Peer Effects and Loan Repayment: Evidence from the Krishna Default Crisis

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Abstract

Around the world, microfinance ties borrowers together using group repayment meetings, shared oaths and often, joint liability. Microfinance institutions (MFIs) have invested heavily in building social capital and generally boast stellar repayment rates. However, recent repayment crises have fueled speculation that peer effects might also reinforce default behavior. I estimate the causal effect of peer repayment on individuals’ repayment decisions in the absence of joint liability following a district-level default in which 100% of borrowers temporarily defaulted on their loans and after which borrowers gradually decided whether to repay. Because the defaults occurred simultaneously, the timing of the shock induced variation in repayment incentives both at the individual and peer group levels. Individuals (or peer groups) near the end of their 50-week loan cycles were closest to receiving new loans and had the strongest incentives to repay; those who had recently received disbursements had the weakest. Using the variation in the peer group’s incentives to instrument for peer repayment, I find that if a borrower’s peers shift from full default to full repayment, she is 10-15pp more likely to repay. Last, I present a dynamic discrete choice model of the repayment decision to estimate the net benefit of the peer mechanism to the MFI. Repayers’ positive influence on others (not non-repayers’ negative influence) mainly drives the effect. Thus, peer effects actually improve repayment rates relative to a counterfactual without peer effects.


1 Introduction

Group lending has always been one of the hallmarks of microfinance. In order to overcome weak contracting institutions, limited borrower wealth and collateral, and the inability for microentrepreneurs to transfer control rights to creditors, microfinance contracts have traditionally relied on dynamic incentives and social capital to provide repayment incentives. The Grameen Bank website claims "there is more to the bank than just the balance sheet; it ties lending to a process of social engineering." The peer lending context has been exported and replicated across the globe to diverse cultures and settings and has remained a key investment for microfinance institutions (MFIs). While microlenders have typically enjoyed very high repayment rates, we know surprisingly little about how the social capital developed during the lending process actually affects a borrower’s repayment decision. Furthermore, as large scale coordinated defaults have begun to creep into the microfinance sector, it is more important than ever to understand if microfinance’s “social engineering” stabilizes or exacerbates a crisis.

I examine microfinance peer effects following a large scale default episode that took place in the Krishna District of Andhra Pradesh, India on March 9, 2006. In order to promote his own financial inclusion agenda, the District Collector announced that his constituents should stop repaying their microloans. Within two days of the announcement, all borrowers had ceased making installment payments. Soon after the defaults, the local microlenders began to reestablish collections in the affected villages and also suspended the joint liability feature of the loans. They offered new loans for those who finished repaying. Some individuals resumed payment within a few months of the crisis, and as of November 2009, 40-50% of individuals had fully repaid their liabilities. I investigate whether peer effects helped or hindered collections in the aftermath of the defaults.

While a mass default episode might seem like a special case in which to look for peer effects, quantifying negative risks during crises is key to understanding the value and long-run viability of MFIs. Markets for securitized microloans continue to grow, and any positive or negative repayment peer effect should affect both the pricing of such securities and the borrowing costs faced by MFIs themselves. Because these borrowing costs are passed through to customers through interest rates, peer effects could play an important role in affecting the

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1 Models of debt usually assume contractible cash flows (Innes 1990), costly state verification (Townsend 1979), pledgeable collateral, or transferrability of control rights (see Burkart et al. 1997, Bolton and Scharfstein 1990, Hart and Moore 1998).
2 See Section 3.1 for a discussion of the limitations of dynamic incentives as an enforcement device.
3 See http://www.grameen-info.org
4 The District Collector is a federal bureaucrat who is the head of the district’s administration.
cost of capital for poor individuals across the globe. The role of peer effects is relevant for
determining whether microlenders should continue to invest in social capital and for shaping
government policies for financial inclusion. In India for example, some new government-
sponsored financial access models do not include peer components.

The relationship between social effects and financial behavior is related to the broader
question of asset correlations during financial crises. Peer effects can also appear in other
危机情境。例如，伊耶尔和普里(2011)和凯利和格拉达(2000)表明，社交网络有助于存款人的撤资
的传染。在美国家庭市场背景下，古索等人(2009)发现，社区内的社交规范会影响到
个体的策略性违约决策。如果一个亲朋好友已经违约，个体更有可能在抵押贷款
上选择战略性违约。微型金融是产生显著的再投资效应的首要候选者，因为对社会
资本的重视在贷款机制中被嵌入。对抵押贷款和微型金融贷款而言，战略性违约
高度公开。此外，个体在邻里和微型金融借贷群体中可能从中获利。在两种情境下，
peer group actions can have direct consequences for an individual’s own repayment
decisions.

Historically, many group lending schemes have been characterized by group-level joint
liability. In these contract structures, there is a direct channel for peer decisions to affect
repayment rates. For example, if one member defaults on her loan, then the remaining
members must bear the cost of that defaulted loan if they intend to receive new loans
in the future. The non-defaulting borrowers could use a local enforcement technology to
coax the defaulter into repaying her loan. Alternately, this extra cost may result in other
repayers choosing to default and walk away from the lending relationship. In both scenarios,
the actions of the peer group have direct consequences for an individual’s own repayment
decisions.

Several theoretical models examine the various mechanisms through which joint liabil-
ity might operate including screening, monitoring and enforcement. Candidate pathways
include moral hazard in project selection (Stiglitz (1990)), moral hazard in project effort
(Banerjee et al. (1994)), adverse selection of borrowers (Ghatak and Guinnane (1999) and
Ghatak (1999)), and village sanctions and limited contract enforcement (Besley and Coate

5 Bond and Rai (2009) show that microfinance borrower default and bank runs have some important
commonalities from a theoretical point of view.

6 For example, Topa et al. (2009) show that neighborhood job referrals have significant effects on labor
market outcomes. See Durlauf (2004) for a survey of research on neighborhood effects. For microfinance
borrowers, strengthening peer networks by participating in a lending center could have long term social
benefits. See discussion of risk sharing networks below.

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Ahlin and Townsend (2007) use data from Thailand to test these theoretical predictions and find that higher degrees of joint liability coincide with lower repayment, as do higher levels of cooperation within borrower groups. Using quasi-random group formation data, Karlan (2007) finds that stronger social connections yield higher repayment rates in joint liability groups in Peru and that socially closer peers monitor fellow members more. He also shows that default is potentially detrimental to social ties. The Besley and Coate (1995) model of strategic default is the most relevant to my empirical setting and highlights the potential for both virtuous and perverse social repayment equilibria. Giné et al. (2011) find evidence for perverse joint liability effects in their investigation of a recent default episode in the Kolar District of Karnataka, India.

