfare is the maximum under non-profits compared to monopoly and competitive for-profits. Banks are assumed to have no access to a information sharing technology, like a central credit rating agency, where they can share information about the borrower's with each other. As over 95% of the microcredit loans are disbursed in the developing countries[20], where it is unlikely to have such technology available, this assumption reflects the scenario in practice.

Since the borrower is penniless, they have no viable assets, which the bank can hold as outside collateral. Further, I assume that the bank's do not impose bankruptcy, in case of default, on the borrowers to liquidate the entire project. Even if the bank's had the legal right to take possession and liquidate a project—given the typical small size of a microfinance enterprise and the fact that liquidation entails a transaction cost—bank's are better of without such a measure. This creates a potential problem, whereby the borrowers can pretend to be unsuccessful and not repay the bank. This behavior is known as strategic or willful default. The only punishment or penalty available to the bank is to prevent future financing. I assume, following Bhole and Ogden (2010), that the bank cancels future financing

[19](2013) finds that pure profit motivation cannot explain branch locations chosen by Grameen or BRAC, two of the celebrated practitioners of microfinance, rather it falls more towards poverty alleviation, which suggests they maximize borrowers welfare.

[20]see Reed (2011) for details

with probability $m$ when the borrowers repays. If the borrower is unsuccessful, then it is canceled with probability $n$. I assume it is socially optimal to repay whenever possible, thus I assume $n\delta V - R_i \geq m\delta V$. Meaning it is socially profitable to repay rather than default.

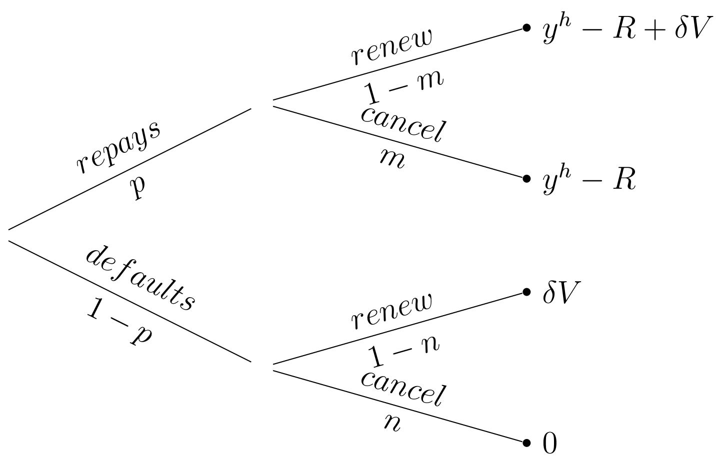


Figure 2: Non-profit banks payoffs.

### 5.3 Non-profit Lenders

### Without Competition

I start with a model of individual liability lending—where the borrower is only responsible to repay her own loan—with no available outside options. As discussed before, the non-profit banks are maximizing the borrowers welfare[21] and offers a loan contract $(R_i, m, n)$ at the beginning of each period. The bank's offer a loan

[21] text

contract Since banks act independently of each other and behave symmetrically, I focus on a single representative bank and a single borrower, thus avoiding subscripts. The bank's objective function is given by

$$\max_{R,m,n} V = p(y^h - R) + [p(1-m) + (1-p)(1-n)]\delta V \tag{1}$$

where $[p(1-m) + (1-p)(1-n)]\delta V$ is the expected benefit to the borrower accruing from future refinancing. Clearly, $\frac{\partial V}{\partial R} < 0$, $\frac{\partial V}{\partial m} < 0$ and $\frac{\partial V}{\partial n} < 0$. Since the bank maximizes borrower's welfare, increasing in the repayment rate reduces welfare. Further, if future contracts are canceled for any reason, borrowers welfare is reduced.

**Assumption 1.** $y^h \geq R$.

This is the *borrower's participation constraint*. This ensures that the borrower has enough incentive to undertake the loan to begin with. If this assumption is violated, then even a certain high income is not enough to repay the loan. Thus the borrower will not participate in this scheme.

**Constraint 1.** $(n-m)\delta V \geq R$.

This is the *borrower's incentive compatibility constraint*. This ensures that the borrower has incentive to repay if successful. $(n-m)\delta V$ is the expected increase in punishment for the borrower if she decides to default when successful. This is parallel to punishment function described in Besley and Coates (1995).[22] Thus if this assumption is violated, it will make it profitable for the borrower to 'run with the money' rather than repay. This also provides an limit limit on how high the repayment rate can be without hurting the borrower's incentive to repay.

**Constraint 2.** $pR \geq \rho$.

This is the *bank's participation constraint* or the non-negative profit constraint. This ensures that the bank is willing to extend loans to the borrowers. Rearranging, we get $R \geq \rho/p$, which gives us a lower limit for the repayment amount R. If the bank wants to earn a non-negative profit, they must charge an amount, inclusive of interest rate, at least as large as $\rho/p$

**Constraint 3.** $0 \leq m \leq 1, 0 \leq n \leq 1$

## Equilibrium Repayment

To induce the borrower to repay, the bank will offer a loan where the amount to be repaid, inclusive of interest, is

$$R^{np} = \frac{\rho}{p}$$

[22] Besley and Coates (1995) does mention that a more theoretically satisfying approach would be endogenously deriving the penalties, that is the penalty for non-repayment is exclusion from future access to credit

Constraint 2 provides us with an upper limit for the repayment amount, while constraint 3 gives us the lower limit. Thus we have $\rho/p \leq R \leq (n-m)\delta V$. Clearly, constraint 3 is binding, because $\frac{\partial V}{\partial R} < 0$, the bank would charge the lowest possible interest rate, which is $\rho/p$. It is unsurprising to see that the amount charged is decreasing in $p$ and, the success probability—as the potentiality of repayment increases—banks can charge lower interest rates to maintain non-negative profits.

As $y^h$ falls, the participation constraint becomes tighter, hence the number of borrowers willing to participate in the lending scheme falls. As $p$ falls, the zero profit constraint tightens. This situation is reflected in the feasibility condition, it gets tighter as $\delta y^h$ and $p$ falls, banks find it increasingly difficult to offer loans. The feasibility condition says that the maximum amount the bank can charge must be less than the borrower's gain from repayment.

### Equilibrium contract cancellation probabilities

Clearly, when the borrower repays, the bank refinances future loans with certainty, thus $m = 0$. This is because $\frac{\partial V}{\partial m} < 0$, thus the lower the $m$ the higher the welfare and lowering $m$ does not violate any other constraints. Also, $\frac{\partial V}{\partial n} < 0$, thus lowering $n$ increases the welfare, but it violates the borrower's incentive compatibility constraint. Allowing for mixed strategies, we find that in the equilibrium, lender's cancel future contract with probability[23]

$$n = \frac{[(1-\delta)R]}{[\delta(py^h - R)]}$$

## With competition

Now I introduce outside options to the model. Overlapping borrowing is defined as a borrower taking a loan from another bank before repaying the previous loan. For the analysis of the model, I assume that the consumer is aware that an outside option exists, which she can exploit, if she is unable to repay the loan.[24] Note, that I don't assume that the borrower takes on another loan, rather like De Quidt et al. (2018), I assume that the borrower receives a continuation value from waiting for a new lender to offer her a contract, after decision to default on the existing loan is made. I will refer to this as the value from outside options, denoted by $\delta U$.

Again, suppressing the subscripts for simplicity and since from before we have $m = 0$, the lender's objective function under overlapping borrowing is given by

$$\max_{R,m,n} V_{mb}^{np} = \frac{p(y^h - R) + n(1-p)\delta U}{1 - \delta[p + (1-p)(1-n)]} \tag{2}$$

[23]See Appendix for proof

[24]See Rabbani and Khalily (2012) for details as to what circumstances can be considered as multiple borrowing.

I still assume it is socially optimal to repay, rather than default, thus $n(\delta V - \delta U) - R_i \geq m(\delta V - \delta U)$. Clearly, the condition is tighter under overlapping borrowing because of the available outside options.

The borrower's *participation constraint* and bank's *participation constraint* remains unchanged under competition. But borrower's *incentive compatibility constraint* changes.

**Constraint 4.** $(n - m)(\delta V - \delta U) \geq R$.

This constraint states that the borrower must have enough incentive to repay and not run with money. The $RHS$ is the discounted expected gain from repaying, while the $LHS$ amount to be repaid as before.

The non-profit lender still charges $R^{np}_{mb} = \rho/p$ in equilibrium as the lender's participation constraint is unchanged and they choose the lowest possible interest rate. The highest possible interest charged is $n(\delta V - \delta U)$ as $\rho/p \leq R \leq n(\delta V - \delta U)$. Binding constraints (3) and (5), we find the upper limit of U.[25]

$$U \leq \bar{U} = \frac{n\delta p^2 y^h - [1 - \delta(1-n)]\rho}{\delta np(1-\delta)}$$

When the borrower’s outside options value is very high, $U > \bar{U}$, lending is not feasible. Lending is feasible when $U \leq \frac{p(y^h - R)}{1-\delta}$ and the lender offers a contract

[25]see Appendix

with:

$$R_{mb}^{np} = \rho/p, m = 0, n_{mb}^{np} = \frac{(1-\delta)R}{\delta[py^h - U(1-\delta) - R]}$$

where $\frac{\partial n}{\partial U} > 0$. Future lending must be canceled with a higher probability than before to induce the borrower to repay whenever she is successful as the borrower finds it profitable to default on the existing loan and wait on the outside option. On the other hand if the outside option value is low, then the borrower finds it profitable to repay the existing contract and expect renewal. Clearly, as $U$ tends to 0, $n_{mb}^{np} \to n$. The bank offers a loan contract with the amount to be repaid, inclusive of interest, set at $R^{IL} = \frac{\rho}{p}$, which is small enough to induce the borrowers to repay when successful, but the borrowers will only repay if they are successful and their outside options value is low.

Similar to the case with no overlapping, the feasibility condition is $\frac{\rho}{p} \leq p(1-m)\delta y^h$. It is counter intuitive but unsurprising to see that the feasibility condition does not depend on the outside options value, since I assumed that the banks do not have access to a information sharing technology, like a central credit rating agency, they are ex ante uncertain about the value of the outside options available to the borrowers. Thus the bank cannot differentiate between the interest rate charged for borrowers who have high outside options value and those who do not, resulting in a unique feasibility condition across all borrowers.

**Proposition 1.** *If* $U \leq \bar{U}$, $n_{mb}^{np} \geq n$. *That is, in the presence of outside options , non-profits have to cancel future contracts with higher probabilities when the borrower defaults on the loan to ensure repayment of* $R = \rho\, p$ *when the borrower is successful.*

As completion improves the borrower's outside options, they find it less costly to default on the loan. And, given the non-profit banks cannot lower interest rates any lower than what they were charging under zero overlapping, these banks must cancel future contracts with a large enough probability to ensure payment whenever the borrower is successful.

**Proposition 2.** $V^{np} = V_{mb}^{np}, \forall U \leq \bar{U}$. *Borrower welfare under overlapping borrowing, regardless of the value of the outside option available to the borrower is equal to the borrower welfare under no overlapping.*

With overlapping borrowing, the borrower has a larger choice set to maximize their payoffs, thus it is counter-intuitive to find that the welfare remains the same. Since it becomes less costly for the borrower to default when outside options are available, for-profit banks must cancel future contracts following a default, which is just large enough to ensure repayment when successful and restore the borrower back to the original welfare level. This result has practical significance. The traditional microfinance institutions, mostly those operating in the Indian subcontinent, have always shy-ed away from implementing lending technology, like information sharing or liquidation. This result suggests that given these banks mostly serve as non-profit social enterprises[26]

### 5.4 For-profit Lenders

In this section the banks maximize their own profits rather than maximizing the borrowers welfare. The timeline of the investment remains unchanged. The bank lends a unit of capital of the borrower, opportunity cost of capital is $\rho$. If the borrower repays in time, the bank receives $R_i$, inclusive of interest rate. Unlike the non-profits, the for-profit lenders maximize the profits for a single investment period. This is because I assume that the lender can costlessly replace the borrowers next period. This assumption is also made in De Quidt et al. (2018). Further I assume that prior to lending, the lender does not know the borrower's return $Y_i$, but the lender does know that $Y_i = [0, y^h]$.[27]

[26] In practice their behavior is more nuanced. Salim (2013) finds that pure profit motivation cannot explain branch locations chosen by Grameen or BRAC, two of the celebrated practitioners of microfinance, rather it falls more towards poverty alleviation

[27] This is a weak assumption since most MFIs does indeed maintain a record of their clients, which include the type of investment and the profession the client is in. See Grameen Bank's annual report as an example.

