COMPETITION BETWEEN MICROFINANCE INSTITUTIONS AND THE FORMAL BANKING SECTOR

by

TIA JANE MONAHAN

A THESIS

Presented to the Department of Economics
and the Robert D. Clark Honors College
in partial fulfillment of the requirements for the degree of
Bachelor of Science

June 2017

An Abstract of the Thesis of

Tia Jane Monahan for the degree of Bachelor of Science
in the Department of Economics to be taken June 2017

Title: Competition Between Microfinance Institutions and the Formal Banking Sector

Approved: ____

Alfredo Burlando

Microfinance Institutions (MFIs) lend to impoverished communities with the goal of spurring increases in income, consumption, business activity, and decision making power. My research looks at how the formal banking sector responds to MFI branch entry. I use data from a randomized control study done by Banerjee et al. (2013) which allows me to control for endogeneity biases associated with MFI entry. I look at how bank loan take-up and bank loan amounts change over the course of the study as well as how clientele characteristics compare between those that borrow from banks and MFIs. I find no significant differences in bank loan take-up or bank loan amount between treatment and control areas, suggesting the banking sector does little to respond to competition from MFIs. I test this zero effect on a variety of different variables and parameters via a multitude of difference in difference estimators and I reach the same zero-effect conclusion. I find multiple significant differences in characteristics between MFI and bank borrowers. I conclude that MFIs and the formal banking sector operate in relatively separate marketspaces with little to no competition.

Acknowledgements

I thank Professor Burlando for helping me at every step of my thesis and taking his time to be an active advisor throughout this process. I also thank Professor Chakraborty for serving as my second reader and Professor Frank for serving as my CHC thesis advisor. I also give big thanks to my roommates for putting up with me daily throughout this process, and to my parents for their constant support during every stress-induced, frantic phone call. Lastly, I send a huge thank you to the understanding, accommodating, and supportive community of peers and mentors I have developed here at the University of Oregon, all of whom have helped me through not only the thesis process but my entire undergraduate career.

Table of Contents

List of Tables

Introduction

This study examines one of the institutions set up to combat global poverty – Microfinance Institutions (MFIs). Specifically, I explore the consequences of competition between microfinance institutions and the formal banking sector, examining initial bank lending response to exogenous MFI branch entry. I use data from a 2005-2009 study performed in Hyderabad, Andhra Pradesh, India by Abhijit Banerjee, Esther Duflo, Rachel Glennerster and Cynthia Kinnan. I examine formal banking outcomes, specifically bank loan take-up and bank loan amounts. The competitive interaction between MFIs and banks highlights issues surrounding MFI efficacy. Does microfinance increase the availability of loans or make it harder for people to borrow in aggregate? What happens to the percentage of people taking up bank loans and to the amount of those loans when an MFI enters? What characteristics make up credit-worthy clientele for a bank, and is there clientele overlap with MFIs? Broadly, I examine the following: what impact does MFI competition have on the banking sector and how do those consequences affect MFI and bank clientele?

There are four competing hypotheses that frame my research. (1) When MFIs enter, banks change their lending behavior to target clientele with higher levels of income, which avoids competition consequences and diminishes their group of risky borrowers. This in turn creates a gap of people with too little income to get a bank loan and too high income to be targeted by an MFI. (2) When MFIs enter, banks directly compete with MFIs for riskier, high interest borrowers. (3) When MFIs enter, banks do not change their behavior as they observe that riskier clients can use MFI loans to finance bank loans. This complementarity creates a slight overlap in clientele and only mild competition consequences. This is tangentially related to a crowding-in hypothesis summarized by Mookherjee and Motta (2016), which is described in the literature review. (4) Banks and MFIs operate in separate markets which do not overwhelmingly affect one another, and therefore MFI entry has little to no effect on banking characteristics.

Previous papers generally examine MFI-bank interaction via panel data extracted from large datasets of MFI outreach and bank outreach over time across a multitude of different countries. The previous papers that examine this bank-MFI relationship have potential endogeneity issues. There are a number of factors, such as area income, which can determine whether MFIs choose to enter certain markets over others. These factors can also be explanatory factors in different outcome regressions, thus creating endogeneity and the possibility of bias. While this method has its obvious benefits in the robustness of data at hand, I look specifically at data from a study which exogenously determined MFI entry into market neighborhoods. I will see how my findings line up with those of other studies, as well as expand upon any complimentary findings presented in my data. Although my dataset lacks the depth and power of others, extrapolating from a controlled study allows me to look at initial bank response rather than overall relationship, which allows me to avoid biases related to endogeneity that previous papers may have experienced.

I find MFI entry to have no causal effects on bank loan outcomes. I test this finding on a variety of area-specific characteristics that could contribute to a bank's decision to compete or retreat in an area with MFI presence and find an overall zero effect. I build clientele characteristics for both banks and MFIs and perform t-tests to determine if there are significantly different borrower characteristics. I find that bank borrowers tend to be significantly different from MFI borrowers. I hypothesize that banks and MFIs operate in two relatively different markets, as MFI entry does not differentially affect banking sector outcomes nor is there significant overlap in clientele.

To describe the state of financial services in the developing world and describe the steps microfinance has taken to improve it, I offer background material on both global poverty and financial services amongst the poor followed by contextual information on microfinance and the state of the institution. I then describe my specific area of exploration followed by a literature review and information on my specific data source. I then give information on my methods followed by my results and a discussion that includes areas for further exploration.

Finance and the Poor

Global poverty has steadily decreased over the past few decades. However, hundreds of millions of people continue to live in poverty. Primarily, global poverty is concentrated in two geographic areas of the globe: Sub-Saharan Africa, that holds 50.7% of the 766.6 million people living in absolute poverty, and South Asia, with 33.4% of the absolute poor. In India, a 2015 census revealed that of the 219 million village households surveyed, less than 10% of households have a job that pays a salary, not even 5% have a high enough income to pay taxes, only 3.5% of students graduate high school, and over 35% of people are illiterate (Katyal, 2015).

Financial services can offer numerous benefits to these communities. They tackle asymmetric information systems between service providers and clients and between individuals and financial structures; allow for greater and more efficient investment, resource allocation and trade; facilitate greater economic choice; and enable risk mitigation amongst households and businesses (Peachey and Roe, 2006). Financial services have the potential to allow people to build up their businesses, incomes, and savings. However, the access to and usage of financial services in the developing world is uneven, and those living in poverty may need financial services even more than others. For example, savings accounts can control for the poor's unsteady and irregular income stream that makes them seem unattractive to lenders, in turn helping them get loans in the future.

A 2009 study by the Financial Access Initiative reported about 2.5 billion adults either lack or choose not to use existing formal financial services, with 2.2 billion of them living in Africa, Asia, Latin America and the Middle East. Further, over two thirds of the adults who do use those services in Africa, Asia, and the Middle East live under the $5 per day mark (Chaia et al., 2009). There is a semi-strong correlation between financial services usage and GDP per capita, although there are notable exceptions including areas in Southeast Asia (Chaia et al., 2009). Over 80% of households use financial services in some form in North America and Western Europe, compared to under 20% in sub-Saharan Africa. In rural India, although 40% have a deposit account, only 20% have active loans (Karlan and Morduch, 2009). In addition, household creditworthiness does not necessarily indicate their intent to borrow. A 2002 Indonesian study showed that while roughly 40% of the poor population was deemed credit worthy by a bank, only 10% borrowed. Of the households that were credit worthy but didn't borrow, only 10% said it was because of lack of collateral (Johnston and Morduch, 2008). This gap could very much be due to debt aversion. Loans also commonly come from informal sources that lend with unfavorable terms. A 2007 study found that 52% of outstanding loans in Hyderabad came from informal money lenders (Banerjee and Duflo, 2007).

Furthermore, practices of formal lenders suggest underserved populations within the realm of consumption-purpose loans. Formal banks mainly lend for entrepreneurial reasons while the informal and non-bank financial sectors many times provide loans for consumption and other individual purposes (Johnston and Morduch, 2007). Loan purpose could be a determinant towards borrowing source for poorer households who take up most of the informal credit sector and who contribute entirely to the industry that is striving to change the impoverished financial services market in the developing world – microfinance.

Microfinance

Microfinance is defined as "financial services, including credit, supplied in small allotments to people who might otherwise have no access to them or have access only on very unfavorable terms." (Todaro and Smith, 2015) MFIs were developed to lend to women for entrepreneurship purposes, hoping to increase female decision power, status, and empowerment in impoverished communities. Many MFIs still only lend strictly to women, and many do still require their loans to be used for entrepreneurial reasons, however in many cases those guidelines have been relaxed. At the end of 2013 MFIs were reaching over 211 million borrowers worldwide (Microcredit Summit Campaign, 2015). The poorest clients made up over 114 million of those borrowers, however that number has been declining since 2010. Of those poorest clients, between 82% and 83% were women (Microcredit Summit Campaign, 2015).

MFI structure differs across firms. MFIs can be either for profit and not for profit, but both operate to help their target clientele (MicroLoan Foundation, 2007). MFIs are similar to banks in structure, however they can differ in methodology, target clientele, funding sources and end goals. Informal moneylenders also differ, and although they play a major role in financial services in impoverished areas they are relatively unfavorable (Banerjee and Duflo, 2007).

Information gathering is consistently shown to be the most difficult aspect concerning lending in the developing world. Because of the difficulty and time-consuming nature of information gathering efforts, such as collecting client characteristics, the costs of lending can skyrocket. To combat these costs, most MFIs use joint liability lending, meaning loans are given to groups of individuals and every member is punished if one member defaults. These groups are usually formed by the clients themselves. These strategies eliminate much of the risk associated with lending to unknown entities. Many MFIs hold mandatory weekly group meetings which are also used as collection platforms for loan officers, which in turn cuts collection costs.

Much of the research on MFIs surrounds their efficacy. The *American Journal of Economics: Applied Economics* published six different articles containing experiments performed across the globe in India, Morocco, Mexico, Ethiopia, Bosnia and Mongolia, testing the efficacy of MFI implementation via randomized experimentation (Banerjee et al., “Six Randomized Evaluations,” 2015). The studies found no evidence of significant changes in poverty levels or income and no evidence of microfinance lifting communities out of poverty. However, the experiments did show some increases in choices relating to consumption and occupation, increases in female decision making power, increased risk management, and small yet significant increased business activity (Banerjee et al., “Six Randomized Evaluations,” 2015). Because transformative effects are apparent in some populations and not in others, both proponents and critics of microfinance can find evidence to back up their claims.