While the joint liability literature gives a rich theoretical framework for thinking about peer effects in lending, contract structure alone may not fully explain the social effects embedded in microfinance. Following the Grameen II model, many MFIs have abandoned joint liability but have maintained group meetings. A small but growing set of empirical work links social capital and microfinance in the absence of joint liability. Giné and Karlan (2006, 2009) randomize between individual and joint liability loan contracts. While varying the contract structure, they maintain the group format of the repayment meetings and loan disbursements. Over 1- and 3-year horizons, moral hazard does not appear to increase when clients are assigned to the individual liability treatment, default rates do not increase, and the individual liability policy attracts more new clients. They do not find any impacts on social networks from switching from joint to individual liability. However, the remaining question is to what effect does the peer format of the individual liability loans contribute to repayment incentives? Feigenberg et al. (2010), examine social effects in the absence of joint liability. The authors find that individuals randomly assigned to weekly versus monthly repayment schedules form stronger ties with their fellow group members, visit fellow group members more frequently, and exhibit more trust. The weekly groups also display better repayment records throughout their second loan cycles. While the experimental design does not allow the authors to confirm a direct link between social capital and repayment, the findings highlight the possibility that groups might affect repayment through social channels even in the absence of any legal link between members. In this paper, I analyze the causal

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8Research such as Townsend (1994) has documented the importance of social networks for risk sharing in developing countries. Ambrus et al. (2010) show that building stronger social ties and increasing cooperation between agents can lead to improved risk sharing.
relationship of peer repayment on an individual’s own repayment decision. Furthermore, along with Giné et al. (2011), this paper is one of the first pieces of evidence on social effects in response to microfinance defaults.

In general, it is both difficult to find exogenous variation in default and hard to estimate peer effects due to omitted correlated covariates, unobserved correlated shocks, and the reflection problem described by Manski (1993). To circumvent these problems, I exploit the random timing of the default shock and propose a novel identification strategy for estimating social effects in borrowing relationships. Microlenders use the promise of new loans to encourage repayment, so borrowers who were closest to receiving a new loan at the time of the defaults have the biggest potential benefits and lowest costs from repayment once collections restart, and indeed I show that these individuals are the most likely to repay. In the standard microfinance contract, borrowers make 50 weekly installment payments following each loan disbursement, so a borrower’s location in this 50-week credit cycle affects her own repayment incentives. Because borrowers have staggered loan disbursements within the peer group, these cyclical repayment incentives also induce variation in the peer group’s overall repayment incentives. Peer groups with a majority of borrowers in weeks 45-50 of their loan cycles will have much stronger overall incentives than peer groups with a majority of borrowers in weeks 0-5. Thus, the 50-week loan cycle provides separate sources of variation to identify both “own” and peer incentives. I use variation in the peer group’s overall repayment burden to instrument for the fraction (or number) of peers who repay, providing consistent estimation of the effect of peer repayment on individual repayment.

I first employ an instrumental variables technique using the average week in cycle to instrument for average peer repayment. The data set comes from Spandana, one of the largest MFIs in India. I control for continuous functions of the total length of time each individual and each aggregate peer group has spent borrowing from Spandana, to eliminate effects from differences in total time spent borrowing from the MFI. Because the discontinuous repayment incentives identify the peer effect, I also apply a regression discontinuity approach to the problem. I compare repayment rates for individuals whose peers have very strong incentives with individuals whose peers have very weak incentives. Since peer groups on either side of the discontinuity look very similar in all regards aside from dynamic repayment incentives, the variation is as good as random. The data set contains information on the full universe of loans, including village of residence and borrowing center membership, and can shed light on which level of peer interaction (i.e., social distance) has the largest effect on repayment.

\footnote{I define the relevant notion of peer group in section \ref{sec:peer}.}
behavior. The case of microfinance is unique since the contract structure defines the relevant peer groups. The administrative records contain all of the necessary peer group definitions.

I find that borrowers are very sensitive to their own dynamic repayment incentives and that each completed week in the loan cycle before the defaults corresponds to a 1pp increase in eventual repayment. I do find that peer repayment behavior influences loan repayment. Borrowers are 10-15pp more likely to repay their loans if their entire center\textsuperscript{10} repays. (The borrowing center is a smaller unit than the village, and all center members attend the same weekly meeting.) The estimates at the village-level peer group are substantially smaller and insignificant and provide suggestive evidence that the peer repayment effect is a largely local phenomenon, fostered by the regular meetings and previous experience of joint liability. Non-linear estimates of the repayment effect show that there are large increases in the probability of repayment if just one peer repays or similarly if all peers have repaid. Furthermore, I find evidence that the peer effect is asymmetric and is largely a positive force, pulling individuals with weak incentives out of default.

To more precisely address the relationship between peer effects and asset values, I estimate a structural model of loan repayment, using the time variation available for a subset of the data. I treat the repayment decision as a dynamic discrete game played with fellow group members. Using the methodology of [Aguirregabiria and Mira (2007)] to deal with the interdependency of players’ actions, I estimate the parameters of a simple repayment model and predict repayment paths under the regime with peer effects and under a counterfactual without a peer mechanism. A structural model is required for two reasons. First, while the reduced form analysis provides estimates for the effects of peer repayment in relative terms, it does not fix the absolute repayment levels under regimes with and without peer effects. Second, pricing the value of the peer effect requires modeling the time structure of each individual’s repayment path. Lenders pay an opportunity cost of capital for every additional week borrowers remain in default. Understanding this time structure requires placing more restrictions on the problem.

I find that firm revenues from loan collections increase by 10% when peer effects are switched on, helping to partially mitigate the costs of default. The greatest increase in potential lender revenues comes from decreasing the time to repayment of those individuals with the highest numbers of payments outstanding. For these individuals with weak “own” repayment incentives, I estimate that peer effects may increase the value of their cash flows.

\textsuperscript{10}Borrowers are assigned to groups of 6-10 individuals. Every 3-5 groups are then combined to form a center. All members of each center meet together at the same time and place each week to make their loan payments.
by as much as 40%. While peer effects potentially have both positive and negative effects on repayment, the virtuous peer effect is stronger at luring these types of individuals back into repayment.

The Krishna default crisis has already been repeated, but on a much larger scale. In October 2010, the government of the state of Andhra Pradesh issued an emergency ordinance severely restricting the operations of all MFIs in the state. The alleged motivations were almost identical to those of the Krishna District Collector: fears of each of over-indebtedness, usurious interest rates, abusive collections practices, and alleged borrower suicides. The results of this study will be helpful in guiding collection efforts in Andhra Pradesh and in informing lenders how to better incorporate the peer forces embedded in microfinance to increase repayment rates in the case of a crisis and ultimately decrease borrower interest costs.

The body of the paper proceeds as follows. Section 2 describes the setting of the natural experiment and the data set used. Section 3 provides a graphical analysis of the key exogenous variables and outlines the intuition behind the identification strategy. Section 4 describes the empirical model in more depth, while Section 5 details the results. I estimate a structural model of the loan repayment decision in Section 6. Section 7 discusses potential mechanisms driving the peer effects, and Section 8 concludes.