## Without competition

Since it is trivial that $m = 0$, as shown previously, I abstract from the assumption that the lender cancels the contract with probability $m$ following a successful repayment, thus the for profit lender's expected per-period profit is given by

$$\Pi^{fp} = pR - \rho \tag{3}$$

The lender maximizes the profits subject to constraints 1-3. Both non-profits and for-profits must satisfy these constraints to ensure repayment and non-negative profits. Unlike the non-profit lenders, the for-profit lender charges the maximum possible repayment rate. We have $\rho/p \leq R \leq min\{n(\delta V - \delta U), y^h\}$. In equilibrium the lender offers the contract[28]

$$R^{fp} = \frac{\delta n p y^h}{1 - \delta(1-n)}, n = 1$$

The higher the probability of success, the higher the demand for loans and hence the banks can charge a higher interest rate. This is counter to the non-profits, who charges an amount just large enough to recover costs. Since the for-profits maximize each period profit and can costlessly replace borrowers each period, they show

[28]see Appendix for proof

zero tolerance of risk.

### With competition

The lender knows the level of competition in the market. Profits are given still given by equation (6). Constraint 3 is replaced by constraint 4. Unsurprisingly, when we account for outside options, meaning there is competition in the market, the for-profit banks charges an amount which is just large enough to ensure repayment when successful and are less tolerant to risk as before, canceling future financing with certainty whenever default occurs.

$$R_{mb}^{fp} = \frac{n[\delta p y^h - \delta(1-\delta)U]}{1-\delta(1-n)}, n_{mb}^{fp} = 1$$

The for-profit lender requires a higher repayment amount than the non-profit. Without competition, the for-profit charges the maximum possible interest rate, which is based on the borrowers returns. Thus the higher the successful borrowers expected return, the higher the interest charged. But with competition the lender charges a smaller interest, with increase in competition, the lender reduces the interest to attract the borrower. Further, even though the lender can costlessly replace the borrower each period, they renew the contracts as long as the borrowers repay.

**Proposition 3.** $n^{fp} = n^{fp}_{mb} > n^{np}$. *For-profit banks are more likely to cancel a contract following default than non-profit banks.*

Clearly, as the lenders can costlessly replace a borrower, they have no incentive to refinance a lender who defaulted. Non-profit banks on the other hand maximize borrowers lifetime value from loan, thus they may still choose to refinance a borrower even after default.

**Proposition 4.** $V^{np} = V^{np}_{mb} > V^{fp}_{mb} \forall U \leq \bar{U}$. *Borrower welfare is greater under non-profits than for-profits. Under for-profits, welfare increase with rise in outside options.*

Under for-profit lending borrower welfare is given by $V^{fp}_{mb} = py^h + \delta U$. Unlike the non-profit case, we can see that borrower welfare depends on the outside options. This is because the interest rates depend on the outside options under for-profits. The higher the outside options value, the higher the welfare. Comparing with the non-profit case, we see that if $\frac{\rho}{p} = R^{np} < R^{fp}_{mb} = \delta py^h - \delta(1-\delta)U$, then $V^{np} = V^{np}_{mb} > V^{fp}_{mb}$. And since we know that the non-profits charge the lowest possible interest rate and for-profit charge the highest possible interest rate, borrower welfare will be higher under non-profit.

# 6 Empirical evidence of assumptions

## 6.1 Strategic Default

While the notion of strategic default is widely used in the microfinance literature, less than a handful research has been conducted to verify its existence in practice. The main problem in studying strategic defaults is that such defaults are de facto unobservable events. While we do observe defaults, we cannot observe whether a default is strategic as strategic defaulters have incentives to disguise themselves as people who cannot afford to pay and hence they are difficult to identify in the data (Guiso et al., 2013). Akhtar Hameed Khan[29], in his memoir, *Reflections on the Comilla Rural Development Projects* provides description of three types of defaults he witnessed on the Comilla Cooperative Project. The first of which is the *natural* default, which occurs because of the borrowers inability to earn a return due to bad state of nature. The last two, dubbed as *willful* and *political* defaults, are defaults without any apparent reason. He specifically mentions that some borrowers knew that sanctions (such as notices and pressure from loan officers) are futile and hence they defaulted with impunity. This is the exact behavior which Besley and Coates (1995) defines as strategic default, i.e. the borrower defaulting when pun-

[29]Khan is often regarded as providing the foundation for microfinance in Bangladesh through the Comilla Cooperaive Project. See Nasim Yousaf, *Akhtar Hameed Khan* (Education About ASIA, 2014) for details.

ishment of default is lower than benefit from repayment. Kono (2006) conducted field experiments in Vietnam and found that under joint liability, if group members observed each others returns, they are more likely to default. The result was consistent even after introducing cross-reporting mechanisms and penalties. Gine et al. (2011), exploiting a natural experiment in India—whereby Muslim borrowers were ordered by religious clerics to default on their repayment obligations—found that both Hindus and Muslims in Muslim-dominated groups showed higher default rates. This provides convincing evidence that microcredit borrowers in joint liability contacts do engage in strategic default. Kurosaki and Khan (2012), utilizing a natural experiment whereby one MFI in Pakistan changed its lending rules, found similar results. Under the old rules, borrowers were prone to default under joint liability, whenever their partners defaulted. Under the new rules, characterized by dynamic incentives and frequent repayments, those defaults were almost completely eliminated. This result provides evidence on the existence of strategic default.

There is evidence of strategic default in the case of individual liability contracts, albeit not from microfinance sources. Guiso et al. (2013), utilizing a unique survey data, finds that there is willingness to default strategically, due to both pecuniary and non-pecuniary reasons (like views on fairness and morality). They also find that respondents who know someone who defaulted are more likely to default, providing further evidence to the findings of Gine et al. (2011).

Overall, these findings are consistent with the strategic default assumption of our model since loans with no collaterals means borrowers could in theory default with impunity. There are microfinance institutions like *Bank Rakyat* and *BRI* of Indonesia which require explicit collaterals. On the other hand, institutions like the Grameen Bank require borrowers to save 5% of the loan in to Grameen Bank's persomal savings account, creating a financial collateral (Armendariz and Morduch, 2010). Our model might not be suitable for microfinance institutions of the former type. But for the later type, borrowers can still choose to default as long as the loan received is greater than the money saved, assuming money is fungible. Thus our assumption is valid to model lending of the later type of institutions.

## 6.2 Lender Behavior

Surprisingly, there is a dearth of research on the post default relation between lender and borrowers. Most theoretical papers assume the relationship is terminated after default, resulting in some pecuniary penalty on the borrower. Empirical research struggles due to most institutions being tight-lipped on this aspect. But in practice there is more depth to it then seen in the literature. Default loans are often restructured, grace periods are offered, interests pardoned—thus requiring only the principal, sometimes forgiven and at times leads to seizure of borrowers assets. In this section I provide empirical support for our assumptions on lenders behavior.

It is trivial in our model that lender's do not cancel future contracting following a successful repayment. Lending is costly to the lender, and more so in microfinance where there are many small borrowers. Gonzalez (2007) estimated that operating expense represented 62% of the interests charged to borrowers. Solli et al. (2015) found that loan officers often go to borrowers who live in such remote areas that visiting two/three of them takes up their whole time. This suggests that the lenders go to great extents to build a financial relationship. Further, with each time repayment, microfinance institutions strengthens trust with borrowers (since most MFIs operate without collateral). Also, losing clients is not sustainable. As the above evidence shows, it is not optimal for lenders to randomly cancel a borrowers contract when they repay, thus refinancing with certainty is a weak assumption.

Second, I assumed that lender's decision to renew following a default is a mixed strategy, i.e it induces a probability distribution or lottery over the possible outcomes. One can argue that loan contracts specifying a random allocation of cancellation rarely occurs in reality, lender's right in the event of default should be deterministic. I argue, in line with Bhole and Ogden (2010), that many products are allocated using lottery in the developing countries, especially those higher population. In Bangladesh government plots are often allocated using lotteries.[30] Also, rotating savings and credit association's (ROSCA)[31] are ubiquitous in a developing countries and mostly employ random allocation to determine which member will get a money. Further, to keep the analysis simple, I just focus on whether a contract in renewed or not, without going to the details of renewal. In reality there is a lot more dynamics to post-default lender-borrower relation.[32]. Solli et al. (2015)—interviewing various lenders from Peru, India and Uganda—found that the lenders seldom offer refinancing to defaulting borrowers, while only few offers some sort of loan restructuring. Successful repayment of a restructured loan does not necessarily lead to future refinancing.

[30] Lottery result of Uttara Apartment,'March'-2019. (n.d.). Retrieved from http://www.rajukdhaka.gov.bd/rajuk/showWebNotice?noticeType=generalNotice

[31] see Armendáriz, Beatriz, and Jonathan Morduch. "The economics of microfinance", p. 53. MIT press, 2010.

[32] Some of which is being explored in another paper by the author

# 7 Empirical Analysis

## 7.1 Testable Predictions

I derive two testable predictions from the theory from Proposition 1 and 2.

i As competition increases, lender's anticipate more default, thus increase threat of termination to extract repayment.

ii For-profit lenders are more likely to deny loans to defaulters than non-profits.

## 7.2 Setting

Several features of the Bangladeshi microfinance market make it ideal for the study in concern. First, Bangladesh is the birthplace of the modern microfinance, with a large number of its population engaged in microfinance activities.[33] This suggests that microfinance is ubiquitous in Bangladesh and hence I can control for the regional differences.

Second, the traditional MFIs in Bangladesh at its advent were non-profit enterprises, with an increasing number of for-profit enterprises in recent years[34] I can exploit this change to capture the effect of profit motive on loan renewals.

[33] There were almost 25 million active borrowers in 2017, representing 15% of the population.

[34] See Khandker, Shahidur R., MA Baqui Khalily, and Hussain A. Samad. "Beyond ending poverty: The dynamics of microfinance in Bangladesh" The World Bank, 2016.

Third, although the oldest, Bangladesh still has a rapidly expanding microfinance market. "Problems with competition have emerged most notably in two countries where microfinance was first to take hold: Bolivia and Bangladesh", Economics of Microfinance (2010). The number of licensed MFIs have gone up by 20.65% from FY 2013 to FY 2017 and the number of MFI branches went up by 16.67% in the same period. Also, there has been an increasing number of MFIs canceling their licenses, which went up from 45 cancelled licenses in FY2013 to 84 in 2017, further suggesting a rise in competition.[35] The span of microcredit operation along with the continuous expansion means Bangladesh has a wide variety of institution sizes, from very small to very large[36] which provides an added dynamic to the analysis.

## 7.3 Data

The primary source of data is a panel on Bangladeshi microfinance institutions collected by the Institute of Inclusive Finance and Development (InM).[37] The dataset was collected as part of the project "Branch Expansion and Institutional Sustain-

[35]see Boyd, John H., and Gianni De Nicolo. "The theory of bank risk taking and competition revisited" The Journal of finance 60, no. 3 (2005): 1329-1343, for survey of literature on how competition may promote failure.

[36]For example, as of June 30, 2017 Adorsho Manob Kollyan had only one office countrywide, catering to around 1,000 borrowers. ASA (Association for Social Advancement) on the other hand had 2959 offices, serving close to 6,800,000 borrowers.

[37]This project used samples and/or data provided by the Institute for Inclusive Finance and Development (InM). The author is thankful to InM for providing access to the data.

ability of MFIs in Bangladesh" and contains three years of data FY2014-2016. Primary survey was conducted in September 2016 and contains basic information on the MFI branch and information on total borrowers and depositors. Data was also collected on financial information, including interest and non-interest income, operating expenses and financial expenses (separating expenses on salary, rent, loan loss provision and depreciation). There is data on assets (including contra-asset loan loss reserve) and liabilities. Further, managers perception on related information was collected for the FY 2016.