Area of Exploration

This study looks at competition between MFIs and the formal banking sector, specifically examining the response of bank lending outcomes to MFI entrance. I empirically explore the change in the number of people with outstanding bank loans and the amount of those loans upon MFI entry. I examine differences in areas with MFI presence and areas without to look at differential effects. From this, I use empirics and theory to examine how banks behave in the midst of competition with MFIs and the definitive benefits and disadvantages of MFI-bank competition for both institutions and clients. I expect to see, upon MFI entry, banks target wealthier clientele and avoid competition, banks directly compete with MFIs for risker, higher interest borrowers, banks do not change their lending behavior upon MFI entry because they observe riskier clients finance bank loans with MFI loans, or banks operate in a completely different market space and are unchanged by MFI entry.

Literature Review

There has been much discussion on competition between MFIs, and direct MFI-MFI consequences can be seen through real world scenarios. The Bangladesh microfinance crisis involved the growth of Grameen Bank, ASA, BRAC and Proshika, four competing MFIs. Throughout the 1990s there was a boom in MFI borrowers coupled with a percentage of borrowers with outstanding loans from multiple sources. By the end of the '90s, multiple MFIs appeared in over 95% of surveyed villages across Bangladesh, and reports showed that 15% of borrowers had loans from multiple MFIs. Grameen Bank's repayment rates fell by almost ten percentage points (Armendariz and Morduch, 2010). A similar scenario played out in Bolivia as well (Armendariz and

Morduch, 2010). Although an MFI might make a rule that a client with an outstanding loan elsewhere cannot continue to borrow, the methods of knowing that information are extremely costly and inadequate as there is relatively little information sharing across the entirety of financial services. Credit bureaus are many times discussed as ways to increase cooperative practices, and although the idea is nice in theory, many would find it difficult to adequately operate credit bureaus in areas like Bangladesh (Armendariz and Morduch, 2010). Theoretically, these or related consequences could be experienced via bank-MFI competition.

Mookherjee and Motta (2016) analyze interactions between informal money lenders and MFIs that can be theorized onto a bank-MFI competition model. Mookherjee and Motta describe the failure of MFI presence to mitigate overbearing informal lender interest rates, listing many possible explanations previously put forth, including the crowding in effect. Crowding in occurs because MFIs create an inflexible repayment atmosphere that in turn increases informal loan demand to repay MFI loans. As borrowers increase their amounts of unpaid loans and add to their debt, default risks increase along with more frequent informal borrowing, a consequence MFIs were created to alleviate. This theory can still be superimposed to the banking sector. Although the formal banking sector has similarly inflexible repayment schedules, a comparable crowding-in scenario could be at play. Assuming there is some overlap in bank and MFI clientele, MFI entry could allow borrowers to finance bank loans with MFI loans. This would create a greater demand for both MFI loans and bank loans and cause larger debt pools for overlapping clients and therefore increase the risk of default and other consequences of overborrowing.

Research done on MFI-bank interaction concludes that competition exists, however there is disagreement on how. Cull, Demirgüç-Kunt and Morduch (2013) researched the effect bank competition has on MFI performance. They look at panel data extracted from datasets on bank outreach and MFI performance. They observe that bank entry pushes MFIs to focus on smaller loans to poorer clientele. They also find MFIs show greater outreach when faced with higher and more concentrated bank competition. However, Vanroose and D'Espallier (2013) come to the opposite conclusion: in areas with less-developed formal banking sectors, MFI outreach is greater, and in areas with more developed formal banking sectors, MFIs and banks compete for the same riskier clients. They also conclude that in areas with developed formal banking sectors, MFIs give smaller loan amounts when competing with banks, suggesting MFIs target poorer clients when faced with large banking sector competition.

Maksudova (2010) finds that bank-MFI competition consequences are dependent upon the income level of the countries in which the institutions operate. The data suggests that low income countries have relatively low financial integration between MFIs and other sources of financial services. Low financial integration implies that an increase in MFI loans does not necessarily produce an increase or a decrease in bank loans, as the sectors are relatively separated. Maksudova finds that the research roughly corresponds with the market failure hypothesis that MFIs work through "filling in the gaps" of formal banking. Vanroose and D'Espellier (2013) find this as well, concluding that MFIs can be viewed as "substitutes" for banks. Substitution means that an increase in MFI loans leads to a decrease in bank loans.

Cull, Demirgüç-Kunt and Morduch (2013) also conclude that MFIs that are commercially funded, offer individual instead of joint liability loans, or take deposits will be more greatly affected by competition than other types of MFIs. Vanroose and D'Espallier (2013) also find institutional characteristics such as age, size, and legal status of the MFI influence MFI-bank competition.

Cull, Demirgüç-Kunt and Morduch (2013) do not find that bank competition negatively affects overall MFI financial performance, however they conclude that financial performance for MFIs with urban clientele that geographically overlap with bank branches is negatively affected. They hypothesize that MFIs cannot adequately use the incentive of future loan denial when there is stronger bank presence, or that MFIs may simply not be able to compete with larger banks when it comes to the services provided and the prices charged.

The research shows that competition consequences are present on an aggregated scale. Differences in country income, MFI institutional characteristics, and level of formal banking sector development all contribute to level of competition between banks and MFIs. The literature suggests competition exists between the two sectors, which would imply that competition would be present in my study. However, the competition being picked up in these studies is on a more aggregated scale than that of the data with which I work, so even though competition is seen on a larger, cross-country and cross-institutional scale, it is not necessarily true that finding no competition in this study would produce a contradictory result to what others have found.

Data

I use data from the paper *The Miracle of Microfinance? Evidence from a Randomized Evaluation* by Abhijit Banerjee, Esther Duflo, Rachel Glennerster and Cynthia Kinnan. The data was downloaded from the American Economic Journal: Applied Economics. Banerjee, Duflo, Glennerster and Kinnan partnered with Spandana, an MFI in India, to test MFI efficacy within a randomized controlled study in Hyderabad, Andhra Pradesh, India. 104 neighborhoods deemed “poor” and that lacked prior-MFI presence were chosen, and 52 of the 104 were randomly assigned as areas to open a new branch of Spandana. Those areas were marked as ‘treatment’ areas, while the other 52 were ‘control’ areas and did not experience Spandana branch entry throughout the study. The researchers tracked lender, borrower, and area characteristics throughout baseline, measured in 2005, endline1 measured 15-18 months after baseline, and endline2, which was measured two years after endline1 and showed longer-term treatment differences, even though by endline2 there was some MFI lending in control areas.

Overall, the study found that while there were some significant changes with MFI entry, MFI entry did not result in enormous changes in poverty levels. They found that business activity, including investment and profits, significantly increased, however many variables such as health and education were left unchanged by MFI entry. The composition of expenditures was changed, as durable good expenditures increased while expenditures on ‘temptation goods’ decreased. Consumption was not significantly changed. By endline2, many of the significant differences reported in endline1 became insignificant, suggesting the areas that had definite MFI access for much longer were not significantly different from the control areas that did not have MFI access or only received access to MFI loans relatively recently.

Spandana is a for-profit MFI, however during the time of this experiment all profits were cycled back into the business. Spandana is a strict joint liability lender, and groups are formed by the clients themselves. Eligibility for Spandana loans falls into four categories: borrowers must be female, between the ages of 18 and 59, reside in the same “area” for the span of at least a year with proof of residence and valid ID, and 80% of each group needs to consist of women who own their home (Banerjee et al., “The Miracle of Microfinance?” 2015). Loans do not have to be for entrepreneurial purposes. Spandana’s interest rates are relatively low compared to other MFIs, however specific rates were not discussed in this experiment.

This dataset has multiple shortcomings. There are a multitude of borrower characteristics that were not measured at baseline or not given in either baseline or endline datasets, such as baseline household income, neighborhood proximity to one another, and type of business operations. Also, interest rate information is absent, so I cannot explore the relationship between Spandana’s and surrounding bank’s interest rates and the effects of MFI entry on bank’s interest rates. Characteristics of the banking sector in Hyderabad are not made readily available in this dataset or in others. Because of this, I cannot compare specific banking sector industry characteristics, or even firm level characteristics, to firm level MFI characteristics. The main shortcoming of this data set, however, is that it is cross sectional data and not panel data, as the panel data does not exist. The major consequence of having to work with cross sectional data in a setting like this is the lack of power. The benefit of using this dataset over other, aggregated panel datasets is that the experiment was set up in such a way that allows for MFI-entry to be examined exogenously instead of the general endogeneity of entry variables, therefore ensuring unbiased estimates.

Table 1 shows how loan likelihood and loan amount for banks, MFIs, the informal credit sector, and all loans change across baseline, endline1, and endline2. All amounts are in rupees, while the loan likelihoods are in percentage points.

Table 1: Dependent Variable Means Across Measurement Periods

VARIABLES	Baseline	Endline1	Endline2
Bank	0.0387	0.0816	0.0736
	(0.193)	(0.274)	(0.261)
Bank Amount	4694.693	8755.339	5683.892
	(115873.4)	(83107.43)	(35692.4)
MFI	0.0157	0.2374	0.3409
	(0.124)	(0.426)	(0.474)
MFI Amount	303.8724	3204.176	6136.486
	(4580.333)	(7414.078)	(12547.23)
Informal	0.6278	0.7337	0.6032
	(0.483)	(0.442)	(0.489)
Informal Amount	27075.4	40725.36	32452.63
	(64573.6)	(86804.74)	(80551.54)
Any Loan	0.6762	0.8576	0.9052
	(0.468)	(0.349)	(0.293)
Any Loan Amount	33701.57	62062.73	90927.75
	(137417.9)	(173419.8)	(149981.7)

Methodology

I use regression analysis to analyze how bank outcomes differentially respond to MFI entry in treatment and control areas. I look at bank loan take-up and amount of bank loans and how those variables change with MFI entry between baseline and endline1 as well as between baseline and endline2. I expect to see some form of differential effects on bank loans between the treatment and control areas, as I expect there to be competition consequences from MFI entry on the banking sector. I perform a specific type of treatment analysis called Differences in Differences, or DiD, to look at the interaction between banks and MFIs. In the simplest form, the regressions look as follows.

$$(1)\ bank_{iat} = \beta_0 + \beta_1 X_{iat} + \beta_2 endline01_t + \beta_3 endline01_t * treatment_a + \alpha_a + \varepsilon$$

$$(2)\ bank\_amt_{iat} = \beta_0 + \beta_1 X_{iat} + \beta_2 endline01_t + \beta_3 endline01_t * treatment_a + \alpha_a + \varepsilon$$

The outcome variable $bank$ refers to bank loan likelihood. $bank$ is equal to 1 if an individual has a bank loan and equal to 0 if the individual does not. The outcome variable $bank\_amt$ refers to the amount of each bank loan. The subscripts $i, a,$ and t represent individual i, area a, and time-period (baseline, endline1, or endline2) t. Each area refers to each of the 104 neighborhoods in the study. The X represents a multitude of control variables put into the regressions. The variable $endline01$ is a binary variable equal to zero if the observation is from baseline and equal to 1 if the observation is from endline1. The variable $treatment$ is a binary variable equal to 0 if the neighborhood was a control area, and therefore did not have MFI entry, and equal to 1 if the neighborhood was part of the treatment. The interaction term $endline01 *$

$treatment$ reflects the differences from baseline to endline1 between treatment and control areas. The coefficient associated with this interaction term, β_3, is my DiD estimator and my main coefficient of interest in both regressions. I include area fixed effects in each regression, α, to account for area-level differences. I then perform these same regressions, replacing $endline01$ with $endline02$, a binary variable equal to zero if the observation is from baseline and equal to 1 if the observation is from endline2, to look at longer-run differences from baseline to endline2 and compare the direction and magnitude of the effects experienced at endline1.