2 Empirical Setting

2.1 Spandana Group Loans

Before describing the default crisis in detail, it is necessary to understand the loan product offered by the MFI from which I have complete repayment data. Spandana Sphoorty Financial Limited was one of the largest MFIs in India and was one of the primary microlenders operating in the Krishna District at the time of the crisis. The standard loan product operates on a 50-week cycle. After loans are disbursed, individuals make 50 equally-sized, weekly installment payments. Upon successful completion of the repayment cycle, individuals are given a new, larger 50-week loan. In normal times, defaulters are sanctioned with the denial of future credit.

These loans, which are typically only offered to women, usually have joint liability provisions. Before the first loan disbursement, each borrower is assigned to a joint liability borrowing group of approximately 10 women. Borrowers in a group tend to all be on the same disbursement and repayment schedule, but individuals within a group may have differ-
ent loan sizes. Every 2-5 borrowing groups within the same village are then combined to form a center. Within a center, groups may have staggered loan disbursements and thus might be at different places in the loan cycle at any point in time. All borrowers belonging to a center meet at the same time and place each week to make their installment payments to the credit officer, who travels from the branch office to the borrower’s village. These meetings begin with a joint oath, which affirms the virtues of making on-time payments and helping fellow borrowers. The credit officer then takes attendance and collects the installment payments from each group. All absences or late payments are made public at the meeting. There is also joint liability at the center level between groups in the case that all members of a borrowing group default. However, this is rarely, if ever, enforced.

For the remainder of the paper, I define the peer group as either the borrowing center or the village. Because I use administrative data, I have complete records of group and center membership. Unlike some peer effects applications, the social format of the lending product leads to a clear definition of the relevant peer groups.

2.2 The Krishna Crisis

The setting for my investigation into peer effects and borrower repayment is a natural experiment from the Krishna District of the state of Andhra Pradesh, India. On March 9, 2006, the District Collector, Navin Mittal, closed over 50 branches of two large MFIs, Share and Spandana. This move resulted in the cessation of all weekly repayments across the district, a potential loss of close to Rs 200cr (~$44mm) of outstanding loans. The district government alleged that MFIs were setting interest rates too high, using unethical means to encourage loan repayment, and stealing clients from state banks and SHGs (self help groups). Furthermore, several farmer suicides were blamed on the stress from having to repay microloans. The local media began a campaign of bad press and personal attacks highlighting the evils of the microfinance industry. There is some weak evidence from the local newspapers that Mittal scheduled his announcement around International Women’s Day, which occurs each year on March 8. Sa Dhan, an association representing community development financial institutions, and an alliance of MFIs put pressure on the government to rescind the District Collector’s statement. A retraction was made in mid-2006 and the worst of the crisis finally came to an end in early 2007.

11I do not consider the borrowing group due to a lack of variation in my instrument within groups.
12Many members of the local media also had financial stakes in chit fund companies that operated in the district. The collector’s statement only affected microfinance institutions, implying that chit funds could expand in the absence of microfinance.
The District Collector’s announcement spurred a diverse set of reactions across the region. Some borrowers started again repaying their loans within a few months of the announcement and picked up where they left off in the repayment schedule. In other parts of the district, angry villagers threatened Spandana and Share field staff and forced branch closures and the halt of all collection attempts. Some defaulters still claim that the District Collector’s statement remains in effect even though Mittal eventually issued a retraction and was transferred to a different region. As of November 2009, approximately 45% of the outstanding portfolio on March 9, 2006 had been repaid. Understanding these repayment patterns and the role of repayment peer effects is the primary concern of this study.

Due to the political climate, Spandana was forced to take a measured response to the crisis. While the defaulted loans had been issued under group joint liability, Spandana immediately abandoned the enforcement of joint liability. The MFI also made the decision to reward repayers with future credit regardless of the time spent in default, and Spandana was able to satisfy all demand for new credit. In effect, the crisis dismantled the strict discipline generally required by an MFI and gave borrowers the option to extend the maturity of their loans at no additional cost. After one year of only marginally successful collection efforts, Spandana also started offering refinancing plans, where small new loans were disbursed to encourage borrowers to begin making regular loan payments and to eventually repay all outstanding debt.

The media’s treatment of the crisis highlights the controversy associated with microfinance in the Krishna District and acknowledges the importance of peer interactions. Between March and June 2006, there were frequent negative articles about microfinance in the Vijayawada edition of The Hindu, the local English language newspaper. A common view seems to be that "the microfinance companies sanction loans to SHGs liberally without insisting on security but charge exorbitant interest and collect the installments using peer pressure of the group." A stronger complaint came in an article entitled "Microfinance victims petition rights panel" [Hin (2006b)], which claimed that borrowers "were caught in a perennial debt trap by the MFIs through machinations. The breach of human rights by the firms drove at least 10 persons to suicide in the district [Hin (2006c)]. It is clear that the media thought that the peer enforcement channel mattered in the process of loan collections. One strongly-worded article notes, "micro-finance institutions have hit upon a new and unscrupulous method of recovering outstanding loans – pitting members of self-help groups against another" [Hin (2006a)]. Whether the peer effect led to increased long term default or repayment is an open

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13 This policy was made clear to all field staff and borrowers beginning immediately after the crisis.
14 I could not find any articles substantiating the link between MFIs and suicides in Krishna District.
question.

Spandana’s Krishna District defaults represent an ideal natural experiment for studying the determinants of microloan repayment. First, the defaults were instigated by a federal bureaucrat, not through a grassroots movement. The defaults did not spread across district borders, indicating that true political upheaval did not drive the crisis. Since loan repayment rates remained at close to 100% in neighboring districts, it is safe to assume that in the absence of Mittal’s announcement, Krishna loan repayment rates would also have remained at almost 100%. Moreover, according to the MIX (Microfinance Information Exchange), Spandana had less than 0.01% of its portfolio overdue more than 90 days in both 2004 and 2005. In 2008, after the crisis had subsided, the reported portfolio at risk > 90 days was again very low at 0.02%. Second, Spandana was one of the largest, most efficient MFIs in the world. The MFI was able to withstand the liquidity shock from the suspension of loan payments on almost 200,000 loans and fulfill its promise of future credit to all repayers. The large commercial bank, ICICI, owned many of the defaulted loans, further insulating Spandana from liquidity effects. Spandana also was able to retain and pay its field staff even when all collections had ceased. Usually default crises are accompanied by other problems endemic to the MFI. Finally, as a result of the crisis, other MFIs decided not to expand their client base into Krishna district. Spandana and Share have also agreed not to add new borrowers in the district. This improves the repayment incentives for defaulted borrowers since alternate sources of MFI credit are not available.

2.3 Data

Spandana graciously shared all of their available electronic records with me. In November, 2009, I visited the District office along with most of the branch offices to collect data. The data used in the analysis represent a close to complete set of loans outstanding during the Krishna crisis and report on loans serviced by all 23 branches that are currently operating in the district. All of the borrowers in the data set are women, which is standard practice for Indian MFIs that follow the Grameen Bank model. The data set includes information on group name, center number and village or slum name as well as details about the specific loans including loan size, date of disbursement, loan cycle and repayment information. The raw data set contains information on 194,312 loans, with a total principal outstanding of >$11mm.