The dataset serves the purpose in five ways. First, the sample contains information on 362 branches from 40 districts of Bangladesh (which represents almost two-thirds of the total districts). Second, the survey contains information on the managers opinion about competition and profit motive, which adds an extra dynamic to the analysis. Third, unlike most related literature, this is not a country-level dataset, thus measures which vary depending on country characteristics, like average loan, are better captured. It also allows me to conduct detailed micro-analysis. Fourth, Since the data is collected by a third party—unlike data from MIX, which is self-reported—it should be more reliable and accurate. Fifth, a stratified random sampling approach has been utilized, ensuring proportional representation of small, medium and large MFIs.

However, there are some limitations to the data. Firstly, there is no information on how much loan were distributed to women or the percentage of female members.[38] I estimate profit motive utilizing average loans—which is the more standard and more widely used measure—instead of percentage of female borrowers, but this reduces a potential robustness check. Further, since the managers perspectives are cross-sectional to only FY 2016, they cannot be specifically controlled for using fixed effects regression. Also, since most managers are in this position for less than 3-years, MFI fixed effects may not mitigate the unobserved heterogeneity due to variances in manager behavior. But most managers are working as a manager for more than 3-years, So I assume their decision making as managers stay constant. The dataset does not contain information on loan delinquencies, 30-day delinquent and 180-day delinquent loans, this effect the measure of loan renewals. As a proxy, I use the Loan Loss Reserve Ratio (LLRR), which shows the expected delinquent loans. Also, by taking differences in between years of loan loss reserves and subtracting the difference with loan loss provision, I can measure the amount of loans written of during a period. But given that there are three years of data, I can only get two years of loan write-offs. In addition, some data before 2016 were collected from manager's recollection, however, most of those data were not used in the primary analysis.

[38]Cull et al (2009) shows that one way to identify profit motive of a MFI is to see how much loan is distributed to women.

## 7.4 Supplemental data

The main dataset is supplemented with various other datasets, which primarily contains data on covariates. Information on inflation which used to measure Financial Self Sufficiency, is collected from Bangladesh Bank. National, rural and urban average incomes, along with income deciles are collected from the Household Income and Expenditure Survey (HIES) 2016, conducted by Bangladesh Bureau of Statistics. Union level population is collected from the Population and Housing Census 2011.

## 7.5 Summary Statistics and Sample Restriction

The general statistics on branches are given in Table. It shows that the average age of the MFIs branches are almost 12 years. Rural branches employ both more officers than urban or suburban branches, which is unsurprising given the field officers at rural branches need to travel more to reach the customers. Suburban branches seem to have the highest dropped to active borrower ratio. Borrowers can drop out due to various reasons, including switching to fixed wage day labor jobs, thus this does not necessarily mean that suburban borrowers are failing more. Rural MFI's are located further from growth centers and nearest concrete road. They also have less number of other MFI branches within a five mile radius.

Table represents the descriptive statistics on the key variables used for analysis. The mean Lerner Index is 0.74, suggesting a tendency towards higher market power. The average loan size as a percentage of the income at the 20th percentile is 102%, suggesting that the average loan is approximately equal to the income at the 20th percentile, these are mostly people who engage in microfinance. The annual average lending rate is around 23%. This is a good approximation of the practice in Bangladesh, where annual interest rate is capped at 27% of MFIs. Also, a study by InM found that the break-even interest rate is around 23-24%. The borrower per officer seems high. But in practice each officer often holds weekly or bi-weekly group meetings with borrowers in a village to collect the payments, even when they are individual loans (Banerjee, 2013). Assuming bi-weekly meetings and the average number of members per group to be around 20, an officer may need to hold 18 group meetings per fortnight, which seems reasonable. The average salary of the officers is above the national income, suggesting that MFIs maintain competitive pay scales. The mean operating cost per unit of currency is at 7%.

The average MFI branch is both operationally and financially self-sufficient. Looking at the percentiles, I see that around 50% of the branches are financially self-sufficient.

I do not impose any sample restriction based on selection criteria. But I impose some restrictions on the regression sample because some branches, either partly or for all three years, have missing values on key observations, like loan loss provisions or operating costs and so on. Few of the variables have been winsorized to get rid of potential outlier bias or in some cases clear misreporting. This reduces the sample size from 1080 observations to 600 observations.

## 7.6 Empirical Strategy

The empirical strategy stems from the theoretical model described above. It is based on the assumption of strategic default on the borrower's sides and heterogenous motives on the lenders side. I argue that if the borrowers have more outside options, it becomes less costly to default on the existing loan, thus the lenders have to increase threat of punishment to induce them to repay. This mechanism relies on the assumption of strategic default, i.e. that the borrower's punishment of default is less than the reward. In a recent paper, Allen (2016) found no evidence of strategic default among the microfinance borrowers. If such is the case, then this mechanism might not be robust.

## 7.7 Constructing measures of Competition

Outside options are defined as the opportunity cost of defaulting, i.e. the value the borrower will get if she decides to default. I assume, following De Quidt et al. (2018), that as competition increase the value received from outside options also increases. Therefore, I use market competition as a measure of outside options. Since, in the theoretical model each borrower can only take one loan at a time, it can be argued that higher competition means that the borrowers's outside option value is higher.

I measure competition using two ways; Lerner Index (Lerner, 1934) and the Boone Indicator (Boone, 2008). These measures have certain benefits over the commonly used concentration ratios like Herfindahl-Hirschman Index (HHI) or three-firm concentration ratio. First, they have the advantage of non-stringent data requirements, unlike the HHI and others which requires information set of all firms to be known. Given the semi-formal nature of the microfinance market and the fact that most thriving microfinance markets are in less developed countries, such information is virtually non-existent.

Second, these measures of competition does not rely on the market shares, i.e. concentration ratios. As shown by Berger et al. (2004), Claessens and Laeven (2003) and others, the link between concentration and competition is weak in banking. Schaeck and Cihak (2010) provides an example whereby a bank is forced to closure due to high competition and it being not efficient enough to compete. A typical concentration ratio will show that the market power of the existing firms went up, misleading the reader to infer that competition lowered.

## Lerner Index

An advantage of the Lerner index is that it can be measured so as to be both MFI- and time-varying, so it can identify different patterns of behavior within the same market and/or between years.

$$\begin{aligned} ln(TC_{it}) = \beta_0 + \beta_1(lny_{it}) + \frac{1}{2}\beta_2(lny_{it})^2 + \sum_{k=1}^{3} b_k(lnw_{k,it}) + \frac{1}{2}\sum_{k=1}^{3} b_k2(lnw_{k,it})^2 \\ + \sum_{k=1}^{3}\beta_3(lny_{it})(lnw_{k,it}) + \sum_{k\neq k\prime} b_k4(lnw_{k,it})(lnw_{k\prime,it}) + \alpha_j + b_t + \epsilon_{it} \end{aligned} \tag{4}$$

Differentiating the total cost function, we get the marginal cost.

$$MC_{it} = \frac{\partial TC_{it}}{\partial y_{it}} = \left(\beta_1 + 2\beta_2(lny_{it}) + \sum_{k=1}^{3}\beta_3(lnw_{k,it})\right)\frac{TC_{it}}{y_{it}} \tag{5}$$

## Boone Indicator

The Relative Profit Differences, RPD (commonly referred to as the Boone Indicator) measures the impact of efficiency on profits or market-share. The underlying assumption is that the more efficient a bank is, i.e. the lower the marginal cost, the better it'll perform under competition, while on the other hand competition weakens the performance of the inefficient banks. This hypothesis is supported by several papers including Nickell (1996), who shows higher competition leads to higher productivity; Porter (1990), Geroski (1995), Nickell (1996) and Blundell et al (1999), who show that competition leads to innovative firm activity.

$$ln\pi_{it} = \sum_{T=1}^{3} \beta_t D_t ln(MC_{it}) + \sum_{T=1}^{3} \beta\prime_t D_t + \epsilon_{it} \tag{6}$$

Where $\beta_t$ are the Boone Indicator for each year. From the perspective of the banking market the Boone Indicator has some advantages over the other structural measures of competition. First, the Boone Indicator may be time dependent, thus it can capture effects of competition over time. Second, it focuses only on a submarket, in this case the loan market rather than the entire banking market, which also includes deposit competition. Third, the Boone Indicator is theoretically more robust than its counterparts, requiring less restrictive assumptions.

Limitation of the Boone Indicator for this dataset is the lack of MFI variance. To counter this, once I measure the Boone Indicator for each year, I construct a measure of outside options available to members of each MFI by utilizing a question in the survey–"how many other MFI's are within 5km of your institution?"

$$Concentration\ \ adjusted\ \ Boone\ \ Indicator = Boone_t \times \frac{x_i}{max\{X\}}$$

Where xi is the number of other MFI branches within 5k.m of branch $i$. Then two branches $i$ and $j$ that have the same Boone Indicator$= -1$, but different number of other MFIs around them, then given max{X}=30. Conc. Adj. Boone for $i = -1 \times \frac{15}{30} = -0.5$ & Conc. Adj. Boone for $j = -1 \times \frac{15}{30} = -0.83$. Thus $j$ operates in a more competitive environment than I and members of firm j has more outside options than $i$.

## 7.8 Measuring profit-motive

I measure profit-motive, following Cull el al. (2009), as the average loan size as a percentage of income at 20th percentile. The assumption is that the lower the size of the loan, the higher the outreach to the marginalized and women borrowers, who tend to take smaller loans, suggesting the MFI is geared more towards betterment of its clients than maximizing profits. Also, smaller loans tend to have higher operating costs, which any profit maximizing firm will avoid.

I separate average income in three groups, national, rural and urban area. The dataset contains information on the area of operation, I exploit that to determine the location of the branch. Data on income levels and income deciles are collected from the HIES 2016, so base income year is 2016.

Most literature in microfinance mission drift uses average loan as a proxy to measure profit motive.[39] In general, MFIs with smaller average loans were found to have greater outreach to the poor (Cull et al.,2009; Gonzalez and Rosenberg, 2006). There are some caveats to this approach as demonstrated by Armendariz and Szafarz (2011). First, average loan size will consist cross-country variances, depending on country income. But controlling for country, there exists a tight link between greater outreach to the marginalized and average loan sizes comparing across institutions as showed by Gonzalez and Rosenberg (2006). Since the data is from a single country, this problem is mitigated, plus I control for three different income levels within the country. Second, in highly populated countries, such as Bangladesh, it is possible to keep the operating cost per loan low, particularly due to the high level of poverty and high population density (which reduces lending costs), while disbursing smaller loans. I control for several cost efficiency measures

[39]see Cull, Robert, Asli Demirgüç–Kunt, and Jonathan Morduch. "Microfinance trade-offs: Regulation, competition and financing." In The handbook of microfinance, pp. 141-157. 2011.

to counter this problem.

There are several other ways profit-seeking motives are proxied, such as profitability and legal status of the MFI, but such proxies have less empirical validity. First, profit-motive cannot be determined by profitability of the institution. Most non-profit banks do earn net positive income, but a non-profit status bank cannot transfer the net earnings out of the business as they wish, rather have to re-invest in the business either to further outreach or pursue other social missions.

Second, another common way profit-seeking motive is measured in the literature is by the legal status of the institutions. Usually NGO's are considered as non-profit while microfinance banks as for-profit. But this measure can be flawed too. The most celebrated MFI, the Grameen Bank is a regulated bank, but thrives towards poverty alleviation. While the largest NGO, ASA's main goal is income generation. Further problem is created as non-bank financial institutions tend to be both (Cull et al. 2009).

Thus the idea is that if a MFI provides larger average loans as a percentage of national income at the 20th percentile, then there is a general tendency towards profit seeking. The dataset has the question about reason to open the branch. Around 33 branches said that it was for the purpose of either poverty alleviation or benefit of the borrowers. Another distinguishing method can be subsidy/donor fund received. For-profits banks hardly received any donor funds, while the median NGO (non-profit) received \$233 subsidy per borrower (Cull et al, 2009).

## 7.9 Illustrative evidence

First, the questionnaire contains a question asked to the manager about the primary reasons for opening the branch in the area. Exploiting that question, we see in Figure 3 that in branches where the managers'responded that poverty alleviation was the primary reason for opening, the median loan sizes are smaller than branches which were opened to expand business or reduce costs.