It is possible that a bank's decision to compete with an MFI is dependent upon area-level characteristics. This would mean that treatment areas with high values of certain area-specific characteristics would have differential bank outcomes as compared to control areas. For example, banks could be competing with MFIs in high literacy areas but not competing in low literacy ones. To examine this, I use five area-specific variables, or value indicators, measured at baseline – previous banking in the area, total area expenditures, total area debt, total number of businesses in the area, and area literacy rate. I use these five as they were all measured at baseline and theoretically would contribute to the credit worthiness of each area.

I create two distinct binary variables for each value indicator and in turn perform triple difference analyses on each of the binary variables. This is to say I look at the differences from baseline to endline1 or endline2, between treatment and control areas, between areas above or below the value indicator of interest. I create two binaries for each value indicator so I can examine robustness of findings. Areas at or above cutoffs are deemed “high value” areas. Table 2 shows the distinct cutoffs for each value indicator.

Table 2: Value Indicator Variable Cutoffs

Value Indicator	Cutoff	Value
Already Banked	1	1
	2	2
Expenditures	50%	998.3371
	75%	1095.726
Debt	50%	34122.68
	75%	38675
Businesses	50%	7.24966
	75%	11
Literacy	50%	0.6823932
	75%	0.7478261

All value indicators besides debt are designed as follows: if the area value indicator is at or above the cutoff, then the value indicator is equal to 1. Otherwise, it is equal to 0. Debt is set up in the opposite way – if area debt is below the cutoff, debt is equal to 1. Otherwise, it is equal to 0. A ‘high value debt area’ still refers to an area with average total debt above the cutoff.

The first value indicator is $already\_banked$ which indicates if an area had banking sector presence at baseline. I use previous banking to proxy for financial sector integration that Cull et al. (2013) and Vanroose and D’Espallier (2013) found to be a determinant for competition. I say that if someone in the area has an outstanding bank loan at baseline then the area is already banked. The second cutoff is if at least two people in an area have an outstanding bank loan at baseline. This is a practical proxy for previous banking as long as borrowers obtain financing from branches or lenders in their own neighborhoods. The other four value indicators have cutoffs based on the mean and upper quartile values. The value indicator $expend$ is the area monthly expenditures at baseline, which I use as a proxy for income. The value indicator $debt$ is the area’s total debt at baseline. The value indicator biz is the total number of businesses in an area at baseline. The value indicator lit is the literacy rate of each area at baseline.

I run four main regressions for each threshold, and then repeat the regressions replacing $endline01$ with $endline02$ and replacing $bank$ with $bank\_amt$. The regressions look as follows:

$$(3)\ bank_{iat} = \beta_0 + \beta_1 X_{iat} + \beta_2 endline01_t + \beta_3 endline01_t * high\_value_a + \alpha_a + \varepsilon$$

$$(4)\ bank_{iat} = \beta_0 + \beta_1 X_{iat} + \beta_2 endline01_t + \beta_3 endline01_t * treatment_a + \beta_4 endline01_t * high\_value_a + \beta_5 treatment_a * high\_value_a + \beta_6 endline01_t * high\_value_a * treatment_a + \alpha_a + \varepsilon$$

$$(5)\ bank_{iat} = \beta_0 + \beta_1 X_{iat} + \beta_2 endline01_t + \beta_3 endline01_t * high\_value_a + \alpha_a + \varepsilon \ if\ treatment = 1$$

$$(6)\ bank_{iat} = \beta_0 + \beta_1 X_{iat} + \beta_2 endline01_t + \beta_3 endline01_t * high\_value_a + \alpha_a + \varepsilon \ if\ treatment = 0$$

The $high\_value$ variable is a place holder for each of the ten value indicators described above (five types, two cutoffs per type). Regression (3) allows me to look at differences in banking across endlines between high and low value areas to see if and how the banking sector is dependent on each area characteristic. Regression (4) is the triple difference regression, which shows differences between treatment and control areas across endlines, dependent on different value indicators. This tells me if the banking sector's response to MFI entry differs for high and low value areas. Regressions (5) and (6) show how banking responds to these different value indicators within treatment and control areas separately. There are multiple cases where the triple difference regression coefficients are insignificant but there are significant coefficients within one or both of the treatment and control samples.

By looking at differences across both baseline to endline1 and baseline to endline2 I can see the robustness of the results across time and look to see what effects, if any, are being picked up only in the short run or only in the long run. I also look at the robustness of the results by using two different cutoffs, the second of which would be assumed to be a stricter cut as less areas are considered high value.

To gain a complete picture of the effects of the interaction, I look at similar outcomes in both the MFI sector and the informal credit sector, specifically looking at differences in treatment and control areas with respect to the value indicators. I examine the two treatment effect regressions, (1) and (2), while replacing the dependent variables with mfi, mfi_amt, $informal$, and $informal\_amt$. I then replace $endline01$ with $endline02$ to look at long term effects. To conclude these sector analyses, I run regressions (4) (5) and (6) with the new dependent variables, however I only use the first cutoff of each value indicator and I only look across endline1 as robustness in these sectors is not the focus of this study. The purposes of looking at the informal sector and the MFI sector are to see how the outcomes of those sectors compare to the outcomes of the banking sector and, more importantly, to use these analyses to examine possible theories as to why banking behavior responds to MFI entry the way it does.

Finally, I examine characteristics that determine bank and MFI loan take-up to look at differences in clientele. This analysis shows how separate the markets are for banks and MFIs. All characteristic analysis is done only on endline1 and endline2 as baseline data on the individual level cannot be matched with endline data on the individual level. I also run the same characteristics through a regression only on the dependent variable $bank$, using only the sample of people that borrow from either an MFI or a bank. Any statistically significant coefficients produced from this regression are statistical differences between clientele characteristics for banks and for MFIs.

I then build a table of means that displays what the average value is for each clientele characteristic when the borrower has borrowed from a bank and the borrower has borrowed from an MFI. In this table, I present t-statistics that show if there are statistically significant differences between the average values for both samples. This shows me whether each characteristic is significantly different between bank and MFI clientele, and allows me to conclude whether bank and MFI clientele are statistically different from one another. This analysis allows me to hypothesize more directly as to whether banks and MFIs operate in significantly different marketspaces.

Variables on the household level are household size, whether the head of the household is male, the age of the head, whether the head has education, whether the household owned a business at least one year before endline1, and whether the household owns land. Area specific variables taken into consideration are area populations at baseline, whether an area has high or low business activity at baseline, whether an area has high or low expenditures at baseline, whether an area has a high or low literacy rate at baseline, and whether an area had previous banking at baseline. All area variables that are used here that were used above are based on the mean variable threshold. Lastly, indexes used in the original study on women employment, income, labor, consumption, and social factors are taken into consideration.

Results

Banking Sector

Table 3: Summary of Banking Sector Treatment Differences

VARIABLES	Baseline to Endline (1,2)	Bank (1)	Bank Amount (2)
Endline (β_2)	1	0.0401***	1,002
		(0.00876)	(3,307)
	2	0.0360***	-1,030
		(0.00867)	(2,588)
Endline*Treatment (β_3)	1	0.000904	5,035
		(0.0123)	(4,631)
	2	-0.00906	3,216
		(0.0120)	(3,573)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I find no impacts of MFI entry on banking usage. This can be seen in tables 5 and 6 as well as table 3 above which summarizes key estimates from tables 5 and 6. There is an increase in bank loan take-up between baseline and endline1 of 4.01 percentage points, however there are no statistically significant differences between treatment and non-treatment areas when it comes to bank loan take-up between baseline and endline1. There are also no significant effects on bank loan amounts between baseline and endline1 as well as no significant differences between treatment and control areas. While there is a 3.6 percentage point increase in bank loans between baseline and endline2, there are again no significant differences between treatment and non-treatment areas when it comes to the number of people with bank loans between baseline and endline2, consistent with the results from the baseline-endline1 regression. There are also no significant increases in bank loan amount between baseline and endline2, nor are there significant differences in bank loan amount between treatment and control areas.

To study whether this result masks heterogenous treatment effects, I turn to the five value indicators that could detriment whether banks choose to compete in specific treatment areas. All results are reported in tables 7-17. All trends are described between baseline and endline1. Endline2 is only discussed if there are drastic differences in effects. Overall, I do not find differential effects between treatment and control areas across endlines when looking at high value or low value areas. I do find some differential effects on bank loan take-up and bank loan amount between high value and low value areas regardless of treatment, and I do find differences between high and low value areas within only treatment or only control areas. Table 4 shows a summary of results from the mean-cutoff regression with each value indicator between baseline and endline1.

Table 4: Summary of Key Mean-Cutoff Value Indicator Variable Coefficients

VALUE INDICATOR	DEPENDENT VARIABLE	High_Value* Endline01* Treatment (1)	High_Value* Endline01 (Treatment) (2)	High_Value* Endline01 (Control) (3)
Already Banked	Bank	0.0103	-0.0550***	-0.0659***
		(0.0238)	(0.0143)	(0.0193)
	Bank Amount	16,773	-2,156	-19,012*
		(10,374)	(2,835)	(10,116)
Expenditures	Bank	-0.0123	-0.00288	0.0104
		(0.0259)	(0.0167)	(0.0201)
	Bank Amount	3,804	3,537	-1,565
		(10,009)	(3,124)	(9,532)
Debt	Bank	-0.0157	0.00922	0.0245
		(0.0238)	(0.0163)	(0.0176)
	Bank Amount	-12,897	4,599	17,766
		(12,358)	(3,100)	(12,049)
Businesses	Bank	0.0256	0.00254	-0.0238
		(0.0264)	(0.0179)	(0.0195)
	Bank Amount	-18,200*	-4,481	13,169
		(10,230)	(2,895)	(9,594)
Literacy	Bank	-0.0305	0.0296**	0.0609***
		(0.0235)	(0.0145)	(0.0186)
	Bank Amount	592.7	3,211	2,299
		(11,230)	(2,721)	(10,828)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Previous Banking

Borrowing in previously unbanked areas, i.e. areas with at least one person who had an outstanding bank loan at baseline, appears to play catch-up to and sometimes surpass borrowing in previously banked areas. All results for the already banked indicator are reported in tables 7 and 8. Areas that were banked at baseline are slightly more likely to have a bank loan at endline1 than baseline, but are 5.99 percentage points less likely to have a bank loan at endline1 than those in previously unbanked areas, significant at the 1% level. Using the second cutoff of already banked, i.e. at least two people who had outstanding bank loans at baseline, the likelihood that people in previously banked areas have a bank loan decreases between baseline and endline1 by 0.17 percentage. The difference in bank loan take-up at endline1 between previously banked and unbanked areas is similar to yet slightly smaller than that of the first cutoff.