\footnote{A research team from the Centre for Microfinance (CMF) collected information from those branches I did not have a chance to visit personally.}
Borrowers are given the chance to take small, interim loans after making many on-time installment payments. The interim loans also require fixed installment payments for 50 weeks and add to the client’s total liability. Once the main loan has been fully repaid, clients are permitted to take a new main loan, even when the interim loans are still outstanding. Thus, it is common for borrowers to have two Spandana loans simultaneously outstanding. For the analysis, I focus only on main loans, since they affect each borrower’s incentives the most. I drop all loans indicated as interim loans in addition to any loans smaller than Rs. 3000, since these are most likely miscoded. The data set does not have unique identifiers, even though many borrowers have both main and interim loans outstanding. I use fuzzy matching on the borrower name, group name, center number, and village name to identify multiple borrowing and to identify the loans to be dropped.

For the empirical analysis, I also drop all villages with fewer than 50 borrowers. This is for two reasons. First, in the peer effects regressions, villages with only one group or center would be automatically dropped since there is no extra-group variation available. Second, it is likely that villages with only a few borrowers have miscoded place names. Additionally, I drop any villages without documented cycle numbers, since it is essential to be able control for functions of an individual’s weeks in the lending relationship with Spandana.

Table 1 gives an overview of the final cleaned data set used throughout the rest of the paper. There are approximately 115,000 unique borrowers included from 574 villages with an average loan size of Rs 7,640 (~$170). This represents 5,340 borrowing centers, or an average of approximately 9 borrowing centers per village. The portfolio at risk on March 9, 2006 in this sub-sample of the data totals approximately $5mm. The average loan at the time of the defaults was disbursed in September 2005. The administrative records also include week-specific payment and delinquency information for a subset of borrowers that allows me to determine when a borrower resumed paying her loan and when she completed making payments on the delinquent loan. Of the 115,000 loans in the analysis sample, approximately 57% are still in arrears as of November 2009.

Spandana also records the stated purpose for the loans. The purposes in the Krishna data set are quite representative of those stated in Indian microfinance more broadly. The most common business use is livestock (26.33%) followed by textiles (saree sales, embroidery, tailoring) and small retail shops. The most common broad non-business category is household and family expenses (8.27%), which include expenses for marriages, home repairs and other household assets. Other non-business uses with less than 5% of the observations include debt refinancing and education costs.
3 Graphical Analysis

3.1 Repayment Incentives Across the Loan Cycle

The key task in this analysis is to find plausibly exogenous variation in the repayment behavior of each borrower’s peer group. Note that each borrower’s own incentive to repay her loan changes over the 50-week cycle. Since loan installments are all the same size and are made weekly, the cost of paying off the remainder of the loan is decreasing as the loan cycle progresses (i.e. as borrowers approach the maturity date of their loans). Additionally, MFIs almost universally use dynamic incentives to encourage repayment. Lenders use the promise of new, often larger amounts of credit to motivate borrowers to repay their loans, and this was true for Spandana even after the defaults, as borrowers who repaid were offered new loans. Thus, as the weeks in the loan cycle progress, the borrower is closer to receiving the next loan disbursement. Hence with discounting, the costs of repaying the remaining loan burden are decreasing and the benefits of paying off the loan in full are increasing. Therefore, repayment incentives are strongest in week 49 and weakest in week 0 of each loan cycle.

Throughout the paper, I rely on the idea that dynamic incentives provide differential repayment motivations depending on where agents fall in their loan cycles at the time of default. Namely, agents are increasingly motivated to repay when the next loan disbursement is expected in a shorter number of weeks. It is important to note, however, that basic dynamic incentives are not sufficient to provide repayment incentives, even without exogenous default forces. Bulow and Rogoff (1989) make this point with respect to sovereign debt. My identification assumptions do not require dynamic incentives to be the only driver of loan repayment, but do require that agents prefer to repay if they are closer to receiving a new loan. There could be a range of additional motivations that lead to pristine loan repayment records in the absence of defaults. For example, microlenders could provide other services that borrowers value such as low-cost inputs or technical assistance. Defaulting on loans would result in the denial of both credit and these other non-credit sources of utility. Alternatively, it has been shown that microfinance can serve as a commitment device that also provides agents with utility above and beyond the value of the loans (see Basu (2008) and Breza and Mullainathan (2010)).

The dashed lines in Figure 1 show the discounted net present value of a borrower’s future cash flows from the MFI as a function of the weeks since taking the first loan. This stylized

\[16\text{both outflows (installments payments) and inflows (new loan disbursements)}\]
relationship between borrower value and week with the MFI shows discontinuities around each multiple of 50 weeks. The value from the borrowing relationship increases over the course of the loan cycle and is highest at the time of each new loan disbursement. The value is the lowest immediately following the receipt of a new loan.

The relationship between week in the loan cycle when the crisis occurred and actual loan repayment following the crisis is displayed in the scatter plot in Figure 1. Each point in the scatter plot represents the average repayment\textsuperscript{17} rate as of November 2009\textsuperscript{18} across borrowers in each week with the MFI. The points between 0 and 50 weeks correspond to borrowers in their first loan cycles, while the points in weeks 50-100 correspond to second loans. Note that the actual repayment patterns follow the overall shapes of the stylized NPV curves with sharp discontinuities at multiples of 50 weeks. Borrowers in the beginning of their loan cycles tend to repay with less than 20% likelihood, while borrowers at the end of their loan cycles repay with upwards of 60% likelihood. Because the Krishna defaults all occurred within days of each other and because the timing of the initial loan disbursements was staggered, Mittal’s announcement induced variation in the repayment incentives of borrowers across the district. As a result, week in the loan cycle is a good candidate for quasi-exogenous variation in repayment both for individuals and their peers.

This argument is presented visually in Figure 2. Suppose that borrower 1 expresses interest in obtaining credit from a local MFI and receives a loan at T=0. The loan cycle is 50 weeks long and if everything goes as planned, the loan will be paid off at T=50, and a second loan will then be disbursed. Also suppose that the MFI is constrained in how quickly it can expand its lending practices. Borrower 2 also expresses interest in taking a loan, and she receives her first loan at T=10, to be paid off at week T=60. Now suppose that the collector makes a statement instructing both borrowers to cease repayment at T=55. At the time of the defaults, borrower 1 is in week 5 of her second loan, while borrower 2 is in week 45 of her first loan. Thus, borrower 2 is only 5 weeks of payments from finishing the loan and receiving a second loan. On the other hand, borrower 1 has 45 installment payments to make before the third loan is disbursed. The difference in dynamic incentives implies that if borrowers 1 and 2 are otherwise identical, the probability that borrower 2 repays will be higher than the probability that borrower 1 repays. The experiment that the exercise most closely mimics is selectively writing off a borrower’s loan and measuring the impact on peer

\textsuperscript{17}For the bulk of the analysis, repayment is an indicator for the individual having repaid the entire loan. \textsuperscript{18}November, 2009, which is three years after the resolution of the collector’s statement, is an appropriate time at which to separate long term repayers from long term defaulters. The Spandana staff predicted that it might be possible to collect at maximum 10% of the remaining debt outstanding in subsequent months.
repayment.