Second, it can also be argued that MFIs who have received some sort of donations tend to be non-profits, there are caveats, but the argument holds true in general. Exploiting that argument, we see that in Figure 4, the mean average loan size as a percentage of income at the 20th percentile is lower for branches which received some grant, indicating non-profit motive, than branches who received some grant.

## 7.10 Constructing Interest Rates

I construct proxies for interest rates, following Dorfleitner et al. (2013) , I call them lending rates following the original authors. [40] [Add formula] Most literature tend to proxy interest rates charged by dividing total loan disbursed by total number of borrowers. [41] Following that I get a mean interest rates of only 11.56%, which is far below the average interest rates charged by the MFI's in Bangladesh. The mean lending rates on the other hand are approx. 22%. According to a study by InM, a premiere research organization on microfinance, average interest rates required to break even is 23-24% and the Bangladesh government has capped the interests at 27%.[42] So, this is seems to be a good approximation of the actual interest rates.

## 7.11 Measuring denial of future access to credit

I use the Loan Loss Reserve (LLR) ratio–percentage of loan loss reserves to average outstanding debt–to proxy credit denial.[43] It shows how much of the loan portfolio has been reserved for future loan losses. A standard commercial bank invests depositor's fund in two major assets, securities or loans, but for most MFI's investing

[40] Note that since I have data for three years and too calculate loan write-offs I lost a year of data, therefore I use the average of loan writes to calculate the write-off ratio.

[41] For example see Ahlin et al. (2011)

[42] Bangladesh caps microfinance rates at 27%. Retrived from https://www.ft.com/content/fd16a1f0-ecea-11df-9912-00144feab49a

[43] Ahlin et al. (2011) and Quayes (2015), both have used loan loss ratios as a proxy to capture anticipated loss from loans.

in the former is rare. Loans typically bear credit risk, i.e. the borrower will fail to repay the agreed amount in part or wholly. The loan loss reserves are allowances for potential loan losses. [44]

The loan loss reserve ratio shows how well a bank is managing delinquency. [45] Loan loss reserve is a stock item in the balance sheet, it is a contra asset. The higher this ratio, the higher the bank's perception of delinquent loans, the higher the probability of future loan denials to the defaulters. For this sequence of actions to be true, the underlying assumption that lenders punish defaulters by cutting off access to loans must hold. Stiglitz and Weiss (1983) provides theoretical evidence as to why termination of contracts may be ideal rather than rise of interest rates in markets with moral hazard problems. Solli et al. (2015) provides empirical evidence on the use of such mechanism by microfinance banks around the world.

Note that loan loss provisions (LLPs), which is a flow item in accounting literature, is not used. LLPs are an expense item which used to adjust the LLR each year. If a bank decides to raise its LLR, then it adds the LLP to the operating expense or subtracts it from the expenses if decides to reduce the LLR. This means that for the latter case the LLP is negative.[46] A bank's intention to reduce LLR doesn't neces-

[44] see details, Walter (1991)

[45] see Ledgerwood (1998), for a detailed analysis of how microfinance institutions utilize the loan losses in practice.

[46] One problem with negative values is the nonexistence of natural logs. Even though is problem can be circumvented by taking cubic roots, interpretation remains a problem. Also, cubic or higher odd roots are uncommon in economics literature.

sarily mean that it is anticipating less credit risk. Banks also tend to reduce LLR usually if the loan disbursement falls, but nonetheless LLR is always positive.

The second mechanism depends on the lenders having heterogenous objective functions. I assume that non-profit lenders focus on maximizing borrower welfare, given they earn non-negative profits. While for-profit lenders maximize profits. Thus, non-profit lender are more lenient towards default than for-profit lenders. Finally, default costs will depend on the amount of interest charged. The higher the interest rates, the easier it is for the borrowers to default and thus lenders have to increase threat of termination to ensure payment when borrower is successful.

## 7.12 Determinants of Interest Rates

In this section I provide evidence that profit-seeking motive and outside options are determinants of interest rate as the theoretical model suggests. If there is evidence of determination then interaction terms must be used in the key model specification. Table shows two linear specifications with time and MFI fixed effects, one with Lerner index as outside options the other one uses the Boone indicator. The estimating equation is

$$LR_{ijt} = \omega m_{ijt} + \Omega(m_{ijt})^2 + \gamma c_{ijt} + X'_{ijt}\beta + a_i + b_t + u_{ijt} \tag{7}$$

where $LR_{ijt}$ = Lending Rates of branch $i$, from MFI $j$ at time $t$. $m_{ijt}$ = Degree of profit-seeking motive for branch $i$ at time $t$. $c_{ijt}$ = Market power of branch $i$ at time $t$. $X'_{ijt}$ = are the branch, MFI and time specific controls. $a_{ij}$ = MFI fixed effects. $b_t$ = Time fixed effects. Hypothesis: $\omega < 0, \Omega > 0, \gamma > 0$.

The sign of $m_{ijt}$ at first glance seems counter to the theory, which suggests profit-seeking MFIs charge higher interest rates. But the squared term provides evidence of a quadratic relation (inverted U).[47] As seen from Table 4, the effect of larger average loans are twofold; first, the higher the size of a loan, the lower the operating costs, hence conditional on operating costs lower interest rates can be charged. Second, as suggested by the literature, profit seeking MFIs disburse large average loans, hence should charge higher interest rates. The third specification with controls for various measures of operating costs and efficiency confirms the hypothesis. Both proxies of outside options, the Lerner index and the Boone indicator show that interest rates rise with increase in competition.

## 7.13 Estimating Equation and Identifying Assumptions

The main estimating equation is:

$$Y_{ijt} = \alpha c_{ijt} + \eta m_{ijt} + X'_{ijt}\beta + a_i + b_t + u_{ijt} \tag{8}$$

[47] see Figure 11

where $Y_{ijt}$ is the Loan Loss Reserve ratio of branch $i$, from MFI $j$ at time $t$. $c_{ijt}$ is the competition faced by branch $i$ at time $t$. $m_{ijt}$ is the profit-motive variable showing the degree of profit-seeking motive for branch $i$, this is also time variable. $a_{ij}$ is a MFI fixed effect. $b_t$ is the time fixed effect. And finally $X'_{ijt}$ are the branch, MFI or time specific controls. I control for MFI productivity, efficiency, general characteristics and also control for branch fixed effects, which allows me to control for differences in management across MFI branches. I cluster standard errors at the MFI head office level to account for individual differences in assessing risk across MFIs as the MFI's were originally chosen on a stratified sample based on size.[48]

The identifying assumption is that, conditional on the included covariates, changes in labor demand at an individual's former coworkers' current firms are uncorrelated with unobserved determinants of mobility or wage growth:0. The primary concern is that there are unobserved changes in the demand for a worker's skill that are correlated with it but not captured by our industry-by-time controls.

## 7.14 Main results

The section provides the main results from the reduced form analysis. The results provide evidence for the last two hypotheses, but not for the first hypothesis. As

[48]Since in practice, following Angrist, clusters of above 40 are suggested for clustered standard errors, I also use robust standard errors, results remain fairly constant.

predicted from the theoretical model, MFI's that usually provide larger loans, indicating profit-seeking motive, are more likely to terminate defaulters contract than a non-profit MFI. Also, I find evidence, consistent with the theoretical model, the higher the interest rate, the more the credit risk and thus the higher the punishment of default. The preferred model is the full specification including the interaction terms (Model 3), regardless of clustered or robust standard errors, because that is more akin to the predictions of the theoretical model, even though I don't find statistical evidence for one of the interaction terms using conventional levels.[49]

## 7.15 Quantitative Results

The Table 4 depicts the estimates of the key variables from equation . The dependent variable is the percentage of loan loss reserves held of outstanding loans as potential bad debt. Average loan as a percentile of National Income at the 20th percentile[50] is scaled such that it indicates the impact of a 10% increase in size of average loan as a percentage of national income. The full specification indicates that a ten-percent increase in average loan size increases the Loan Loss Reserve ratio by 3.549+0.169LR. Assuming, lending rates at the first quartile—11%–the marginal effect is 5.41%. If maximum allowed interest rates are assumed, which is 27% for

[49] These papers and articles show that statistical significance is misused in the literature: 'The ASA Statement on p-Values: Context, Process, and Purpose' and 'Scientists rise up against statistical significance'

[50] which I'll just refer to as average loan from now on for simplicity

Bangladesh, then the marginal effect is 8.112%. The sign of the coefficient corresponds the theoretical model, the more profit seeking lenders and more likely to terminate loan contracts and the effect is magnified if coupled with higher interest rates. The is consistent with the idea that lenders maximizing profits enforce larger threat to not-renegotiate in case of default, which is seen through their higher default costs. Comparing the specifications, it can be seen that the estimates of average loan goes up once the controls are added, suggesting a downward bias in the baseline model. Also, the slight reduction in the estimate from specification (2) to (3) is captured in the interaction term.

The small magnitude can be explained by the fact that increase in average loan sizes has two effects on the Loan Loss Reserve Ratio; i) one from the profit seeking motive, which has a positive impact on the dependent variable as explained before, ii) larger loan sizes makes it easier to manage loans, reducing operating, i.e. monitoring costs, thus have a negative impact on the LLE. This is further confirmed by looking at the 95% confidence intervals in figure, which includes stretches to negative. The second specification, without the interaction terms, shows that a ten-percent increase in average loan sizes increases the LLR ratio by 4.29%. Both the preferred specifications suggest a similar finding. Changing to robust standard errors does not bring about any significant changes to the model.

Lending rates indicate the impact of a percent increase in lending rates on LLRR. The full specification model shows that a 10-percent rise in lending rates effects LLRR by 5.013+ 0.169avgloan. Assuming mean values—average loan 100—the marginal effect is an increase of 21.913% in the LLRR, suggesting higher probability of contract termination.

In all the specifications, the measure of competition has a high p-value [robustness check with Boone indicator index provides similar results], suggesting little evidence against the null. But the preferred specification has the lowest p-value (0.19), while still suggesting no evidence against the null at conventional levels, the sign of the coefficient is consistent with the theoretical prediction. The negative sign, counter-intuitively, signifies that if competition goes up, meaning a reduction in the Lerner Index, outside options go up, LLR ratio goes up. Therefore, if the Lerner Index is reduced by 0.1, then LLR ratio increases by 1.075%. The coefficient on Lerner [0, 1] is slightly bigger but has a very high p-value. This result is consistent with the interaction term described above, which has a much lower p-value, 0.245.

## 7.16 Heterogeneity

**Competition**.

**Geographical Location**. I check whether results are driven by geographical location of the MFIs. Flatland vs irregular land. I find that flatlands are 1.3 times more likely to terminate a contract than the irregular land MFIs. I then double check the results by regression with interaction of distance from nearest concrete road. MFI's which have do not have concrete road nearby, suggesting remote locations, hence greater outreach have lower impact of average loan size.

**Firm Size**. I check whether results are driven by firm size. As can be seen by the table, the effect of average loan size on LLE is mostly driven by the small and medium size MFIs. This makes sense, because larger MFI's can give larger loans because there client base is more diverse, on the other hand smaller mfi provide loans to poorer individuals, thus it is more likely that small mfi's which provide larger loans are more profit seeking.

## 7.17 Robustness Check

### Different measure of outcome variable

The threat of termination from the theoretical model clearly increases the cost, thus it is the cost of default. Hence I measure the denial to access to future credit using the Loan Loss Expense (LLE) rate, following Ahlin et el. (2011), which is the loan loss provisions over loans outstanding. The loan loss provision is an expense item (flow) in the income statement. As seen from Table 6, the measures are all consistent. All the coefficients, except Lerner Index, is statistically significant, the signs are consistent too. The coefficient on Lerner Index is negative as expected and has $p - value = 0.1692$.

### Alternative measure of competition

As described in Section 8.1.2, a alternative measure of competition is measured using the Boone Indicator.

# 8 Conclusion, Policy Implication and Future Work

In summary, microfinance has revolutionized lending without the use of collaterals and monitoring by using non-traditional techniques, one of which is providing dynamic incentives. In this paper I studied the change in the lender's optimal contract when facing competition. I find that when the market becomes competitive, borrowers find it less costly to default because they derive utility waiting on the available outside options. Lenders respond by increasing the ex-ante threat of contract cancelation; however, they charge a lower interest rate due to competition as expected. For-profit lenders charge a higher interest rate than non-profits and are more likely to implement the threat of cancelation than non-profits. I then test the key predictions from the theoretical model: i. As competition increases, lender's increase the threat of non-renewal, ii. For-profits are more likely to deny loan to a defaulter than non-profits. I find statistical evidence for the first hypothesis and while I don't find statistical evidence for the second hypothesis, there is a slight trend.