While there are differences between previously banked and unbanked areas, there are no significant differential effects of previous banking on bank loans between treatment and control areas. Within treatment areas, people in already banked areas are 5.50 percentage points less likely to have a bank loan at endline1 than people in previously unbanked areas. Within control areas, people in areas that were previously banked are 6.59 percentage points less likely to have an outstanding bank loan at endline1 than people in areas that were previously unbanked. All results are significant at the 1% level. The second cutoff produces similar results, with the difference in bank loan take-up within treatment areas becoming slightly larger while said difference within control areas becomes slightly smaller and is significant at the 5% level. Although there are significant differences within treatment and within control areas, the effects are of similar direction and magnitude which explains the insignificant coefficients in the triple interaction.

There are significant effects on bank loan amounts. People in already banked areas see a decline in average bank loan amounts between baseline and endline1 by a factor of 10,610 Rs. in comparison to areas that were previously unbanked, significant at the 5% level. This difference is so large that people in previously banked areas see a decrease in bank loan amount while people in previously unbanked areas experience an increase between baseline and endline1. Using the second cutoff, this effect becomes insignificant.

There are no significant effects on bank loan amount for the triple interaction nor within treatment areas. Within control areas, people in previously banked areas have smaller bank loan amounts than their previously unbanked counterparts by 19012 Rs. at endline1, significant at the 10% level. Again, this difference is large enough that people in control and previously banked areas experience a decline in bank loan amounts between baseline and endline1 while those in control and previously unbanked areas experience an increase. Effects become insignificant at endline2 when using the second cutoff.

Business Activity

All results for the business indicator are in tables 9 and 10. High value business areas have no significant differential effects on bank loan take-up across endlines, regardless of cutoff. There are also no significant differential effects between treatment and control areas, nor are there significant effects within either sample of treatment areas or control areas.

There are significant effects on bank loan amounts. The triple interaction regression concerning treatment, endlines, and high value business areas is significant. For high value business areas, treatment areas have on average bank loans that are 18200.06 Rs. less than those in control areas at endline1, using the first business cutoff. The second cutoff produces a slightly larger difference. Both of these results are significant at the 10% level. This result becomes insignificant when looking at endline2.

Using the second business cutoff, there are significant estimates within the treatment sample. People in high value business treatment areas have smaller bank loans at endline1 by 6015 Rs. than those in low value business treatment areas, significant at the 10% level. There are no significant estimates for treatment areas using the first cutoff nor are there significant estimates for control areas.

Debt

All results for the debt indicator are in tables 11 and 12. There are no significant differential effects of either debt variable on bank loan take-up across baseline and endline1. There are no significant effects of high value debt areas on bank loan take-up between treatment and control areas across endlines, nor are there significant differences in bank loan take-up within the treatment sample nor within the control sample.

There are no significant differential effects of high value debt areas on bank loan amounts between treatment and control areas. There are no significant effects within control areas nor within treatment areas at endline1. However, there are some significant estimates. People in low value debt areas on average have bank loan amounts at endline1 that are 11479 Rs. larger than those in high value debt areas, significant at the 10% level when using the first debt cutoff. This result is insignificant when looking at endline2 or when using the second debt cutoff. However, using both debt cutoffs at endline2, low value debt treatment areas are shown to have larger bank loan amounts than high value debt treatment areas, significant at the 10% level. The second cutoff produces a slightly larger difference than the first.

Expenditures

All results for the expenditure indicator are reported in tables 13 and 14. I find no significant differences in bank loan take-up or bank loan amount between high and low value expenditure areas. There are no significant differential effects of high value expenditure areas between treatment and control areas. There are also no differential effects of high and low expenditures on bank loan take-up or bank loan amount within treatment areas nor within control areas. These trends are true for both cutoffs.

Literacy Rates

All results for the literacy indicator are in tables 15 and 16. People in high value literacy areas are 4.49 percentage points more likely to have a bank loan at endline1 than those in low value literacy areas, using the first cutoff. The triple interaction term is not significant between baseline and endline1. However, between baseline and endline2 the triple difference estimate is significant for both literacy cutoffs. At endline 2, high value literacy treatment areas are 4.13 or 5.38 percentage points less likely to have a bank loan relative to high value literacy control areas, respective to each cutoff. The first cutoff is significant at the 10% level while the second cutoff is significant at 5%.

Those in high value literacy treatment areas are 2.96 percentage points more likely to have a bank loan at endline1 than those in low value literacy treatment areas, significant at the 5% level, using only the first cutoff. Those in high value literacy control areas are 6.09 percentage points more likely to have a bank loan than those in low value literacy control areas at endline1, significant at the 1% level. The second literacy cutoff produces a similar yet slightly smaller difference. There are no significant effects of high value literacy areas on bank loan amounts, nor are there significant differential effects of literacy on bank loan amounts between treatment and control areas nor within either sample of treatment or control areas.

Informal and MFI sectors

I examine informal loans and MFI loans to get a sense of how treatment affected these types of loans and to compare effects against bank loans. As neither informal sector effects nor MFI sector effects are the focus of this study, I do not check effects as extensively as with the banking sector. I do not show the results against endline2 or against the second cutoff for each value indicator. Only the triple difference coefficients are reported in the tables, however I do explain some within-sample trends that, while not affecting the banking sector, are interesting to note.

Informal

Tables 18 and 19 show results for the informal credit sector. There are significant increases in informal loan take-up and informal loan amount between baseline and endline1. There is a significant decrease in informal loan take-up at endline2, while the estimate for bank loan amount at endline2 is insignificant. There are no significant differences between treatment and control areas when it comes to informal loan take-up and informal loan amounts between baseline and endline1. There also exist no significant differences between treatment and control areas when it comes to previous banking, high value expenditure areas, high value business areas, high value debt areas, or high value literacy areas. There are also no significant differences within treatment areas nor within control areas when it comes to previously banking, high value expenditure areas, or high value literacy areas.

In treatment areas, people in high value business areas experience smaller amounts of informal loans as compared to their low value business area counterparts at endline1. This effect is insignificant in control areas. There is also no significant effect on informal loan take-up in neither treatment nor control areas with respect to high value business areas.

People in low value debt control areas have a higher likelihood of having an informal loan at endline1 as compared to their high value debt control area counterparts. There is no such significant difference for treatment areas. People in low value debt areas experience significantly larger informal loans than those in high value debt areas at endline1 in both samples of treatment and control areas.

MFI

Tables 20 and 21 show results for the MFI sector. There are significant positive effects on the number of people with MFI loans between baseline and endline1 as well as the amount of those MFI loans. There are positive differential effects between treatment and control areas, as treatment areas have much higher loan take-up and loan amounts. All effects become insignificant at endline2.

There are no significant differential effects for either MFI loan take-up or amount between treatment and control areas when it comes to previous banking, high value expenditure areas, high value business areas, or high value literacy areas. There are also no significant differences in loan take-up or loan amount within treatment nor within control areas between previously banked or unbanked areas, high or low expenditure areas, or high or low literacy areas. High value business areas are 8.19 percentage points less likely to have MFI loans than those in low value business areas at endline1. No such significant effects appear in control areas, nor when it comes to bank loan amount.

The only significant triple interactions come from the debt variable. People in low value debt treatment areas are 12.03 percentage points more likely to have an MFI loan than those in low value debt control areas. People in low value debt treatment areas also experience larger MFI loan amounts than those in low value debt control areas. Within treatment areas, people in low value debt areas are 11.95 percentage points more likely to have an MFI loan than those in high value debt areas. They also have higher loan amounts than those in high value debt areas. All estimates for control areas are insignificant.

Characteristics of MFI and Bank loan take-up

I examine whether banks and MFIs loan to individuals based on characteristics measured in the study. I look at how those characteristics compare to one another in the two different sectors. I then examine the means of all characteristics for both banks and MFIs, and test for statistical differences between means. I find there are multiple characteristics significant in one group and not the other. I also find many statistically different means between groups of borrowers, suggesting strong differences in clientele between banks and MFIs.

Significant Borrower Characteristics

Both borrower characteristic regression results for endlines1 and 2 combined can be seen in table 22. Statistically significant banking characteristics are as follows: household size, the age of the head of the household, the household owning a business well before endline1, high area literacy, the household owning land, the income index, the consumption index, the social index, and the area being already banked at baseline all contribute positively to the likelihood of having a bank loan. The head having no education, the women employment index, and the labor index all contribute negatively to the likelihood of having a bank loan.

Statistically significant MFI characteristics are as follows: household size, the household owning a business well before endline1, the women employment index, the labor index, the consumption index, and the social index all contribute positively to the likelihood of having an MFI loan. The age of the head of the household contributes negatively to the likelihood of having an MFI loan.

Household size contributes about twice as much to bank loan take-up than to MFI loan take-up, as an increase in household size leads to 3.93 percentage point greater likelihood that a person has a bank loan, relative to the 1.27 percentage point greater likelihood that a person has an MFI loan. The age of the head of the household contributes more to MFI loan take-up than to bank loan take-up, as a one-year increase in the head’s age leads to a 0.0798 percentage point increase in bank loan take-up while it leads to a 0.251 percentage point decrease in MFI loan take-up. A household that has an old business at least one year before endline1 is 1.6 percentage points more likely to have a bank loan, while they are 8.07 percentage points more likely to have an MFI loan. An increase in the women employment index leads to a decrease in bank loan take-up by 1.15 percentage points, while it leads to an increase in MFI loan take-up by 3.97 percentage points and is much more significant. The labor index is similar in that an increase leads to a decrease in bank loan take-up by 1.57 percentage points while it leads to an increase in MFI loan take-up by 9.81 percentage points. The consumption index has a positive relation to both bank and MFI loan take-up, with an increase leading to a 4.7 percentage point increase for the banking sector and a 1.41 percentage point increase in the MFI sector. The social index also contributes positively to both sectors' loan take-up, with a one unit increase leading to a 2.71 percentage point increase in the banking sector and a 4.23 percentage point increase for MFI loans.

There are changes between endline1 and endline2. Concerning banking characteristics, the education of the head, owning an old business, literacy rates, and the social index all become insignificant at endline2 while they are significant at endline1. Being already banked at baseline is the only significant estimate in endline2 that is not significant at endline1. Concerning MFI characteristics, having a male head, being already banked at baseline, and the social index are all significant at endline1 but not significant at endline2. The consumption index is the only significant estimate for endline2 that is not significant at endline1.