Figure 2 also brings to light some of the assumptions required for identification of repayment incentives using weeks in the loan cycle. First, it must be the case that conditional on observables, the individuals that fall to one side or the other of the 50-week point are not systematically different. For example, it might be the case that local leaders are the first to adopt microfinance in any given village or neighborhood. Then the difference in repayment outcomes between borrowers 1 and 2 might also pick up varying tendencies to repay as a function of leader status. However, since I know when each borrower started taking loans from the MFI, I can control for smooth functions of this timing variable. A similar argument might be made for loan size, since the loan size increases at each new disbursement. Again, I can include controls for functions of loan size and use the variation in timing for identification, partiailling out these other effects.

Another concern would be that the district collector timed his statement to coincide with the loan cycles of key constituents. The assumption required for identification is that the timing of the announcement was not related to any of the cyclical timings of borrowers. It would also be problematic if the announcement coincided with some change in Spandana’s expansion strategy 45-55 weeks prior. This is unlikely since Spandana was only one of several MFIs in the area and since borrowers were geographically dispersed across the entire district. Also, Spandana borrowers were in a range of loan cycles at the time of the defaults, making it hard to privilege any specific group with the announcement.

Because I can only observe a borrower if she held a loan on March 9, 2006, it would also be problematic if large numbers of borrowers decided not to take cycle 2 loans from Spandana. This could mean that borrowers in weeks 45-50 of their cycle 1 loans might be different from borrowers in weeks 0-5 of their cycle 2 loans. Figure 3 plots the distribution of the number of loans by the borrower’s week with Spandana on the date of the defaults. The solid line is a local linear regression, run seapartately for borrowers in cycles 1, 2 and 3. The dashed lines represent 95% confidence intervals. The largest concentration of loans occurs between 40-50 weeks before the defaults. However, notice, that the number of loans outstanding begins to decline before week 50 and continues its decline across the discontinuity. Thus, it is likely that the large peak around 45 weeks is due to Spandana’s loan expansion pattern, and not to selective borrower drop out. There is a second, smaller spike in loan concentration around week 80. It is also comforting that this increase does not coincide with any multiple of 50. There is no detectable difference in the number of loans across either discontinuity. The figure also shows that relatively few of the borrowers were on their third loans at the time of the defaults. This pattern could be the result of slow initial growth in loan disbursements.
when Spandana entered the district.

The collector's statement threatened the discipline that was one of microfinance's hallmarks. Mittal transferred significant value to clients by allowing them both to choose when to make payments and to effectively borrow at 0% interest indefinitely. Since the peer lending format also potentially affected repayment, to what extent did persistent peer effects contribute to the 45%-50% repayment rates. If the peer decisions did play a role, was the peer effect on net virtuous of vicious for repayment? The peer channel constitutes one possibly significant driver of either speedy repayment or extended default.

3.2 Preliminary Peer Effect Evidence

Figure 4 provides evidence that there might be repayment peer effects, at least at the center peer group level. The graph plots the kernel density estimates of the fraction of repayers across all villages in Panel A and all borrowing centers in Panel B. The resulting village distribution is single peaked, with the largest fraction of villages experiencing repayment rates around 50% - 60%. However, the center-level distribution has a distinct double peaked shape with mass clustered around 0 and 1, representing full default and full repayment. Very few villages, however, have close to universal default or universal repayment. These density plots give preliminary evidence of repayment peer effects at the center level. The striking difference in the repayment profile over villages versus centers also suggests that social mechanisms might be stronger at closer social distances. However, other sources of correlation within peer groups might also be responsible for these patterns, so it is necessary to use the quasi-random variation induced by the timing of the shock to say something more definitive.

Finally, Figure 5 presents even stronger evidence of a repayment peer effect. The figure plots a local linear approximation of the individual’s repayment likelihood as a function of the modal borrowing center week in cycle. The relationship is non-parametrically estimated within each loan cycle (i.e. 0-50 weeks, 50-100 weeks, and 100+ weeks). Functions of the individual’s and center’s week in the loan cycle, week with the MFI, and loan size are partialled out of the repayment variable. The picture indicates that the likelihood of repayment jumps downward by approximately 5pp as the center’s modal number of weeks crosses from 49 to 51 weeks in the loan cycle and from 99 to 101 weeks. In other words, borrowers are 5pp more likely to repay if their peers switch from very bad to very good.

19The distribution of incentives across the centers is much more smooth and evenly spread out across the 50 weeks in the cycle. See Figure 9 in Appendix D.
incentives. There are not many data points for average modal center weeks past 110, so I limit the scale of the x-axis for readability. The discontinuities in the figure suggest quite substantial peer effects in loan repayment.

4 Empirical Strategy

The graphical analysis shows a relationship between individual repayment and peer repayment, and shows how the discontinuity in repayment incentives allows for the estimation of the peer effect. Before a further discussion of the results, it is important to understand the statistical inference problem at hand. The equation of interest is

\[
\text{repay}_i = \beta^0 + \beta^1 \text{repay}_{p(i)} + \beta^2 X_{i,p(i)} + \varepsilon_{i,p(i)}
\]  

where \( i \) indexes the individual and \( p(i) \) indexes the peer group net of the individual. The variable, \( \text{repay}_i \) is a measure of individual \( i \)'s loan repayment, \( \text{repay}_{p(i)} \) is a measure of repayment by \( i \)'s peers, and \( X_{i,p(i)} \) is a set of additional individual and peer-level controls.

The biggest problem confronting most peer effects or social learning empirical identification strategies is that the peer effect cannot be separated from correlated shocks or other omitted group-level characteristics using an OLS framework. In a simple OLS regression, shocks to the entire peer group could be misinterpreted as peer effects. Manski (1993) shows that without an instrument or strong restrictions on the form of the peer effect, \( \beta^1 \) can’t be identified, and that the OLS estimate \( \hat{\beta}^1 \) would pick up any correlation between \( \text{repay}_{p(i)} \) and the error term.

Peer effects questions frequently arise in the labor and development economics literatures, and researchers have developed several approaches to consistently identify the setting-specific equivalents of equation 4.1. One set of approaches involves separating the peer group from the common shock group. In their paper on learning about new technologies in Ghana, Conley and Udry (2010) identify information peers and use geographical neighbors to control for common growing conditions. Similarly, in their study of social views towards contraception, Munshi and Myaux (2006) separate each individual’s own religious group from other religious groups in the same village. The authors use the fact that the relevant social norms for any individual come exclusively from her own religious group. Others have tried an instrumental variables approach to solve the identification problem. For example, Duflo and Saez (2002) instrument peer behavior with average group characteristics when analyzing social effects on 401K contributions. The identification of education externalities also faces the same
problems. Acemoglu and Angrist (1999) use separate instruments for own education and for the education of an individual’s peers. In order to estimate education externalities across age cohorts in Indonesia, Duflo (2004) finds an instrument for peer education that is orthogonal to the individual’s own educational attainment.