The results have several policy implications. First, the paper highlights the importance of information sharing technology, like credit bureaus, in the market. Such a technology will prevent the incidence of strategic default by limiting the borrower's outsides options and thus reduce the lender's need for increasing ex-ante threat of non-renewal. This will benefit less serious defaulters, i.e. first timers or borrowers who suffered some adverse shock, as lenders would know that it is difficult to avail the outside options without repaying the existing loan because the credit bureau shares information with other lenders, thus making the industry more sustainable and make contract renegotiation easier for the borrowers. This will also reduce client turnover and hence reduce the operating costs for the lenders. Also, the sustainability of the market can be ensured better with such a system in place.

In a quasi-experimental study focused on credit reporting in Guatemala[51], BASIS researchers found that after the implementation of credit sharing bureau, default rates decreased significantly for individual liability loans. This result is consistent with my model, information sharing technologies limit the incidence of strategic default, hence the worse borrowers should repay under such a system.

Second, both the theoretical and empirical analysis suggests that for-profit lenders are more likely to exclude borrowers from future loans following default. Since many defaults occur due to some adverse shock, thus with the rise in for-profits, financial exclusion of the marginalized might rise as they will eventually target borrowers who are less prone to income shocks. This might defeat the purpose of microfinance. The model suggests that non-profits only increase threat of cancela-

[51] see McIntosh et al. (2006) for details

tion to mitigate incidence of strategic default, with proper systems to build credit histories of borrowers, such institutions are in a better position to combat poverty than for-profits.

Third, in the short-run, as long as the borrowers can avail the outside options, competition is beneficial for the borrowers. One implication of the theoretical model is that borrower welfare under non-profit lending is same for every value of feasible outside options. Under for-profit lending, borrowers are benefitted by the lower interest rates and no matter the value of outside options, the lender's ex-ante loan non-renewal is the maximum. Therefore, under non-profits, borrower's welfare remains unchanged, while with for-profits they gain as long as they can keep on borrowing.

One limitation of the paper is that I have limited information on the number of loans cancelled due to default and the average loan sizes in some cases might not have captured the true profit motive properly. Future work can use updated data, specially using transaction level data to test the predictions from the hypothesis. Also, one direction of research is to find a proper measurement of profit motives. This will not only help researchers but also provide a guide to impact investors, who can use such measures to investigate whether their investment is being utilized properly. On the theoretical side, one direction of research is to endogenize the profit motive parameter to find the optimal motive given the rise in competition and impact investment in the market.

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# A Theoretical Appendix

*Proof. Derivation of n under non-profit banks without competition*

$$\begin{aligned}
\max_{R,m,n} \quad & V^{np} = \frac{p(y^h - R)}{1 - \delta[p(1-m) + (1-p)(1-n)]} \\
\text{s.t.} \quad & y^h \geq R \\
& (n-m)\delta V \geq R \\
& pR \geq \rho \\
& 0 \leq m \leq 1, 0 \leq n \leq 1
\end{aligned} \tag{9}$$

□

*Proof. Derivation of n under non-profit banks with competition*

$$\begin{aligned}
\max_{R,m,n} \quad & V^{np}_{mb} = \frac{p(y^h - R) + [mp + n(1-p)]\delta U}{1 - \delta[p(1-m) + (1-p)(1-n)]} \\
\text{s.t.} \quad & y^h \geq R \\
& (n-m)(\delta V - \delta U) \geq R \\
& pR \geq \rho \\
& 0 \leq m \leq 1, 0 \leq n \leq 1
\end{aligned} \tag{10}$$

As before $m = 0$ and $R = \rho/p$. Taking partial derivatives of $n$ on $v$ we find that

$$\frac{\partial V}{\partial n} = \frac{(1-p)\delta U[1-\delta(1-n(1-p))] - \delta[p(y^h - R) + n(1-p)\delta U][1-p]}{[1-\delta[1-n(1-p)]]^2}$$

$$\begin{aligned} &\text{therefore either } \delta = 0 \text{ or p=1 or} \\ &= \frac{U - \delta U[1-n(1-p)] - p(y^h - R) - \delta U n(1-p)}{[1-\delta[1-n(1-p)]]^2} \\ &= \frac{(1-\delta)U - p(y^h - R)}{[1-\delta[1-n(1-p)]]^2} \end{aligned} \tag{11}$$

$\therefore \frac{\partial V}{\partial n} < 0$ if $U \leq \frac{p(y^h - R)}{1-\delta}$. Meaning as $n$ decreases $V$ increases. Now we substitute $V$ in the borrower's incentive compatibility constraint.

$$n\delta[\frac{p(y^h - R) + [n(1-p)]\delta U}{1-\delta[1-n(1-p)]} - U] \geq R \tag{12}$$

differentiating the L.H.S w.r.t n, we get

$$\begin{aligned} \frac{\partial LHS}{\partial n} &= \frac{[\delta p(y^h) + 2n\delta^2 U(1-p)][1-\delta[1-n(1-p)]]}{[1-\delta[1-n(1-p)]]^2} \\ &\quad + \frac{[n\delta p(y^h - R) + \delta^2 U n^2(1-p)]\delta(1-p)}{[1-\delta[1-n(1-p)]]^2} - \delta U \\ &= \frac{\delta^3 n^2 U(1-p)^2 + [\delta p(y^h - R) + 2n\delta^2 U(1-p)](1-\delta)}{[1-\delta[1-n(1-p)]]^2} \\ &\quad + \frac{\delta U[1-\delta[1-n(1-p)]]^2}{[1-\delta[1-n(1-p)]]^2} \\ &= \frac{\delta(1-delta)[p(y^h - R) - U(1-\delta)]}{[1-\delta[1-n(1-p)]]^2} \end{aligned}$$

$\therefore \frac{\partial LHS}{\partial n} > 0$ if $U \leq \frac{p(y^h - R)}{1-\delta}$. Meaning the L.H.S decreases as $n$ decreases, but given constraint (2), it will decrease until constraint (2) becomes an equality. Thus we have

$$
\begin{aligned}
& n\delta p(y^h) + \delta^2 n^2 U(1-p) = (R + n\delta U)[1 - n(1-p)] \\
& \implies n[(\delta p(y^h - R) - \delta U(1-\delta)) - \delta R(1-p)] = R(1-\delta) \\
& \therefore n = \frac{r(1-\delta)}{\delta[py^h - U(1-\delta) - R]}
\end{aligned} \tag{13}
$$

□

*Proof. Derivation of $n$ and $R$ under for-profit banks without competition*

$$
\begin{aligned}
\max_{R,m,n} \quad & \Pi^{fp} = pR - \rho \\
\text{s.t.} \quad & y^h \geq R \\
& (n-m)\delta V \geq R \\
& pR \geq \rho \\
& 0 \leq m \leq 1, 0 \leq n \leq 1
\end{aligned} \tag{14}
$$

□

*Proof. Derivation of $n$ and $R$ under for-profit banks with competition*

$$
\begin{aligned}
\max_{R,m,n} \quad & \Pi_{mb}^{fp} = pR - \rho \\
\text{s.t.} \quad & y^h \geq R \\
& (n-m)(\delta V - \delta U) \geq R \\
& pR \geq \rho \\
& 0 \leq m \leq 1, 0 \leq n \leq 1
\end{aligned}
\tag{15}
$$

From constraints 1, 3 and 4, we get the range of values of $R$, $\rho/p \leq R \leq min\{n(\delta V - \delta U), y^h\}$. We know that the for-profit bank will charge the maximum possible interest rate, thus $R = min\{n(\delta V - \delta U), y^h\}$. Suppose the bank charges $n(\delta V - \delta U)$, then we get

$$R = \frac{\delta n p y^h}{1 - \delta(1-n)} \tag{16}$$

Comparing it to $y^h$, we get that $R = y^h$ if

$$2n\delta p y^h - n\delta pR - n\delta U(1-\delta) - y^h[1-\delta+\delta n] \geq 0 \implies y^h[n\delta(p-1)-(1-\delta)] \geq n\delta U(1-\delta) \tag{17}$$

Which is a contradiction unless $p = \delta = 1$, which we rule out as too extreme. Therefore

$$R = \frac{\delta n p y^h}{1 - \delta(1-n)} \tag{18}$$

Substituting the value of $R$ in the profit function we get

$$\Pi = \frac{n[\delta p^2 y^h - n\delta U(1-\delta)]}{1-\delta(1-n)}$$

Taking derivatives w.r.t to n, we get

$$\frac{\partial \Pi}{\partial n} = p\delta(1-\delta)[py^h - U(1-\delta)]$$

Thus when $U \leq \frac{py^h}{1-\delta}$, $\frac{\partial \Pi}{\partial n} > 0$, meaning as $n$ increase $\Pi$ increases, hence the bank will choose the maximum possible $n$, which is 1. $U \not> \frac{py^h}{1-\delta}$, because $\frac{py^h}{1-\delta} > \bar{U}$. $\square$

# B Tables and Figures

## 2.1 Tables

Table 1: Summary Statistics: General

| | All | Rural | Suburban | Urban |
|---|---|---|---|---|
| **Branch** | | | | |
| Branch age | 11.83 | 11.19 | 12.22 | 13.62 |
| | (6.25) | (6.26) | (5.99) | (6.66) |
| Total employees | 7.84 | 8.23 | 7.41 | 7.40 |
| | (3.80) | (4.02) | (3.73) | (2.78) |
| Total field employees | 4.78 | 5.00 | 4.63 | 4.29 |
| | (2.38) | (2.50) | (2.41) | (1.56) |
| No. of loan products | 4.04 | 4.04 | 4.13 | 3.84 |
| | (1.68) | (1.59) | (1.83) | (1.66) |
| Dropped:Active | 0.31 | 0.29 | 0.36 | 0.25 |
| | (0.51) | (0.40) | (0.69) | (0.24) |
| **Location** | | | | |
| On flat land | 0.82 | 0.82 | 0.78 | 0.93 |
| | (0.39) | (0.39) | (0.42) | (0.26) |
| Dist. from nearest GC | 2.36 | 2.78 | 1.96 | 1.59 |
| | (3.57) | (4.20) | (2.71) | (1.81) |
| No. of MFI within 5km | 13.10 | 11.72 | 15.03 | 13.93 |
| | (8.34) | (8.18) | (8.49) | (7.54) |
| Nearest concrete Rd. | 1.32 | 2.12 | 0.49 | 0.22 |
| | (7.78) | (10.46) | (2.38) | (0.58) |
| Observations | 1080 | 573 | 378 | 129 |

Note: The first entry in each row is the mean. The standard deviation is in parentheses. *GC* stands for growth centers, which are usually the largest bazaar in the area. Distance to nearest concrete road has been winsorized, p(1 99), to remove a potential discrepency.