Significant Differences in Borrower Characteristics

I run the same regression on bank likelihood as before, however I restrict the sample to only people who have outstanding bank or MFI loans at endline1 or endline2.

All results for this regression can be seen in table 23. This regression does produce multiple statistically significant estimates. The age of the head, area literacy rate, the women employment index, and the labor index are all statistically significant and positive. The head having no education, owning land well before endline1, and the income index are all statistically significant and negative. This means all these coefficients are statistically different for banks and for MFIs. The p-value for the regression's f-statistic is 0.00 which allows me to conclude the coefficients are jointly significant and different.

The means of the variables show there are statistically different average values for many of the coefficients between bank borrowers and MFI borrowers. The table of means and related t-statistics can be seen in table 24. Many of the coefficients that were insignificant in the characteristic build up are significantly different from one another between bank and MFI clientele. In fact, ten out of sixteen variables have significantly different means between bank and MFI clientele. Male head, head age, head no education, area population, literacy, own land, women employment index, income index, labor index, and consumption index are all statistically different. This shows there is a greater separation in clientele pools than the initial characteristic regressions suggest.

Discussion

Overall, there is little evidence of any effects of MFI entry on banking characteristics. The lack of treatment differences in the banking sector shows that banking characteristics are not affected by MFI competition, as bank loan take-up and bank loan amounts are not statistically different between treatment and control areas.

Examining the five area-specific value indicator variables – already banked, expenditures, debt, total businesses, and literacy rates – allows for a more specific analysis of MFI-bank competition. Banks could be operating differently dependent on these specific neighborhood characteristics. However, the only statistically significant difference in bank loan take-up between treatment and control areas is for high value literacy areas at endline2, significant at both literacy cutoffs. People in high value literacy treatment areas are less likely on average to have bank loans. The only statistically significant difference in bank loan amounts between treatment and control areas is at endline1 with concern to high value business areas, significant at both business cutoffs. People in high value business treatment areas have on average smaller bank loans.

If anything, the effects that are statistically significant suggest a possible substitution effect between MFI loans and bank loans. This substitution effect agrees with Maksudova (2010) and Vanroose and D'Espallier (2013). Both value indicators that produce statistically significant triple difference estimates produce negative coefficients, meaning people in areas with MFI presence are either less likely to borrow from banks or have smaller bank loan amounts than control area counterparts.

Results from the business value indicator suggests that businesses could be substituting portions of their bank loans with MFI loans, causing areas with many businesses to have on average bank loan amounts that are less than those in control areas. Results from the literacy value indicator could suggest that, as literacy and education level are correlated, borrowers in high literacy areas have more education surrounding financial services, or are at least more able to educate themselves on financial services, and in turn find themselves more capable of crossing the barriers to borrow from new sources. Results could also have to do with differences in lending type between MFIs and banks. As Spandana is a strict joint liability lender, it could be that those in higher literacy or higher business activity areas find it more appealing to pool their risk and operate in a joint liability format.

However, it is important to note the specificity required to achieve these significant coefficients. Only when combining a specific endline measurement with a specific value indicator is there a statistically significant result. This only happens in four out of forty instances tested: both business cutoffs at endline1 on bank loan amount and both literacy cutoffs at endline2 on bank loan take-up. The lack of robust results suggests that, while these specific significant differences should not be ignored, an overall zero effect of MFI competition on banking characteristics is witnessed.

There do exist differences in high value indicator areas that appear within treatment or within control areas only, however most triple differences are insignificant. This most likely means the significant effects in one sample are being matched by similar effects, significant or not, within the other sample. For instance, there are no significant differences on bank loan take-up between treatment and control areas with respect to previously banked and unbanked areas. However, there are significant differences between previously banked and unbanked areas within treatment areas as well as within control areas. In both samples, those in previously banked areas are less likely to have a bank loan at endline1 than their previously unbanked area counterparts at endline1. Because this effect is witnessed in both samples, there is no statistically significant estimate for differences between the two samples. This can also happen when only one sample has a statistically significant coefficient, as directional similarity and significance level can contribute to no statistically significant triple difference estimates. Because differences between treatment and control areas are what are being tested in this study, differences within samples, while interesting, do not contribute to whether banks act differently with MFI presence and are not discussed in more depth.

Although differences between treatment and control areas are not witnessed, there exists a massive increase in lending throughout the period, seen in Table 1. MFI loan take-up skyrockets due to the nature of the study, with baseline take-up being only 1.57% and endline2 having a take-up of 34.09%. However, both banks and informal lending institutions experienced increases as well, at least between baseline and endline1. Bank loan take-up goes from 3.87% at baseline to 8.16% at endline1 to 7.375% at endline2. The informal sector even experiences an increase in loans between baseline and endline1, as take-up increases from 62.78% to 73.37%, however by endline2 the take-up rate drops to 60.32%. Overall, the likelihood of anyone having any type of loan increases from 67.62% to 90.52% between baseline and endline2.

There are a number of possibilities for why there is such an increase. This increase could by cyclical. Perhaps Hyderabad went through a period of massive lending and much of these increases are uncorrelated with anything concretely measured. However, these banking and informal increases could be due to a spillover effect. Even though there does not appear to exist differential effects between treatment and control areas, it could be that banks are not operating on an area-by-area basis. This would happen if the banks think of the market differently, outside of the area-based markets and instead within a much larger market scope than what is measured. This would mean that much of what is measured here are spillovers from local markets to one another, and perhaps the area-based definition of a market is too small for the banking sector.

However, it has been shown in previous research that informal lenders operate within these smaller, area-based local markets. Because of this type of operation, the informal sector sheds light on this spillover hypothesis. If it is true that many of these measurements are spillovers, there would have to exist significant triple difference coefficients for the informal sector. However, the triple differences are insignificant. This means that even the informal sector does not experience statistically significant differences between areas with MFI presence and those without. Therefore, the spillover theory has no empirical backing, as local markets are not differentially affected. This again supports a zero effect of MFI entry on the formal banking sector.

While there is a massive increase in lending throughout the study period, the lack of treatment differences demonstrates the lack of crowding-in effects in the sense of MFI-bank interactions. If people began financing bank loans with MFI loans, there would be some differential in bank loan take-up between treatment and control areas, as treatment areas would supposedly see an increase in bank loans as MFI lending becomes commonplace. The lack of differences reveals the lack of crowding-in effects, both for bank-MFI sector interactions and for informal-MFI sector interactions.

Clientele characteristics for both banks and MFIs do have some overlap. Because there is some overlap in characteristics, this would instinctively mean that there is overlap in clientele. However, there are a multitude of variables that work against a person's ability to have a loan in one sector and for their ability in another, such as head age, women employment index, and labor index. There are also a multitude of variables that are significant for one sector and not for the other. For instance, the variable ownland is strongly significant for banks yet insignificant for MFIs. This represents a characteristic of MFIs which is that they do not require collateral, so owning land does not matter as much for MFIs as it does for banks. The income index, lit, and head_no_education are three other variables that are only significant for banks and could contribute to the idea of why banks and MFIs lend. The income index and area literacy rates contribute positively to bank loan likelihood while the head having no education contributes negatively. Increased literacy, education, and income all signify less risky borrowers. As MFIs operate first and foremost to eradicate poverty while banks operate primarily as profit-generating institutions, it makes sense that these variables mean more to a bank than to an MFI.

The regression to explain differences between MFI and bank borrowers produces some significant coefficients, showing there are significant differences in clientele between banks and MFIs. Furthermore, the table of means for those characteristics sheds light on how different these clientele groups really are. Because there are so many variables that have statistically significant different means, clients are significantly different between banks and MFIs. Although both sectors might act positively toward a characteristic, such as both MFIs and banks becoming more likely to lend as the consumption index increases, clientele pools for each sector have statistically different average values for those characteristics.

The fact that competition is not witnessed between the two industries is baffling, as I expected to see some competition between two sectors which both lend to individuals in the same areas. Yet, this zero-effect is the clear conclusion from what is shown in the difference in difference regressions that produced mostly insignificant estimates and the statistically different clientele characteristics between the two sectors. The effects seen in previous papers could be due to endogeneity consequences of their aggregated panel data, but it also could be that the differences found in those other papers simply cannot be picked up by this type of dataset. These other studies have focused on MFI activity surrounding bank presence, whereas I look at bank activity surrounding MFI presence. While I would still expect to see competition between MFIs and banks, much of the competition mentioned in previous research would not be picked up here. For instance, the differences between banking sector development described by Vanroose and D'Espallier cannot be seen here as this study looks at one banking sector. Nor can differentials between MFI structures, investigated by Cull, Demirgüç-Kunt and Morduch, be examined as this study is based off one MFI. The country level income differences examined by Maksudova also cannot be accounted for because this data is collected in one city.

While these papers conclude competition effects between the banking sector and the MFI sector, their conclusion is not necessarily contradictory to mine. My zero-effect conclusion is on the local scale, and none of their results described differential effects on the local scale. My results add to, rather than contradict, their findings – while there might exist differences in MFI outreach dependent on banking sector differences, MFI institutional differences, and income differences across countries, local markets are relatively separated in MFI lending and bank lending. Because of this market separation, competitive and non-competitive areas within a city are not differentially affected. Because this zero effect is witnessed, formal banking sectors in areas where MFIs operate need not create hostile environments to drive out MFI competition, as MFIs are seen to not be direct competitors with banks. Instead, banks could work to aid MFIs in their goal to alleviate poverty, which some larger banks already do. This finding could also support potential government funding of MFIs as concerns surrounding negative competition consequences between growing sectors can be mitigated.

Further research on this topic could cover a multiple of different characteristics. A more robust dataset, specifically a panel dataset, collected from a controlled study likened to this one would be extremely beneficial. A more thorough look at bank clientele, MFI clientele, and informal clientele characteristics could be derived from such a dataset and used to determine how clientele characteristics shift with MFI entry. While I attempt to begin this analysis, I cannot perform it thoroughly as all characteristic data comes from the two endlines and is not tracked over time on an individual level, only on an area level. Having such a panel would be an excellent complement to this analysis and would allow for a more intricate look at MFI entry effects on the banking sector.

It would also be interesting to continue a more exhaustive analysis of different value indicators. This could be done by both expanding the amount of value indicators collected at the time of the study as well as looking at bank and MFI behavior based upon these different indicators. One could even move away from bank-MFI competition and examine the intricacies of how banks and MFIs act dependent on these indicators. This analysis would ignore treatment versus control to focus on bank and MFI lending behavior in high versus low value areas. This would contribute to the knowledge pools of MFI and formal banking determinants and efficacy in the developing world.