My strategy for identification involves using the week in the loan cycle at the time of default conditional on other observables as an instrument for individual and peer repayment incentives. One important identifying assumption is required: the timing of Mittal’s announcement was as good as exogenous. This assumption seems plausible for the reasons discussed in the previous section.

Table 2 compares the average week in the loan cycle at the time of default with village characteristics from the Census of India. Ideally, village characteristics will not be correlated with the distribution of weeks remaining in the loan cycle for the borrowers who live there. The Indian Census has information on population, caste break-down, education facilities, medical facilities, access to taps or wells, communication facilities, banking facilities and types of roads. The table only includes information for rural villages and may be incomplete due to different spellings of village names between the Spandana data and the Census. However, for the 310 matched villages, the average weeks variable does not seem to be related to many of the covariates available in the census that capture demographic information, land area, access to finance, access to education, and access to health care.

The first column examines the relationship between various village covariates and the average village week for the full sample. Each regression coefficient comes from a separate univariate regression, and standard errors are in parentheses below. Most of the variables are not correlated with weeks in the cycle. However, places with lower week averages tend to have higher populations, might be marginally farther from the nearest town and have fewer primary schools per capita. It would be problematic if Mittal chose to make the announcement when his cronies had most to gain, so I also include the fraction of the village between weeks 0 and 5 and the fraction between 45 and 50 in the loan cycle as regressors. Columns 2-3 show the coefficients from regressions of village characteristics on both the fraction of the village in weeks 0-5 and the fraction in weeks 45-50. Again, most of the coefficients are not significantly different from 0. There is a positive relationship between distance to town and both of these variables. However, the difference is not significant.

In the estimation procedure, the implicit baseline first stage for each individual, is

\[
{\text{repay}}_j = \alpha + \gamma^1{\text{weeks}}_j + \gamma^2 f_1({\text{loanamount}}_j) + \gamma^3 f_2(MFI_{\text{weeks}}_j) + \delta^1 X_{p(j)} + \epsilon_j
\]  

(4.2)
where, \( week_j \) is the number of weeks elapsed in the loan cycle at the time of default. The variable \( loanamount_j \) provides a control for each individual’s loan size, which is endogenous to other peer factors. Before disbursing loans, Spandana tries to assess a borrower’s debt capacity, so wealthier households are generally allocated larger loan sizes. This could interact with the peer network in the community, so I add a third degree polynomial of the loan size. Similarly, the order in which villagers signed up for their initial Spandana loans might also be correlated with peer structures. Since the gap in the loan cycle is correlated with this ordering variable, I also control for functions of \( MFI\_weeks_j \), the number of weeks at the time of default since the disbursement of the borrower’s first loan. Identification comes from the fact that loan cycles only last 50 weeks. Those individuals who are early in their second loan cycles should have similar characteristics (i.e. continuous, not discrete differences) to individuals late in the first loan cycle. \( X_{p(j)} \) is a vector of peer group controls, explained below.

Again the key peer effects equation of interest is

\[
\text{repay}_{i,p(i)} = \beta^0 + \beta^1 \text{repay}_{p(i)} + \beta^2 weeks_i + \beta^3 X_{i,p(i)} + \varepsilon_{i,p(i)} \tag{4.3}
\]

Where \( \text{repay}_{p(i)} = \sum_{j \in p(i), j \neq i} \frac{\text{repay}_j}{N_{p(i)}} \) is average peer repayment in person i’s peer group \( p(i) \) of size \( N_{p(i)} \), excluding person i. For most of the analysis, I assume a linear peer effect. \(^{20}\) In this case, the endogenous peer repayment term can be instrumented using the average weeks in the loan cycle conditional on average village loan sizes and starting dates with Spandana. See Appendix C for a discussion. Let \( weeks_{p(i)} = \sum_{j \in p(i), j \neq i} \frac{weeks_j}{N_{p(i)}} \) be the average weeks with the MFI of the peer group. The key requirement for identification is that \( weeks_i \perp weeks_{p(i)} | X_{i,p(i)} \). Because of this requirement, all peer group characteristics are calculated excluding the borrowing group. So, \( p(i) \) is either village ex group or center ex group in the various specifications. I argue that all of the peer group information lies in the length of time the members of the group have been taking loans from Spandana. Thus, the orthogonality requirement is plausible conditional on functions of average weeks with the MFI. \(^{21}\)

The peer-group level first stage is

\[
\text{repay}_{p(i)} = \delta_0 + \delta_1 weeks_{p(i)} + \delta_2 X_{i,p(i)} + \eta_{p(i)} \tag{4.4}
\]

\(^{20}\)In Section 5.3, I analyze non-linear peer effects. In Section 5.4, I analyze alternate functional forms for the peer effect.

\(^{21}\)This requirement can be somewhat relaxed by using a regression discontinuity strategy on average peer week, holding difference between an individual’s week and average peer week constant.
where $X_{i,p(i)}$ are the appropriate individual- and peer-level controls. Because I assume that the functional form of the peer effect is linear, I use a linear first stage in the average weeks in cycle of the peer group.

As an alternate specification, I also estimate the peer effects regression using the following aggregate first stage:

$$repay_{p(i)} = \gamma_0 + \sum_{j \in p(i), j \neq i} \left( \gamma_1 \frac{1(0 \leq weeks_j < 5)}{N_{p(i)}} + \gamma_2 \frac{1(45 \leq weeks_j < 50)}{N_{p(i)}} \right) + \gamma_3 X_{i,p(i)} + \psi_{p(i)}$$

(4.5)

In this specification, the instruments are the fraction of the peer group in weeks 0-5 of the loan cycle and the fraction of the peer group in weeks 45-50 of the loan cycle. I also use dummy variables indicating whether at least a threshold fraction of the peer group falls into one of these categories. In the vector of controls $X_{i,p(i)}$, I include the highest and lowest values of both number of weeks with Spandana and loan size within the relevant peer group.