Table 2: Summary Statistics of Key Variables

| | All | Non-profit | For-profit | Low-comp | High-comp |
|---|---|---|---|---|---|
| **Outcome variables** | | | | | |
| Loan Loss Reserve ratio | 0.82 | 0.70 | 0.94 | 0.77 | 0.88 |
| | (2.26) | (2.17) | (2.34) | (2.31) | (2.19) |
| Loan Loss Expense ratio | 0.27 | 0.31 | 0.24 | 0.15 | 0.45 |
| | (2.92) | (1.00) | (3.90) | (3.57) | (1.57) |
| **Key Variables** | | | | | |
| Lerner Index | 0.74 | 0.69 | 0.80 | 0.86 | 0.62 |
| | (0.38) | (0.49) | (0.20) | (0.05) | (0.51) |
| Avg. loan % N.I.(P20) | 102.08 | 48.02 | 156.14 | 115.17 | 81.58 |
| | (131.63) | (18.50) | (168.79) | (144.45) | (105.52) |
| Lending Rate | 14.40 | 16.84 | 12.06 | 14.83 | 13.89 |
| | (18.40) | (24.70) | (8.25) | (19.36) | (17.22) |
| **Covariates** | | | | | |
| Size (tot. asset) | 23.21 | 15.35 | 30.47 | 25.45 | 19.95 |
| | (28.26) | (13.56) | (35.46) | (22.91) | (34.38) |
| Productivity | | | | | |
| Borrower per officer | 359.65 | 508.33 | 231.40 | 415.68 | 262.99 |
| | (638.53) | (898.59) | (167.71) | (769.09) | (276.76) |
| Loan disb. per officer | 9.85 | 7.79 | 11.62 | 11.80 | 6.48 |
| | (16.34) | (9.58) | (20.29) | (19.92) | (5.02) |
| Salary:Natl. income | 1.14 | 0.94 | 1.32 | 1.27 | 0.93 |
| | (1.73) | (0.68) | (2.26) | (2.13) | (0.50) |
| Cost per unit lent | 0.07 | 0.08 | 0.05 | 0.06 | 0.07 |
| | (0.08) | (0.10) | (0.06) | (0.07) | (0.09) |
| Efficiency | | | | | |
| Financial self suff. | 1.41 | 1.34 | 1.47 | 1.55 | 1.22 |
| | (1.04) | (0.94) | (1.12) | (1.13) | (0.89) |
| Operational self suff. | 2.69 | 2.38 | 2.96 | 2.86 | 2.43 |
| | (2.33) | (1.83) | (2.67) | (2.39) | (2.22) |
| Return on Asset | 1.04 | 0.79 | 1.25 | 1.54 | 0.32 |
| | (6.90) | (6.06) | (7.54) | (8.29) | (4.12) |
| Operational efficiency | 3.45 | 2.88 | 3.94 | 3.68 | 3.07 |
| | (6.93) | (5.28) | (8.08) | (7.85) | (5.08) |
| Op. Cost: Tot. asset | 1.72 | 1.47 | 1.94 | 2.41 | 0.75 |
| | (10.51) | (7.07) | (12.75) | (13.32) | (3.76) |
| Funded liability | 9.49 | 6.77 | 11.88 | 10.51 | 7.84 |
| | (13.24) | (5.93) | (16.92) | (13.59) | (12.50) |
| Observations | 1080 | 499 | 581 | 687 | 393 |

Note: Size, loan disbursed per credit officer and funded liability are in million Takas. Lending rates winsorized at 1% and 99% to get rid of potential outliers.

Table 3: Summary Statistics: Regression Sample

| | Mean | Std. Dev. | P25 | P50 | P75 |
|---|---|---|---|---|---|
| **Outcome variables** | | | | | |
| Loan Loss Reserve ratio | 0.82 | 2.26 | 0.01 | 0.08 | 1.02 |
| Loan Loss Expense ratio | 0.27 | 2.92 | 0.00 | 0.02 | 0.28 |
| **Key Variables** | | | | | |
| Lerner Index | 0.74 | 0.38 | 0.74 | 0.80 | 0.85 |
| Boone Indicator | -0.05 | 0.03 | -0.08 | -0.04 | -0.02 |
| Concentration adj. B.I | -0.01 | 0.01 | -0.02 | -0.01 | -0.01 |
| Avg. loan % of natl. inc(P20) | 102.08 | 131.63 | 51.92 | 73.27 | 100.44 |
| Lending rates | 22.86 | 201.94 | 10.70 | 12.00 | 13.33 |
| **Covariates** | | | | | |
| Size (tot. asset) | 23.21 | 28.26 | 9.19 | 17.90 | 29.81 |
| Productivity | | | | | |
| Borrower per officer | 359.65 | 638.53 | 170.83 | 245.44 | 312.37 |
| Loan disb. per officer | 9.85 | 16.34 | 4.86 | 7.05 | 9.09 |
| Salary:Natl. income | 1.14 | 1.73 | 0.71 | 0.97 | 1.21 |
| Cost per unit lent | 0.07 | 0.08 | 0.04 | 0.05 | 0.06 |
| Efficiency | | | | | |
| Financial self suff. | 1.41 | 1.04 | 0.91 | 1.25 | 1.57 |
| Operational self suff. | 2.69 | 2.33 | 1.60 | 2.32 | 2.96 |
| Return on Asset | 1.04 | 6.90 | 0.02 | 0.05 | 0.09 |
| Operational efficiency | 3.45 | 6.93 | 1.86 | 2.50 | 3.21 |
| Op. Cost: Tot. asset | 1.72 | 10.51 | 0.06 | 0.08 | 0.10 |
| Funded liability | 9.49 | 13.24 | 4.31 | 6.53 | 11.13 |
| Observations | 1080 | | | | |

Note: The first column is the mean. Subsequent columns show the standard deviation, 25th percentile, median and the 75th percentile respectively. Size, loan disbursed per credit officer and

Table 4: Impact of Competition and Profit Motive on Interest Rates

| | Baseline (1) | with F.Es (2) | plus controls (3) | Boone (4) |
|---|---|---|---|---|
| Avg. loan % of N.I(P20) | -0.4031** | -0.4399* | -0.3743* | -0.2963* |
| | (0.1598) | (0.2538) | (0.1926) | (0.1518) |
| Av.loan–sqrd | 0.0004** | 0.0003* | 0.0003* | 0.0002* |
| | (0.0002) | (0.0002) | (0.0001) | (0.0001) |
| Lerner Index | 20.1794 | 81.9773 | 3.2652* | |
| | (19.8708) | (78.9843) | (1.8520) | |
| Boone Indicator | | | | 2.4119 |
| | | | | (1.75432) |
| R-sqrd within | 0.0116 | 0.015 | 0.109 | 0.102 |
| Indivudal fixed effects | no | yes | yes | yes |
| Year fixed effect | yes | yes | yes | yes |
| Clustered S.Es | no | no | yes | yes |
| Robust standard errors | no | yes | no | no |
| Controls | no | no | yes | yes |

Note: This table presents estimates of the main regression equation. Outcomes vary by row; specifications vary by column. All regressions control for branch and time fixed effects. Standard errors are clustered at the MFI level. Levels of significance: *10%, ** 5%, and *** 1%.

Table 5: Impact of Competition and Profit Motive on Future loan denials

| | Baseline (1) | with int. (2) | plus gen. cont. (3) | with all cont. (4) |
|---|---|---|---|---|
| Lerner Index | -2.1285 | -1.2843 | -2.1498 | -10.7494 |
| | (0.5983) | (0.8844) | (0.7764) | (0.1936) |
| Avg. loan % of N.I.(P20) | 0.0905*** | 0.0761*** | 0.1606* | 0.3549** |
| | (0.0025) | (0.0079) | (0.0812) | (0.0413) |
| Lending Rate | -0.0042*** | -0.0025 | 0.0440 | 0.5013** |
| | (0.0000) | (0.3604) | (0.3300) | (0.0148) |
| Avloan × LR | | 0.0044 | 0.0032 | 0.0169* |
| | | (0.4328) | (0.5829) | (0.0650) |
| Lerner × LR | | -0.0397 | -0.0132 | 0.4618 |
| | | (0.6782) | (0.9216) | (0.1015) |
| R-sqrd within | 0.048 | 0.050 | 0.065 | 0.213 |
| Indivudal fixed effects | no | yes | yes | yes |
| Year fixed effect | yes | yes | yes | yes |
| Clustered S.Es | yes | yes | yes | yes |

Note: P-values in parenthesis. This table presents estimates of the main regression equation. Outcomes vary by row; specifications vary by column. All specifications control for branch and time fixed effects, except the first one. Standard errors are clustered at the MFI level. The first specification is the baseline, the next adds the interactions as suggested in Section 8.5. The third specification adds general controls and the final, which is the preferred specification, adds all controls. Levels of significance: *10%, ** 5%, and *** 1%.

Table 6: Impact of Competition and Profit Motive on Loan Loss Expense Rate

| | Baseline (1) | with int. (2) | plus gen. cont. (3) | with all cont. (4) |
|---|---|---|---|---|
| Lerner Index | 0.9453 | -0.2540 | -3.1128 | -11.8916 |
| | (0.8140) | (0.9635) | (0.6071) | (0.1692) |
| Avg. loan % of N.I (P20) | 0.0864*** | 0.0912*** | 0.1197 | 0.2823* |
| | (0.0003) | (0.0008) | (0.2853) | (0.0723) |
| Lending Rate | -0.0024* | -0.0083** | -0.0273 | 0.3521** |
| | (0.0790) | (0.0437) | (0.4332) | (0.0393) |
| Avloan × LR | | 0.0046 | 0.0034 | 0.0194** |
| | | (0.3151) | (0.4460) | (0.0249) |
| Lerner × LR | | 0.2730 | 0.4770** | 1.6686*** |
| | | (0.1273) | (0.0416) | (0.0009) |
| R-sqrd within | 0.033 | 0.037 | 0.046 | 0.216 |
| Indivudal fixed effects | no | yes | yes | yes |
| Year fixed effect | yes | yes | yes | yes |
| Clustered S.Es | yes | yes | yes | yes |

P-values in parenthesis. This table presents estimates of the main regression equation. Outcomes vary by row; specifications vary by column. All specifications control for branch and time fixed effects, except the first one. Standard errors are clustered at the MFI level. The first specification is the baseline, the next adds the interactions as suggested in Section 8.5. The third specification adds general controls and the final, which is the preferred specification, adds all controls. Levels of significance: *10%, ** 5%, and *** 1%.

Table 7: Summary Statistics: Regression Sample

| | LLR ratio (1) | LLE rate (2) | LLR ratio (3) | LLE rate (4) |
|---|---|---|---|---|
| Lerner Index | -7.7352 | -1.3152 | -7.7633 | -1.3702 |
| | (0.3760) | (0.8767) | (0.3765) | (0.8734) |
| Av. loan × Regular | 0.4839** | 0.4514* | | |
| | (0.0429) | (0.0626) | | |
| Av. loan × Irregular | 0.3717 | 0.3771 | | |
| | (0.1539) | (0.1939) | | |
| Lending Rate | 0.4698** | 0.4351** | 0.4696** | 0.4303** |
| | (0.0178) | (0.0413) | (0.0148) | (0.0336) |
| Av. loan × Near Rd. | | | 0.4887** | 0.4598** |
| | | | (0.0340) | (0.0485) |
| Av. loan × No near Rd. | | | 0.3175 | 0.2645 |
| | | | (0.2509) | (0.3260) |
| $R^2$-within | 0.199 | 0.173 | 0.200 | 0.174 |
| Indivudal F.E | yes | yes | yes | yes |
| Year F.E | yes | yes | yes | yes |
| Clustered S.E | yes | yes | yes | yes |
| MFI controls | yes | yes | yes | yes |

Note: The first column is the mean. Subsequent columns show the standard deviation, 25th percentile, median and the 75th percentile respectively. Size, loan disbursed per credit officer and