Conclusion

In this study, I examine differences in banking outcomes in response to MFI entry. I analyze whether banks compete with MFIs based on certain area characteristics, or value indicators, or whether the two institutions operate in separate marketplaces. I do this analysis by running differences in differences and triple difference regressions that take into consideration differences between measurement periods in the study, differences between treatment and control areas, and differences between value indicators that represent area characteristics banks and MFIs could be working off. I supplement my regression analyses with a clientele characteristic analysis to examine whether there is overlap in bank and MFI clientele.

I find there exists little to no effect of MFI entry on banking outcomes. There are no significant estimates of differential treatment effects on bank loan take-up or bank loan amount. Very few estimates that examine differences from baseline to an endline between treatment and control areas with respect to differences in area characteristics come out significant. While these significant exceptions are notable, the overarching conclusion supports a zero effect estimate of MFI entry on banking sector outcomes. There is also no support of a spillover hypothesis as the informal sector, a sector known to operate on an extremely local scale, also experiences no significant triple difference estimates. This zero-effect finding leads to the conclusion that banks and MFIs are operating in different marketspaces. This is backed up by the clientele characteristic analysis. While there does exist some overlap in characteristics, many characteristics have significantly different means between the two clientele pools, which means banks and MFIs have statistically different clientele.

While there are many conclusions this dataset cannot produce, the brilliance of this study allows me to thoroughly conclude that exogenous MFI entry does not appear to affect bank loan take-up or bank loan amounts. While there could be competition differentials on a larger scale, the lack of competition here shows that bank and MFI sectors operate in significantly different marketspaces and, on a local scale, interactions between the sectors do not statistically affect one another's lending outcomes.

Tables

Table 5: Banking Sector – Treatment Differences from Baseline to Endline1

	Bank		Bank Amount	
VARIABLES	(1)	(2)	(3)	(4)
Male Head		-0.00237		-141.0
		(0.00923)		(3,485)
Head Age		0.00101***		428.7***
		(0.000268)		(101.2)
Head No Education		-0.0378***		-9,304***
		(0.00607)		(2,293)
Household Size		0.00505***		2,084***
		(0.00135)		(509.0)
Endline01	0.0459***	0.0401***	2,968	1,002
	(0.00967)	(0.00876)	(5,187)	(3,307)
Endline01 * Treatment	0.000325	0.000904	4,823	5,035
	(0.0127)	(0.0123)	(5,399)	(4,631)
Constant	0.0359***	-0.0144	3,647*	-20,829***
	(0.00467)	(0.0152)	(1,912)	(5,738)
Observations	9,242	9,205	9,242	9,205
R-squared	0.036	0.043	0.018	0.024

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Banking Sector – Treatment Differences from Baseline to Endline2

	Bank		Bank Amount	
VARIABLES	(1)	(2)	(3)	(4)
Male Head		0.0161**		1,678
		(0.00760)		(2,269)
Head Age		0.000859***		211.5***
		(0.000267)		(79.73)
Head No Education		-0.0234***		-4,615**
		(0.00621)		(1,854)
Household Size		0.00109		416.6
		(0.00115)		(343.1)
Endline02	0.0403***	0.0360***	206.9	-1,030
	(0.00883)	(0.00867)	(4,614)	(2,588)
Endline02 * Treatment	-0.00985	-0.00906	3,063	3,216
	(0.0111)	(0.0120)	(4,704)	(3,573)
Constant	0.0381***	-0.00792	4,120**	-6,369
	(0.00392)	(0.0141)	(1,620)	(4,221)
Observations	8,573	8,549	8,573	8,549
R-squared	0.027	0.031	0.019	0.021

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Banking Sector – Effects of Previous Banking Differences between Treatment and Control from Baseline to Endline1 on Bank Loan take-up

		Bank		
			Treatment	Control
VARIABLES	(1)	(2)	(3)	(4)
Male Head	-0.00353	-0.00290	0.0201	-0.0259*
	(0.0101)	(0.0103)	(0.0134)	(0.0140)
Head Age	0.00104***	0.00101***	0.00106***	0.000986**
	(0.000230)	(0.000235)	(0.000271)	(0.000383)
Head No Education	-0.0365***	-0.0385***	-0.0356***	-0.0410***
	(0.00615)	(0.00626)	(0.00838)	(0.00935)
Household Size	0.00500***	0.00510***	0.00519**	0.00501***
	(0.00128)	(0.00129)	(0.00200)	(0.00165)
Endline01	0.0748***	0.0799***	0.0701***	0.0796***
	(0.00887)	(0.0165)	(0.00901)	(0.0165)
Endline01 * Treatment		-0.00948		
		(0.0187)		
Endline01 * Already Banked	-0.0599***	-0.0655***	-0.0550***	-0.0659***
	(0.0115)	(0.0191)	(0.0143)	(0.0193)
Endline01 * Treatment * Already Banked		0.0103		
		(0.0238)		
Constant	-0.0146	-0.0141	-0.0361**	0.00651
	(0.0139)	(0.0143)	(0.0164)	(0.0224)
Observations	9,560	9,205	4,757	4,448
R-squared	0.047	0.046	0.041	0.052

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Banking Sector – Effects of Previous Banking Differences between Treatment and Control from Baseline to Endline1 on Bank Loan Amount

	Bank Amount			
			Treatment	Control
VARIABLES	(5)	(6)	(7)	(8)
Male Head	-236.2	-236.4	-411.0	-825.5
	(1,515)	(1,567)	(2,621)	(1,656)
Head Age	432.3**	429.7**	93.94	791.5*
	(201.0)	(209.2)	(83.69)	(422.4)
Head No Education	-9,285***	-9,426***	-7,869***	-11,111**
	(2,580)	(2,667)	(1,658)	(5,293)
Household Size	2,034***	2,082***	1,488*	2,773**
	(655.1)	(666.2)	(790.1)	(1,109)
Endline01	9,622***	12,511*	7,658***	12,015*
	(3,221)	(7,106)	(1,383)	(6,838)
Endline01 * Treatment		-5,329		
		(7,466)		
Endline01 * Already Banked	-10,610**	-18,933*	-2,156	-19,012*
	(5,184)	(10,028)	(2,835)	(10,116)
Endline01 * Treatment * Already Banked		16,773		
		(10,374)		
Constant	-20,559**	-20,863**	-6,649	-35,822*
	(9,889)	(10,276)	(4,368)	(20,401)
Observations	9,560	9,205	4,757	4,448
R-squared	0.025	0.025	0.029	0.027

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Banking Sector – Effects of Business Differences between Treatment and Control from Baseline to Endline1 on Bank Loan take-up

	Bank			
			Treatment	Control
VARIABLES	(1)	(2)	(3)	(4)
Male Head	-0.00304	-0.00259	0.0205	-0.0257*
	(0.0100)	(0.0103)	(0.0133)	(0.0141)
Head No Education	-0.0358***	-0.0379***	-0.0351***	-0.0404***
	(0.00612)	(0.00624)	(0.00827)	(0.00941)
Head Age	0.00105***	0.00101***	0.00107***	0.000991**
	(0.000230)	(0.000236)	(0.000271)	(0.000383)
Household Size	0.00495***	0.00503***	0.00507**	0.00499***
	(0.00128)	(0.00131)	(0.00202)	(0.00166)
Endline01	0.0452***	0.0503***	0.0398***	0.0502***
	(0.00806)	(0.0132)	(0.00958)	(0.0133)
Endline01 * Treatment		-0.0105		
		(0.0162)		
Endline01 * Biz	-0.0102	-0.0229	0.00254	-0.0238
	(0.0131)	(0.0193)	(0.0179)	(0.0195)
Endline01 * Biz * Treatment		0.0256		
		(0.0264)		
Constant	-0.0154	-0.0147	-0.0368**	0.00612
	(0.0139)	(0.0144)	(0.0163)	(0.0228)
Observations	9,560	9,205	4,757	4,448
R-squared	0.045	0.043	0.039	0.049

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: Banking Sector – Effects of Business Differences between Treatment and Control from Baseline to Endline1 on Bank Loan Amount

	Bank Amount			
			Treatment	Control
VARIABLES	(5)	(6)	(7)	(8)
Male Head	-98.07	-4.415	-377.6	-395.4
	(1,523)	(1,585)	(2,624)	(1,664)
Head No Education	-9,184***	-9,229***	-7,782***	-10,802**
	(2,551)	(2,587)	(1,655)	(5,124)
Head Age	431.7**	424.5**	94.34	780.3*
	(200.4)	(206.2)	(83.43)	(416.0)
Household Size	2,022***	2,101***	1,492*	2,805**
	(653.9)	(671.3)	(789.9)	(1,122)
Endline01	1,728	-5,059	8,395***	-5,438
	(4,037)	(7,672)	(1,955)	(7,948)
Endline01 * Treatment		13,052*		
		(7,688)		
Endline01 * Biz	4,274	13,531	-4,481	13,169
	(5,147)	(9,811)	(2,895)	(9,594)
Endline01 * Biz * Treatment		-18,200*		
		(10,230)		
Constant	-20,424**	-20,766**	-6,959	-35,270*
	(9,767)	(10,180)	(4,430)	(20,166)
Observations	9,560	9,205	4,757	4,448
R-squared	0.025	0.025	0.029	0.026

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: Banking Sector – Effects of Debt Differences between Treatment and Control from Baseline to Endline1 on Bank Loan take-up

	Bank			
			Treatment	Control
VARIABLES	(1)	(2)	(3)	(4)
Male Head	-0.00287	-0.00222	0.0205	-0.0250*
	(0.0100)	(0.0102)	(0.0132)	(0.0139)
Head No Education	-0.0358***	-0.0377***	-0.0351***	-0.0401***
	(0.00612)	(0.00622)	(0.00830)	(0.00932)
Head Age	0.00105***	0.00101***	0.00107***	0.000980**
	(0.000231)	(0.000236)	(0.000272)	(0.000384)
Household Size	0.00494***	0.00505***	0.00507**	0.00504***
	(0.00128)	(0.00130)	(0.00201)	(0.00165)
Endline01	0.0295***	0.0244**	0.0347***	0.0242**
	(0.00779)	(0.00994)	(0.0121)	(0.00996)
Endline01 * Treatment		0.0104		
		(0.0155)		
Endline01 * Debt	0.0173	0.0250	0.00922	0.0245
	(0.0118)	(0.0174)	(0.0163)	(0.0176)
Endline01 * Debt * Treatment		-0.0157		
		(0.0238)		
Constant	-0.0151	-0.0147	-0.0370**	0.00647
	(0.0141)	(0.0146)	(0.0162)	(0.0232)
Observations	9,560	9,205	4,757	4,448
R-squared	0.045	0.043	0.039	0.049

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Banking Sector – Effects of Debt Differences between Treatment and Control from Baseline to Endline1 on Bank Loan Amount