The figures in Section 3 suggest a possible RD interpretation of the week in loan cycle variation. Hahn et al. (2001) and van der Klaauw (2002) establish a strong connection between IV and fuzzy regression discontinuity designs. One option, which is used by Angrist and Lavy (1999), is to run the same IV specification, but with the sample restricted to only the data points close to the discontinuities. In their paper on the application of regression discontinuity, Imbens and Lemieux (2008) reiterate the equivalence between local linear regression on either side of the discontinuity and Two Stage Least Squares using a dummy variable for data points to right of the threshold as the instrument. This procedure also involves restricting the sample to a small window around the discontinuity. The new first stage is

$$R_{p(i)} = \delta_0 + \delta_1 W_{p(i),T} + \delta_2 X_{i,p(i)} + \eta_{p(i)}$$

(4.6)

where

$$R_{p(i)} = repay_{p(i)}$$

$$W_{p(i),T} = 1 \left( \sum_{j \in p(i)} \frac{(45 \leq weeks_j < 50)}{N_{p(i)}} > T \right)$$

and T is the threshold. The regressions are restricted to peer groups for which either

$$1 \left( \sum_{j \in p(i)} \frac{(45 \leq weeks_j < 50)}{N_{p(i)}} > T \right) = 1$$
These regressions are also performed for both definitions of the peer group and only use information close to the discontinuity. As in the other specifications, the vector $X_{i, p(i)}$ contains smooth functions of the peer group and individual-level running variables (weeks with the MFI) in addition to loan size controls. Finally, I perform these regressions eliminating centers in weeks 0 – 5 with a majority of borrowers in the first loan cycle. First cycle borrowers with weak repayment incentives do not have a natural comparison group with strong incentives.

5 Results

5.1 OLS Estimates and Determinants of Repayment

Table 3 details the OLS estimates of equation 4.1 and shows very high associations between own and peer repayment. Throughout the analysis, I focus on the village peer effect and the center peer effect excluding the group. Column 1 shows a relationship of 81pp between village repayment and individual repayment controlling for own and peer loan size as well as functions of own and peer weeks with the MFI and branch fixed effects. This means that when the entire village switches from full default to full repayment, the individual borrower tends to make the same switch with 81% likelihood. Column 2 separates the village peer effect, 30pp, from the center peer effect, 56pp. Note that approximately two-thirds of the peer association comes from the smaller borrowing center. Column 3 shows the center peer effect alone, at 64pp. The high center level repayment correlations are also consistent with the shape of Figure 4. Again, caution is necessary in interpreting the OLS results, as these types of estimates tend to be greatly overstated in the case of unobserved correlated covariates or shocks. The instrumental variables approach has the potential of eliminating bias from the causal estimates.

It is rare to have the opportunity to analyze the determinants of loan repayment following a universal microfinance default. Before treating the IV peer effects estimates, I pause to first discuss the relationship of an individual’s repayment decision with loan size, length of

For the remainder of the analysis, all peer variables exclude the borrowing group. Most borrowers within a group receive their loans on the same day, so there is little to no variation in weeks in loan cycle at the group level. In contrast, groups within a given center may have staggered loan disbursements.
experience borrowing from the MFI and the number of payments made in the loan cycle before the defaults occurred.\footnote{These variables will be used as covariate controls in the subsequent regression specifications.} Table 4 captures these correlations. Column 1 shows the coefficients from a simple OLS regression of repayment on week in the loan cycle, loan size, and total number of weeks spent borrowing from Spandana. This basic specification indicates that individuals with larger loan sizes are slightly less likely to repay (0.5 pp per Rs 1,000) and that individuals with longer borrowing histories are also less likely to repay (13pp per loan cycle). Columns 2-4 include peer level covariates as well as branch fixed effects. The loan size effect loses significance in the more robust specifications. This absence of a large effect may indicate that Spandana is successful in calibrating loans to a borrower’s repayment capacity. However, there does appear to be a more robust relationship between repayment and length of a borrower’s relationship with Spandana. The column 4 estimates suggest that a borrower in loan cycle 2 is more than 4-5 percentage points (~10%) less likely to repay than a borrower in cycle 1. This evidence might suggest that the dynamic incentives lose their power as borrowers complete more cycles. Borrowers could become satiated with credit after having had previous opportunities to use microfinance loans for investment or durable purchases.

In all specifications, one additional week in the loan cycle at the time of the defaults corresponds to a 1 percentage point greater likelihood of repayment. In other words, individuals in week 50 are 50 percentage points more likely to repay their loans than borrowers in week 0 of their loan cycles. The standard errors of all of the estimates are extremely small. Note that the 1pp coefficient is not very sensitive to the inclusion of branch fixed effects or village level peer group controls. Borrowers who had made more payments before the defaults occurred are indeed more likely to repay. This relationship between loan repayment and number of payments made at the time of the defaults is the building block for the instrumental variables approach used to estimate the peer effects.

5.2 Reduced Form and Instrumental Variables Estimates

The first stage regressions used in the IV estimates are aggregated versions (in means) of the specifications appearing in Table 4. The resulting regression coefficients inevitably look quite similar\footnote{5th order polynomials of individual and peer group weeks with the MFI are included in all subsequent first stage, reduced form and instrumental variables regressions. The individual specifications in Table 4 only include linear and squared weeks with the MFI terms.} Table 5 includes the first stage coefficients corresponding to equation 4.4 in columns 1-4 for both the village and center definition of the peer group. In all specifications,
average peer group repayment increases by approximately 1pp for every unit increase in the average weeks peer group variable. In specifications where I estimate both the village ex center and the center ex group peer effects, I use two instruments, village ex center and center ex group average weeks in cycle. Columns 2 and 3 show both the village and center level first stage regressions for the combined village and center specifications. Note that there is no effect (or an extremely small effect) of village ex center average weeks on center repayment levels in column 4. This regression can be interpreted as a reduced form regression for the effect of village repayment on center repayment. The absence of a relationship is preliminary evidence that the village peer effect is not very strong.

Columns 5-7 of Table 5 display results for the reduced form regressions of individual repayment on the peer group weeks in loan cycle and all weeks with MFI polynomial controls. Column 5 presents the reduced form using the village-ex-group peers. The weeks variable is not significant in column 1. Column 2 includes village-ex-center and center-ex-group weeks variables. The coefficient on the center level peer group instrument is 0.00105, which is much larger than the coefficient on the village peer group variable. It is also of the same magnitude as the coefficient in column 1 and statistically significant. However, since the estimate on the village variable is so imprecise, I cannot conclude that the village and center peer effects are different. Column 7 shows results for the reduced form using only the center-level variables. The magnitude of the coefficient suggests that if the whole center moved from week 0 to week 49 in the loan cycle, individual repayment would increase by 6 percentage points. In general, the reduced form regressions give evidence that there is a repayment peer effect and that the effect is stronger at the more local level.

I also estimate the peer effects model using the fraction of peers with extremely good or extremely bad incentives as instruments. Table 6 displays the first stage and reduced form results using these extreme weeks instruments. The results are qualitatively very similar to the average weeks instruments described above. If the peer group shifts from from 0% of members in weeks 0-5 (45-50) to 100% of members in weeks 0-5 (45-50), the repayment likelihood decreases (increases) by 20-30pp. The sum of the coefficients on the 0-5 and 45-50 variables are indistinguishable from zero, implying a symmetric effect of weeks in the loan cycle on repayment incentives. Again, notice that the village peer variables are not significant in the center repayment regressions, supporting the notion that the village peer effect is not detectable.