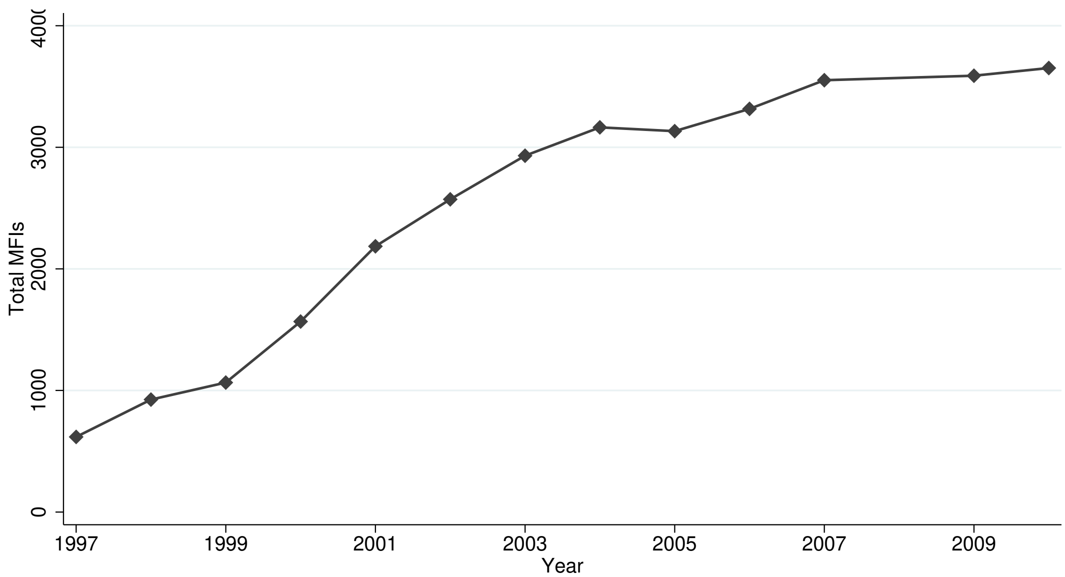
Table 8: Impact of Competition and Profit Motive on Loan Loss Expense Rate

| | Lerner | | Boone | |
|---|---|---|---|---|
| | Low-comp<br>(1) | High-comp<br>(2) | Low-comp<br>(3) | High-comp<br>(4) |
| Lerner Index | 123.4317** | -18.8360*** | | |
| | (56.1442) | (2.4167) | | |
| Avg. loan % of N.I(P20) | 0.0751 | 0.2568 | 1.4341** | -0.1034 |
| | (0.0442) | (0.2701) | (0.5087) | (0.1840) |
| Lending Rate | 2.2434*** | 9.0528*** | -1.3546 | 0.5677 |
| | (0.5708) | (2.6084) | (1.6400) | (0.6614) |
| Avloan $\times$ LR | 0.0399*** | -0.0363 | -0.0844** | 0.0349** |
| | (0.0116) | (0.0448) | (0.0333) | (0.0158) |
| Lerner $\times$ LR | -2.0018*** | -7.1297* | | |
| | (0.4867) | (3.5856) | | |
| Boone Indicator | | | 248.1545** | -2.7954 |
| | | | (112.8289) | (5.6600) |
| Boone $\times$ LR | | | -1.15e+03*** | 8.7688 |
| | | | (352.3648) | (23.2963) |
| R-sqrd within | 0.439 | 0.578 | 0.548 | 0.333 |

Note: This table presents estimates of the main regression equation. Outcomes vary by row; specifications vary by column. All regressions control for branch and time fixed effects. Standard errors are clustered at the MFI level. Levels of significance: *10%, ** 5%, and *** 1%.

## 2.2 Figures

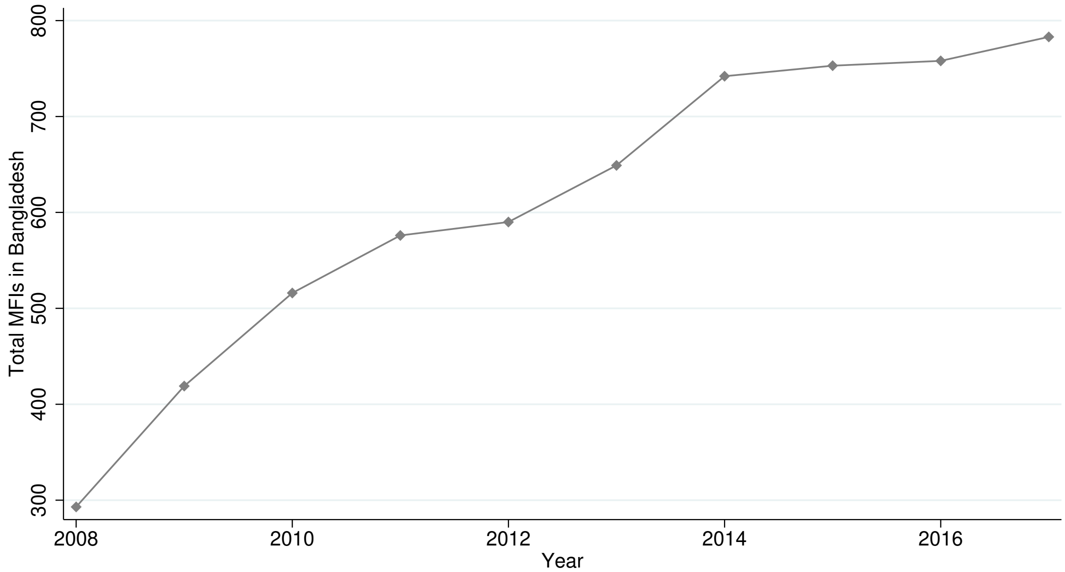
Figure 3: Evolution of Total Number of MFIs Reporting




Source: State of the Microcredit Summit Campaign Report, 2012.

Note: The figure shows the rapid rise in number of MFIs in the market. In particular, this figure shows the number of MFIs who reported to have a program.

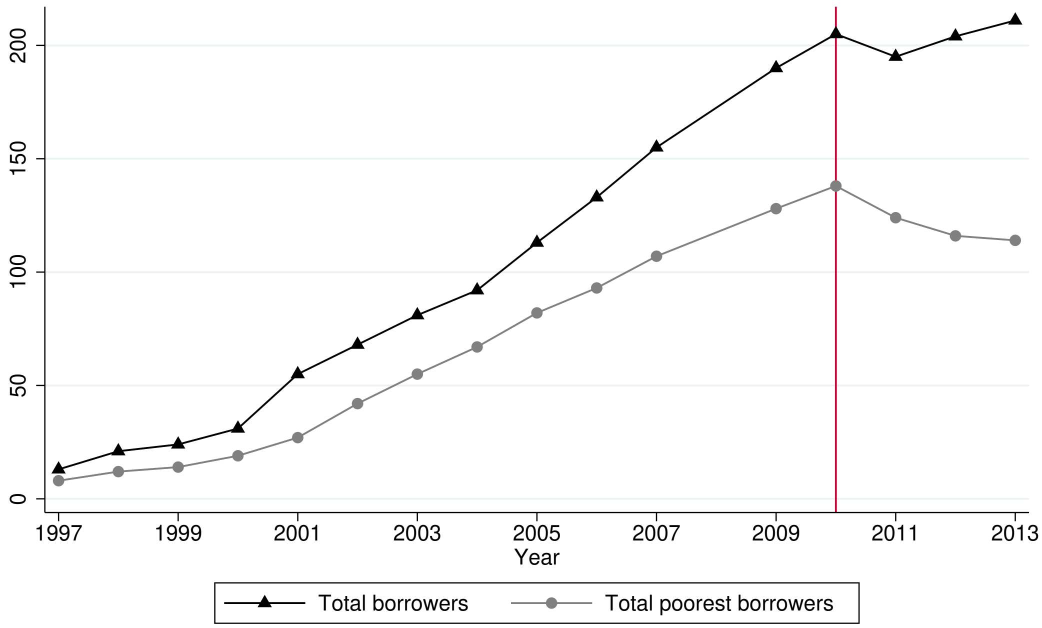
Figure 4: Evolution of Total Number of MFIs in Bangladesh




Source: "NGO-MFIs in Bangladesh". Microfinance Regulatory Authority, 2017

Note: The figure shows the rapid rise in number of MFIs in Bangladesh. A particularly mature market, Bangladesh still has high number of firms entering and exiting the market. The date coincides with the sample period FY2014-16.

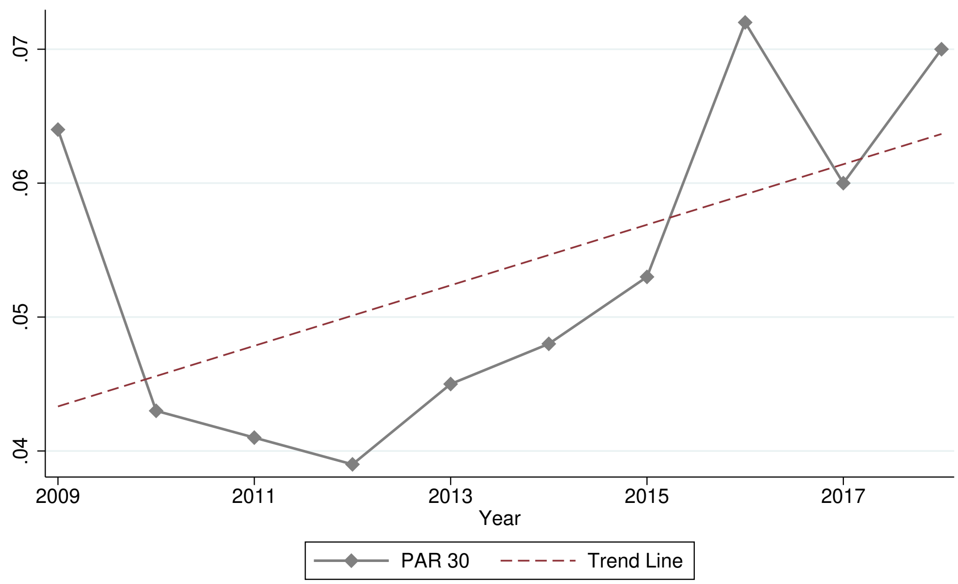
Figure 5: Total vs Poorest Borrowers




Source: State of the Microcredit Summit Campaign Report, 2015.

Note: In 2009, the campaign did not collect or verify any data, so figures for 2008 are missing. From 1997 till 2010, the number of total borrowers and the number of poorest borrowers increased together, correlation 0.9966. This is expected since microcredit is mostly targeted towards poor borrowers. But after 2010, we can see a divergence between the two, correlation -0.9660. This is one of indications of the fact that as for-profit firms are getting more prevalent, outreach is going down, MFIs are targeting better-off borrowers, the so-called mission drift.

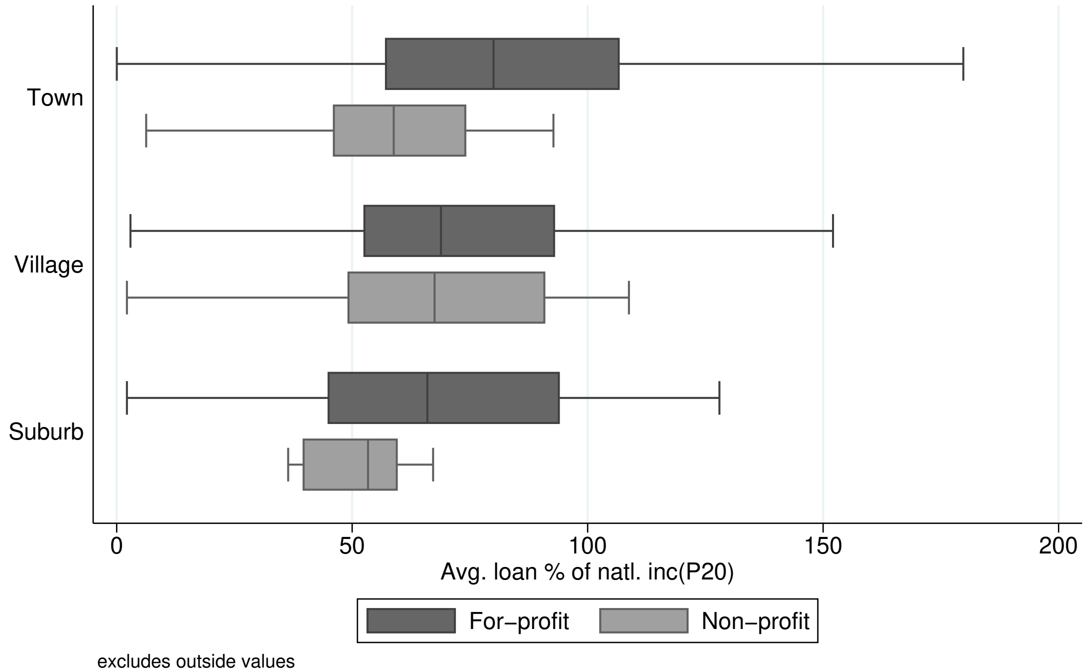
Figure 6: Evolution of Portfolio at Risk > 30days