	Bank Amount			
			Treatment	Control
VARIABLES	(5)	(6)	(7)	(8)
Male Head	-78.22	-36.96	-394.5	-447.6
	(1,523)	(1,580)	(2,625)	(1,651)
Head No Education	-9,132***	-9,241***	-7,850***	-10,746**
	(2,517)	(2,577)	(1,673)	(5,090)
Head Age	434.5**	430.6**	94.97	791.9*
	(201.9)	(209.7)	(83.71)	(423.3)
Household Size	2,023***	2,083***	1,483*	2,781**
	(652.1)	(666.9)	(790.3)	(1,111)
Endline01	-3,881	-10,062	3,425	-10,705
	(6,183)	(11,263)	(2,333)	(11,597)
Endline01 * Treatment		12,951		
		(11,258)		
Endline01 * Debt	11,479*	17,591	4,599	17,766
	(6,468)	(12,016)	(3,100)	(12,049)
Endline01 * Debt * Treatment		-12,897		
		(12,358)		
Constant	-20,737**	-20,997**	-6,702	-36,026*
	(9,973)	(10,381)	(4,354)	(20,596)
Observations	9,560	9,205	4,757	4,448
R-squared	0.025	0.025	0.029	0.026

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Banking Sector – Effects of Expenditure Differences between Treatment and Control from Baseline to Endline1 on Bank Loan take-up

	Bank			
			Treatment	Control
VARIABLES	(1)	(2)	(3)	(4)
Male Head	-0.00298	-0.00240	0.0206	-0.0254*
	(0.0100)	(0.0102)	(0.0132)	(0.0139)
Head No Education	-0.0359***	-0.0378***	-0.0350***	-0.0403***
	(0.00611)	(0.00622)	(0.00830)	(0.00931)
Head Age	0.00104***	0.00100***	0.00107***	0.000969**
	(0.000231)	(0.000236)	(0.000272)	(0.000384)
Household Size	0.00493***	0.00505***	0.00508**	0.00502***
	(0.00129)	(0.00130)	(0.00200)	(0.00167)
Endline01	0.0389***	0.0346**	0.0422***	0.0339**
	(0.0100)	(0.0161)	(0.0124)	(0.0161)
Endline01 * Treatment		0.00744		
		(0.0202)		
Endline01 * Expend	0.00366	0.01000	-0.00288	0.0104
	(0.0129)	(0.0199)	(0.0167)	(0.0201)
Endline01 * Expend * Treatment		-0.0123		
		(0.0259)		
Constant	-0.0146	-0.0141	-0.0372**	0.00794
	(0.0142)	(0.0146)	(0.0165)	(0.0229)
Observations	9,560	9,205	4,757	4,448
R-squared	0.045	0.043	0.039	0.049

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Banking Sector – Effects of Expenditure Differences between Treatment and Control from Baseline to Endline1 on Bank Loan Amount

	Bank Amount			
			Treatment	Control
VARIABLES	(5)	(6)	(7)	(8)
Male Head	-139.3	-151.2	-425.6	-642.2
	(1,520)	(1,576)	(2,621)	(1,673)
Head No Education	-9,166***	-9,303***	-7,844***	-10,882**
	(2,537)	(2,621)	(1,661)	(5,190)
Head Age	432.6**	428.7**	93.82	789.8*
	(201.9)	(209.8)	(84.23)	(423.7)
Household Size	2,021***	2,078***	1,470*	2,785**
	(654.7)	(668.4)	(791.1)	(1,114)
Endline01	3,212***	1,427	4,882***	1,314
	(977.4)	(1,516)	(1,151)	(1,623)
Endline01 * Treatment		3,210*		
		(1,874)		
Endline01 * Expend	737.9	-774.2	3,537	-1,565
	(5,309)	(9,505)	(3,124)	(9,532)
Endline01 * Expend * Treatment		3,804		
		(10,009)		
Constant	-20,549**	-20,723**	-6,360	-35,860*
	(9,902)	(10,310)	(4,346)	(20,501)
Observations	9,560	9,205	4,757	4,448
R-squared	0.024	0.024	0.029	0.026

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Banking Sector – Effects of Literacy Rate Differences between Treatment and Control from Baseline to Endline1 on Bank Loan take-up

	Bank			
			Treatment	Control
VARIABLES	(1)	(2)	(3)	(4)
Male Head	-0.00341	-0.00265	0.0201	-0.0254*
	(0.0100)	(0.0102)	(0.0133)	(0.0138)
Head No Education	-0.0364***	-0.0384***	-0.0352***	-0.0413***
	(0.00610)	(0.00621)	(0.00831)	(0.00927)
Head Age	0.00105***	0.00101***	0.00108***	0.000964**
	(0.000232)	(0.000237)	(0.000274)	(0.000385)
Household Size	0.00487***	0.00499***	0.00497**	0.00501***
	(0.00128)	(0.00131)	(0.00203)	(0.00165)
Endline01	0.0164***	0.0115	0.0227***	0.0110
	(0.00607)	(0.00890)	(0.00757)	(0.00901)
Endline01 * Treatment		0.0108		
		(0.0118)		
Endline01 * Lit	0.0449***	0.0608***	0.0296**	0.0609***
	(0.0114)	(0.0185)	(0.0145)	(0.0186)
Endline01 * Lit * Treatment		-0.0305		
		(0.0235)		
Constant	-0.0130	-0.0124	-0.0357**	0.00964
	(0.0138)	(0.0143)	(0.0159)	(0.0229)
Observations	9,560	9,205	4,757	4,448
R-squared	0.046	0.045	0.040	0.052

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Banking Sector – Effects of Literacy Rate Differences between Treatment and Control from Baseline to Endline1 on Bank Loan Amount

	Bank Amount			
			Treatment	Control
VARIABLES	(5)	(6)	(7)	(8)
Male Head	-169.2	-165.7	-437.6	-658.4
	(1,519)	(1,579)	(2,630)	(1,668)
Head No Education	-9,206***	-9,334***	-7,864***	-10,921**
	(2,525)	(2,601)	(1,668)	(5,144)
Head Age	433.0**	428.9**	95.33	788.2*
	(201.7)	(209.6)	(83.92)	(423.1)
Household Size	2,017***	2,078***	1,472*	2,780**
	(654.4)	(668.0)	(791.7)	(1,113)
Endline01	1,684	-181.8	4,541***	-618.8
	(1,132)	(1,475)	(1,570)	(1,705)
Endline01 * Treatment		4,302**		
		(2,138)		
Endline01 * Lit	3,498	2,523	3,211	2,299
	(4,905)	(10,893)	(2,721)	(10,828)
Endline01 * Lit * Treatment		592.7		
		(11,230)		
Constant	-20,466**	-20,703**	-6,541	-35,603*
	(9,904)	(10,298)	(4,358)	(20,439)
Observations	9,560	9,205	4,757	4,448
R-squared	0.025	0.024	0.029	0.026

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Banking Sector – Robustness Table, Value Indicator Variable Triple Interaction Coefficients

		Baseline-Endline1		Baseline-Endline2	
		(1)	(2)	(3)	(4)
VALUE INDICATOR	Cutoff	Bank	Bank Amount	Bank	Bank Amount
Already Banked	1	Table 7	Table 8	-0.00461	12,412
		(Table 7)	(Table 8)	(0.0187)	(7,981)
	2	-0.0186	-8,253	-0.00616	-808.7
		(0.0282)	(8,088)	(0.0215)	(6,970)
Expenditures	50%	Table 13	Table 14	-0.0302	2,098
		(Table 13)	(Table 14)	(0.0217)	(8,864)
	75%	-0.00203	8,758	-0.0355	8,148
		(0.0275)	(15,451)	(0.0243)	(13,623)
Debt	50%	Table 11	Table 12	-0.000414	-10,648
		(Table 11)	(Table 12)	(0.0227)	(12,324)
	75%	-0.0142	-16,188	-0.0126	-13,566
		(0.0239)	(14,438)	(0.0234)	(15,045)
Businesses	50%	Table 9	Table 10	-0.0111	-9,772
		(Table 9)	(Table 10)	(0.0217)	(8,492)
	75%	0.0175	-20,101*	-0.0258	-10,043
		(0.0297)	(12,015)	(0.0225)	(6,885)
Literacy	50%	Table 15	Table 16	-0.0413*	5,141
		(Table 15)	(Table 16)	(0.0220)	(10,038)
	75%	-0.0571	-5,558	-0.0538**	8,592
		(0.0393)	(17,148)	(0.0255)	(15,276)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Informal Sector – Treatment Differences from Baseline to Endline1 and Endline2

VARIABLES	(1) Informal	(2) Informal Amount	(3) Informal	(4) Informal Amount
Male Head	0.00650	-1,882	0.00339	1,041
	(0.0167)	(2,859)	(0.0162)	(2,124)
Head No Education	0.0661***	-3,107*	0.0620***	-76.50
	(0.0113)	(1,627)	(0.0122)	(1,813)
Head Age	-0.00207***	553.1***	-0.00166***	379.9***
	(0.000557)	(89.46)	(0.000631)	(82.73)
Household Size	0.0137***	4,106***	0.0103***	2,687***
	(0.00234)	(538.7)	(0.00269)	(474.5)
Endline01	0.107***	9,474***		
	(0.0259)	(2,645)		
Endline01 * Treatment	-0.0509	1,028		
	(0.0324)	(4,046)		
Endline02			-0.0448**	46.04
			(0.0214)	(2,694)
Endline02 * Treatment			-0.00881	979.6
			(0.0294)	(3,997)
Constant	0.631***	-12,399**	0.634***	-1,836
	(0.0315)	(5,070)	(0.0305)	(4,771)
Observations	9,205	9,205	8,549	8,549
R-squared	0.064	0.046	0.040	0.038

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Informal Sector – Value Indicator Variable Triple Interaction Coefficients for Endline1

VARIABLES	(1) Informal	(2) Informal Amount
Already Banked	0.0391	7,487
	(0.0700)	(7,830)
Expenditures	0.00926	-2,096
	(0.0647)	(8,040)
Debt	-0.0613	-4,491
	(0.0591)	(9,366)
Businesses	0.0335	-12,501
	(0.0652)	(7,931)
Literacy	0.00282	-8,650
	(0.0646)	(7,779)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All coefficients are for triple interaction terms. That is, the term that interacts high value indicator, endline01, and treatment.