Source: Microfinance Barometer. 2019

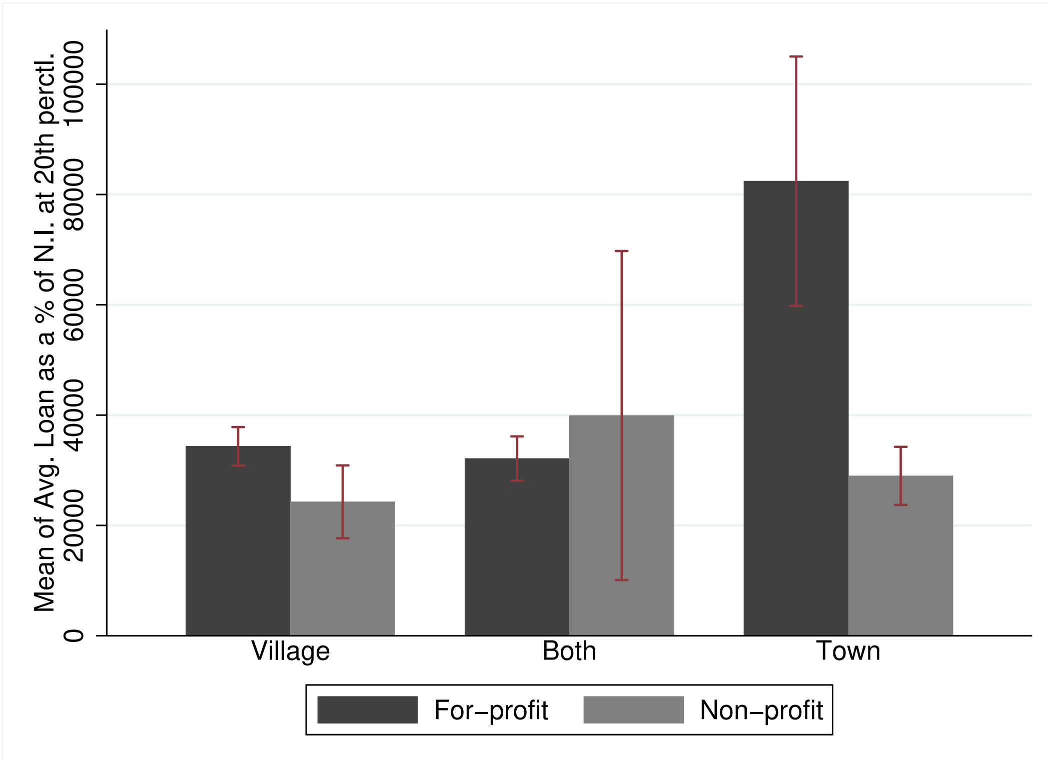
Note: As the trend line shows, there is a rise in portfolio at risk greater than 30 days, which coincides with the increase in competition in the market.

Figure 7: Box-plot of Average Loan Size at 20th Percentile over Profit-motive and Operation Area



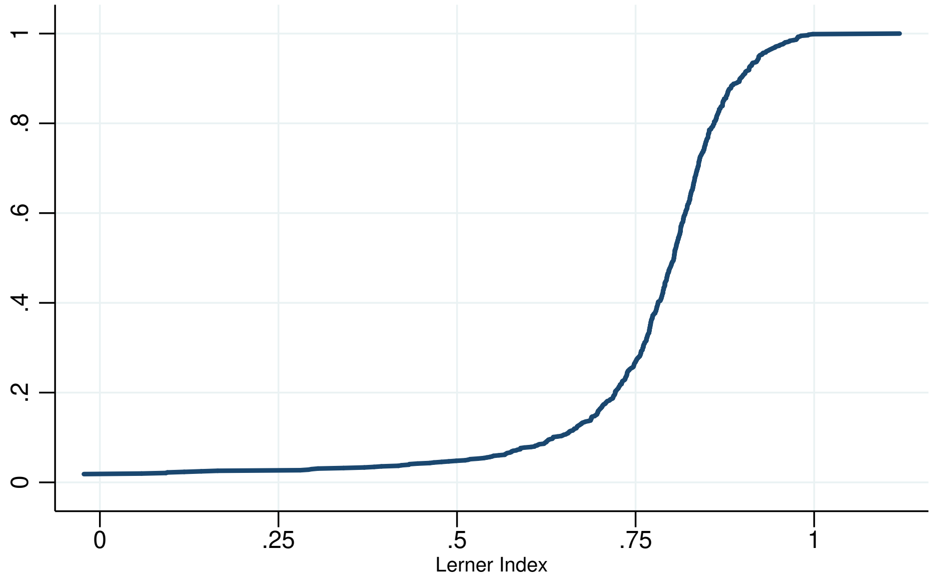

Note: The figure utilizes a question in the questionnaire, where the manager was asked about the primary focus of the branch. The one's who answered poverty alleviation are considered non-profits. Further, the branches are divided in to operating areas to get a better picture.

Figure 8: Mean of Avg. Loan size at 20th percentile with confidence intervals



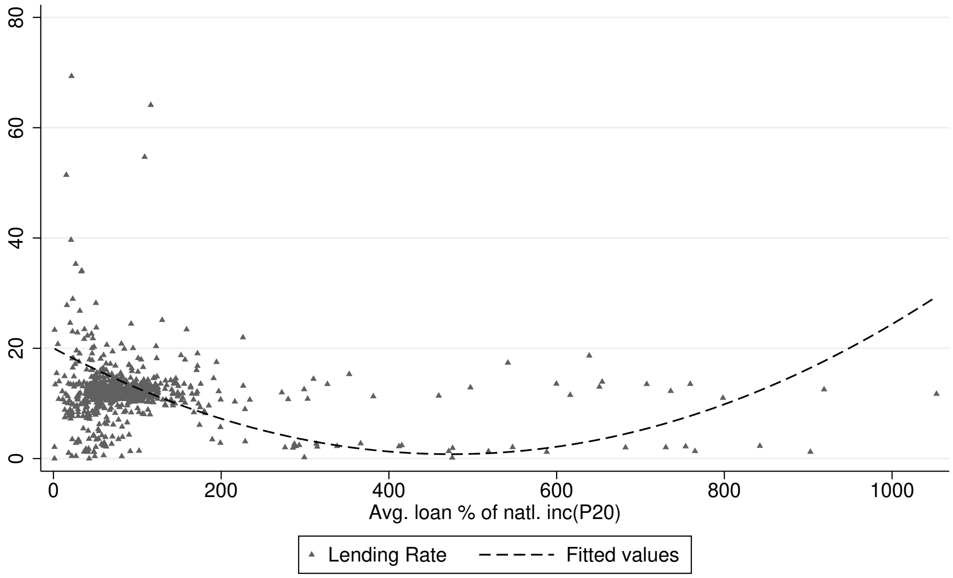

Note: This figure utilizes the the same question as the figure before. Shows the mean and confidence intervals. Clearly, for-profits have larger loan sizes.

Figure 9: Cumulative Distribution of Lerner Index



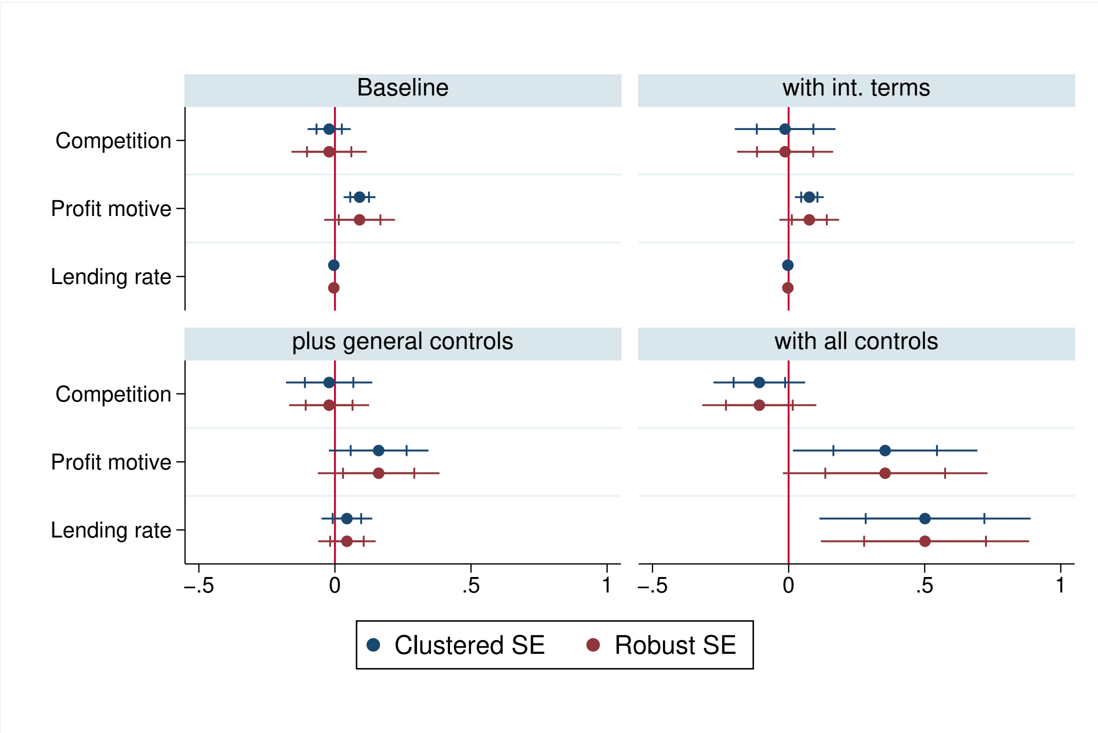

Note: This figure plots the cumulative distribution function of the Lerner Index, as calculated for the Bangladesh microfinance market for FY2014-2016. The index was calculated using the procedure described in Section 7.1.1.

Figure 10: Quadratic Relation between Lending rates and Avg. loan at N.I. (P20)




Note: Both axes curtailed to enhance details.

Figure 11: Main results from reduced form regression




Note: This plot represents the key coefficients from equation (7). The coefficient on *competition* is scaled by 10 to improve visualization. The coefficients are fairly consistent across the specifications. Consistency is preserved in both clustered and robust standard errors. Whiskers indicate the 95% confidence intervals, with the vertical dashes signifying the 75% confidence intervals.

# C Measures of Covariates

Number of Loan products offered: The shows the flexibility of the bank. The higher the types of loans offered the more flexible a bank is, thus I presume they should have a lower default cost. Size: I proxy the size of the MFI using log of total assets. A quadratic relation is expected, which is consistent with standard economics literature. Active borrower per credit officer: This is measured by dividing the number of active borrowers by the number of field officers of the branch. While maintaining a high number might seemingly reduce operating costs, but if the number is too high then field officers might find it difficult to maintain credit relations and hence default might increase, adversely effecting cost. Since I abstract from whether loans are individual or joint liability in this paper, I do not consider how many members are part of a group, which may have some effect, which I hope will be captured in the MFI fixed effects. Loan disbursed per credit officer: This measure gives us an idea as to how much monetary load each credit officer carries. A credit officer might carry a large number of small loans resulting in less monetary load than an officer who carries a few very large loans. In accounting terms this is a flow item, thus associated with the costs. Average compensation as percentage of national income: This is measured by dividing average salary by national income. I categorize national income into urban, rural and suburban. Average salary is measured by dividing the total salary expense by the number of total employees. This shows whether the employees are compensated enough for their job. Lower ratios might result in inefficient monitoring. Operational Self-Sufficiency: This indicates whether or not enough revenue has been earned to cover the MFI's direct costs, excluding the (adjusted) cost of capital but including any actual financing costs incurred (Microfinance Handbook). [add formulas] Financial Self-Sufficiency: This measure indicates whether or not enough revenue has been earned to cover both direct costs, including financing costs, provisions for loan losses, and operating expenses, and indirect costs, including the adjusted cost of capital (Microfinance Handbook). Which essentially shows whether the MFI can generate sufficient revenue to cover its cost and operate without ongoing subsidies or grants. Numbers above 1 indicate they are able to do so, number below 1 indicate otherwise. MFI usually achieve OSS first and then FSS. [add formulas] Return on Asset: ROA is an indicator of how profitable a company is relative to its total assets. Cost per Unit of Currency Lent measures the cost of operating expenses, including training and development, travel costs, per unit of currency lent. The cost per unit of currency lent ratio highlights the impact of the turnover of the loan portfolio on operating costs. The lower the ratio, the higher the efficiency. Operating Cost Ratio provides an indication of the efficiency of the lending operations. This ratio is affected by increasing or decreasing operational costs relative to the average portfolio. Operational Efficiency shows the efficiency of a company's management by comparing the total operating expense (OPEX) of a company to net sales. The operating ratio shows how efficient a company's management is at keeping costs low while generating revenue or sales. The smaller the ratio, the more efficient the company is at generating revenue versus total expenses. Funded Liability shows the amount of loans made by creating liability.