Table 20: MFI Sector – Treatment Differences from Baseline to Endline1 and Endline2

VARIABLES	(1) MFI	(2) MFI Amount	(3) MFI	(4) MFI Amount
Male Head	0.0200	300.8	0.00630	191.9
	(0.0127)	(229.3)	(0.0148)	(324.6)
Head No Education	0.00844	26.48	0.000995	-296.1
	(0.00973)	(161.6)	(0.0101)	(296.4)
Head Age	-0.00108***	-10.89	-0.00227***	-29.84***
	(0.000386)	(7.787)	(0.000391)	(11.06)
Household Size	0.0129***	262.7***	0.0118***	380.2***
	(0.00235)	(45.93)	(0.00226)	(71.15)
Endline01	0.151***	1,749***		
	(0.0204)	(295.7)		
Endline01 * Treatment	0.0838**	1,255**		
	(0.0320)	(592.5)		
Endline02			0.300***	4,631***
			(0.0222)	(506.5)
Endline02 * Treatment			0.000143	686.7
			(0.0338)	(808.9)
Constant	-0.0122	-602.7	0.0534**	-149.6
	(0.0251)	(432.1)	(0.0229)	(590.2)
Observations	9,214	9,205	8,558	8,549
R-squared	0.161	0.110	0.184	0.114

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: MFI Sector – Value Indicator Variable Triple Interaction Coefficients for Endline1

VARIABLES	(1) MFI	(2) MFI Amount
Already Banked	0.0335	611.7
	(0.0638)	(1,133)
Expenditures	-0.0508	-425.4
	(0.0627)	(1,146)
Debt	0.120*	2,318*
	(0.0647)	(1,386)
Businesses	-0.0401	-992.0
	(0.0637)	(1,231)
Literacy	0.0211	914.3
	(0.0669)	(1,307)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All coefficients are for triple interaction terms. That is, the term that interacts high value indicator, endline01, and treatment.

Table 22: Bank and MFI Loan Take-up Characteristics at Endline1 and 2

VARIABLES	(1) Bank	(2) MFI
Household Size	0.00393***	0.0127***
	(0.00102)	(0.00241)
Male Head	0.00333	0.00969
	(0.00921)	(0.0176)
Head Age	0.000798***	-0.00251***
	(0.000243)	(0.000499)
Head No Education	-0.0190***	0.000729
	(0.00570)	(0.0114)
Old Business	0.0160**	0.0807***
	(0.00617)	(0.0106)
Area Population (baseline)	-1.53e-05	6.93e-05
	(2.56e-05)	(9.31e-05)
Already Banked (baseline)	0.0156**	0.0392
	(0.00761)	(0.0284)
Biz (baseline)	-0.0110	-0.0110
	(0.00873)	(0.0307)
Expend (baseline)	-0.00372	-0.0398
	(0.00732)	(0.0287)
Lit (baseline)	0.0197**	-0.0336
	(0.00972)	(0.0258)
Own Land (baseline)	0.0171***	0.00549
	(0.00606)	(0.0150)
Women Employment Index	-0.0115*	0.0397***
	(0.00619)	(0.0136)
Income Index	0.0196***	0.00719
	(0.00540)	(0.00740)
Labor Index	-0.0157***	0.0981***
	(0.00542)	(0.0134)
Consumption Index	0.0470***	0.0141*
	(0.00546)	(0.00823)
Social Index	0.0271***	0.0423**
	(0.0102)	(0.0197)
Constant	0.0106	0.260***
	(0.0179)	(0.0504)
Observations	12,689	12,689
R-squared	0.028	0.045

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

These regressions are built from the sample of everyone in the study, not solely people who borrow, in order to look at loan take-up characteristics.

Table 23: Loan Take-up Characteristic Differentials for Source Type at Endline1 and 2

VARIABLES	(1) Bank
Household Size	0.00203
	(0.00270)
Male Head	0.0102
	(0.0229)
Head Age	0.00414***
	(0.000785)
Head No Education	-0.0522***
	(0.0166)
Old Business	-0.00894
	(0.0130)
Area Population (baseline)	-7.02e-05
	(8.83e-05)
Already Banked (baseline)	-0.0139
	(0.0308)
Biz (baseline)	0.0191
	(0.0272)
Expend (baseline)	0.0161
	(0.0266)
Lit (baseline)	0.0407**
	(0.0161)
Own Land (baseline)	-0.0464***
	(0.0152)
Women Employment Index	0.0269***
	(0.00840)
Income Index	-0.0809***
	(0.0132)
Labor Index	0.0937***
	(0.0127)
Consumption Index	0.0354
	(0.0217)
Social Index	0.0160
	(0.0257)
Constant	0.0404
	(0.0559)
Observations	4,374
R-squared	0.057

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This sample is limited people that have either an MFI or bank loan. The statistically significant coefficients show the difference in bank borrowers from MFI borrowers.

Table 24: Loan Take-up Characteristic Means and Statistical Differences at Endline1 and 2

VARIABLES	Variable Mean (Standard Deviation) Bank	MFI	Difference (t-stat)
Household Size	6.176412	6.249798	-0.0733856
	(2.345757)	(2.478231)	(-0.8435)
Male Head	0.8937438	0.8575283	0.03621***
	(0.3083184)	(0.3495804)	(2.9869)
Head Age	42.86879	41.09724	1.7715***
	(10.10958)	(9.555749)	(5.149)
Head No Education	0.2085402	0.2976769	-0.08914***
	(0.4064668)	(0.4572984)	(-5.6117)
Old Business	0.497992	0.5274966	-0.0295
	(0.7010373)	(0.7683152)	(-1.0941)
Area Population (baseline)	300.6065	313.1471	-12.54059**
	(145.2239)	(144.6328)	(-2.44)
Already Banked (baseline)	0.617443	0.5990299	0.0184131
	(0.4862525)	(0.490161)	(1.0599)
Biz (baseline)	0.3548067	0.3629749	-0.0081682
	(0.478692)	(0.4809225)	(-0.4789)
Expend (baseline)	0.4380575	0.3893829	0.0486746
	(0.4963943)	(0.4876761)	(2.8004)
Lit (baseline)	0.5698712	0.5184586	0.051412***
	(0.4953395)	(0.4997265)	(2.9031)
Own Land (baseline)	0.3568588	0.3034557	0.053403***
	(0.4793109)	(0.4598124)	(3.2369)
Women Employment Index	-0.01242	0.034934	-0.047354***
	(0.4721381)	(0.5093493)	(-2.6588)
Income Index	0.1733441	0.0287202	0.144624***
	(1.266404)	(0.6780349)	(4.8543)
Labor Index	-0.0082099	0.0883006	-0.096510***
	(0.412083)	(0.4864337)	(-5.7648)
Consumption Index	0.2544555	0.0136535	0.240802***
	(0.8283451)	(0.5493359)	(10.9465)
Social Index	0.0331547	0.0162216	0.0169331
	(0.3043466)	(0.329294)	(1.4714)

*** p<0.01, ** p<0.05, * p<0.1

Bibliography

Armendariz, Beatriz and Jonathan Morduch. 2010. *The Economics of Microfinance*. Cambridge (MA): The MIT Press.

Banerjee, Abhijit, Dean Karlan, and Jonathan Zinnman. 2015. "Six Randomized Evaluations of Microcredit: Introduction and Further Steps." *American Economic Journal: Applied Economics* 7(1): 1-21. http://dx.doi.org/10.1257/app.20140287

Banerjee, Abhijit and Esther Duflo. 2007. "The Economic Lives of the Poor." Author manuscript *National Center for Biotechnology Information*. Originally published *Journal of Economic Perspectives* 21(1): 141-167. http://www.anderson.ucla.edu/faculty/bhagwan.chowdhry/Banerjee-Duflo.pdf

Banerjee, Abhijit and Esther Duflo. 2011. *Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty*. New York: PublicAffairs.

Banerjee, Abhijit, Esther Duflo, Rachel Glennerster, and Cynthia Kinnan. 2015. "The Miracle of Microfinance? Evidence from a Randomized Evaluation." *American Economic Journal: Applied Economics* 7(1): 22-53. http://dx.doi.org/10.1257/app.20130533

Chaia, Alberto, Aparna Dalal, Tony Goland, Maria Jose Gonzalez, Jonathan Morduch, and Robert Schiff. 2009. "Half the World is Unbanked." Financial Access Initiative. http://mckinseyonsociety.com/downloads/reports/Economic-Development/Half_the_world_is_unbanked.pdf

Collins, Daryl, Jonathan Morduch, Stuart Rutherford and Orlanda Ruthven. 2009. *Portfolios of the Poor: How the World's Poor Live on $2 a Day*. New Jersey: Princeton University Press.

Cull, Robert, Asli Demirgüç-Kunt, and Jonathan Morduch. 2013. "Banks and Microbanks." *Journal of Financial Services Research*. 46(1): 1-53. doi: 10.1007/s10693-013-0177-z

Johnston Jr., Don, and Jonathan Morduch. 2008. "The Unbanked: Evidence from Indonesia." *World Bank Economic Review*. 22(3): 517-537. https://doi.org/10.1093/wber/lhn016

Karlan, Dean and Jonathan Morduch. 2009. "Access to Finance." Chapter 2, *Handbook of Development Economics*, Volume 5. http://www.financialaccess.org/publications-index/2009/access2finance

Katyal, Ritika. 2015 Aug 2. "India census exposes extent of poverty," *CNN*. http://www.cnn.com/2015/08/02/asia/india-poor-census-secc/

Maksudova, Nargiza, 2010. "Macroeconomics of Microfinance: How Do the Channels Work?" *Center for Economic Research and Graduate Education – Economics Institute.* Working Paper Series No. 423. https://www.cerge-ei.cz/pdf/wp/Wp423.pdf

Microcredit Summit Campaign. 2015. "State of the Campaign." https://stateofthecampaign.org/2015/12/09/read-the-full-2015-report/

MicroLoan Foundation. 2007. "Charity or commerce? The different structures of microfinance." http://www.appg-microfinance.org/files/Different%20forms%20of%20microfinance.pdf

Mookherjee, D. and A. Motta. 2016. "A theory of interactions between MFIs and informal lenders." *Journal of Development Economics.* 121(C): 191-2000.

Peachey, Stephen and Alan Roe. 2006. "Access to Finance – What Does It Mean and How Do Savings Banks Foster Access." World Savings Banks Institute. https://www.microfinancegateway.org/sites/default/files/mfg-en-paper-access-to-finance-what-does-it-mean-and-how-do-savings-banks-foster-access-jan-2006_0.pdf

The World Bank. Poverty Headcount Ratio at $1.90 a day. http://data.worldbank.org/indicator/SI.POV.DDAY?end=2013&locations=1W&name_desc=false&start=1981&view=chart

Todaro, Michael and Stephen Smith. 2015. "Finance and Fiscal Policy for Development." In *Economic Development, 12th Edition*, 793. New Jersey: Pearson.

Vanroose, Annabel and Bert D'Espallier. 2013. "Do Microfinance Institutions Accomplish Their Mission? Evidence from the Relationship Between Traditional Financial Sector Development and Microfinance Institutions' Outreach and Performance." *Applied Economics* 45(15): 1965-1982. http://dx.doi.org/10.1080/00036846.2011.641932

World Bank Group. 2016. "Taking on Inequality." Poverty and Shared Prosperity Series. *International Bank for Reconstruction and Development.* Washington DC. doi:10.1596/978-1-4648-0958-3.