The reduced form estimates using the extreme weeks instruments also provide support for the existence of center level peer effects. Having a peer group move from 0% to 100% of members in weeks 45-50 increases an individual’s likelihood of repaying by approximately
4 percentage points. However, there is no detectable effect of having a large fraction of the peer group in weeks 0-5. For the specification in column 6, a Wald test indicates that the sum of the center coefficients is greater than zero. Therefore, the reduced form estimates suggest that the peer effect is asymmetric and driven by repayers pulling individuals out of default rather than defaulters luring individuals to remain in default.

The results of the 2SLS estimation procedure on the full sample are detailed in Table 7. Parameter estimates of equation 4.3 are shown using the average weeks instrument in columns 1-3 and the fraction extreme weeks instruments in columns 4-6. As in the reduced form, only the center peer effects are significantly different from zero. The magnitude of the peer effect is approximately 10pp using the average weeks instruments and 14pp using the extreme weeks instruments. This translates into a 1.0-1.4pp increase in the probability of repaying the loan for every additional 10pp repayment likelihood in the peer group. The peer effect results are also robust to restricting the data set to those individuals with centers with especially high or especially low incentives. Table 8 presents the average weeks IV specifications restricting the sample by center mode and by the fraction of peers in the extreme weeks.

Finally, Table 9 presents the reduced form and IV regression specifications corresponding to the fuzzy RD interpretation as suggested by Imbens and Lemieux (2008). Since the village effects do not appear to be very strong, I limit the analysis to the center peer effect. The regressions are restricted to sub-samples of centers with either very high or very low incentives. Columns 1 restricts the sample to centers where at least 75% of borrowers were at weeks 0-5 or weeks 45-50 of the loan cycle when the defaults occurred. While columns 2 and three use 80% and 85% thresholds, respectively. Furthermore, I exclude centers in their first loan cycle with extremely weak incentives at the time of the defaults (weeks 0-5 of their borrowing relationships with Spandana). All of the specifications of Table 9 indicate that the peer group moving from low incentives to high incentives (i.e. weeks 0-5 vs. weeks 45-50) increases the repayment probability by 5.5-7.0pp. This translates into IV repayment peer effect estimates of 11-14pp.

The peer effects estimates are robust to a number of alternative specifications. First, the center-level results look very similar under the inclusion of village rather than branch level fixed effects. We would not expect fixed effects to change the instrumental variables estimates if the instruments are indeed as good as randomly assigned across villages. Second, the estimates are robust to the inclusion varying polynomial degrees of average peer group

25Recall that all of the regression tables describe specifications with branch fixed effects.
and own characteristics. All specifications in the tables include fifth order polynomials, but the results are qualitatively the same under second or third order polynomials. The results also do not depend on the inclusion of minimum and maximum peer weeks variables, which partially control for the variance of the peer group’s weeks distribution. Third, one might be concerned that the individual’s own weeks profile is not adequately controlled for in the reduced form regressions. However, the peer effects estimates are robust to restricting the regression samples to only include individuals with similar “own weeks” in the loan cycle. Lastly, while the specifications in Table 9 pool peer borrowing centers into high and low incentive groups, the results are robust to more flexible regression discontinuity specifications. The reduced form estimates implied by Figure 5 (using local linear regression and Silverman’s rule of thumb bandwidth) closely correspond to the IV and RD reduced form estimates in the tables. Also, the results again look very similar under a local linear RD specification that uses the optimal bandwidth choice proposed by Imbens and Kalyanaraman (2009).

5.3 Non-Linear Peer Effects

I also investigate whether a non-linear peer effect may be partially driving the stark shape of repayment observed in Figure 4. While linear peer effects do lead to hump shaped adoption/repayment patterns, non-linear peer effects might help to explain why there is so much bunching towards the poles of full repayment and full default. I am interested in estimating

\[ \text{repay}_{i,p(i)} = \beta_0 + g(\text{repay}_{p(i)}) + \beta_2 \text{weeks}_{i} + \beta_3 \text{X}_{i,p(i)} + \epsilon_{i,p(i)} \]

where the function \( g(.) \) is not necessarily linear. Using the nonparametric IV, control function approach of Newey et al. (1999), I plot the non-linear center peer effect in Figure 6. The estimates use series regression with fifth order polynomials.\(^{26}\) The error bars are bootstrapped. The shape of the estimated peer repayment relationship is not linear. It is characterized by steep regions around 0 and 1 and a much shallower slope between 0.2 and 0.8. However, the error bars are quite large. It is practically only possible to conclude that \( g(1) > g(0.2) \) and \( g(0.2) > g(0) \). It is also interesting how symmetric this curve appears to be, with an inflection point around 50% peer repayment. Along with the asymmetric results of Table 6, this relationship suggests that the greatest marginal effects come from the first and the last peer deciding to repay. This shape also suggests that coordinating on

\(^{26}\) The controls and running variable functions are the same as those included in the previous linear regressions.
full default may not be a stable peer equilibrium, since the curve is so steep near full peer default.

5.4 Partial Repayment Peer Effects and Alternate Functional Forms

Finally, exploring other specifications can help to shed light on the nature of the peer effect. Columns 1-3 of Table 10 shows the IV coefficients using partial repayment as the outcome of interest. Note that the peer effect estimates are quite a bit larger than in the case of full repayment. If an entire villages switches from making 0 payments to making 1 payment, then an individual borrower is 35.6 percentage points more likely to make one payment. Column 2 shows that a lot of this effect (22.2pp) comes through the center level, but the coefficient on village ex center repayment is quite large, at 17.4pp, although insignificant. Unlike in the full repayment specifications, the village and center effects are of the same magnitude. Column 3 shows the center only specification, where the peer effect estimate is 30.1pp. The peer effect is two to three times larger for individuals making one payment vs. making the full set of remaining payments.

Column 4 of the same table shows the peer effect as a function of the number of peers who fully repay their loans. The coefficient of 0.0115 implies that the repayment likelihood increases by 1 percentage point for each peer who repays. The effect of each additional peer is approximately the same as one additional week in the loan cycle. The average size of the center ex group is 27, so the entire peer center repaying would cause an individual to be 27pp more likely to repay her own loan. The size of this estimate is twice as big as in the average peer repayment specifications.

6 Structural Estimation

The preceding results demonstrate that peer repayment (or lack thereof) can have both virtuous and perverse effects on an individual’s own behavior. However, on net, does the MFI benefit from this peer effect? How much better or worse would revenues be if the peer mechanism were disabled? Because positive lender profits can be passed through to the customer in the form of lower borrowing costs, the effect of peer influences on collections has broad welfare implications.

MFIs lose the foregone interest from delayed borrower payments, so understanding the

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27I define partial repayment as making at least 1 payment to the MFI after the collector’s statement. The amount of the payment can be arbitrarily small.
time path of repayment is central to evaluating welfare impacts of the peer lending model. While the reduced form identification strategy allows for estimates of the size of the total repayment peer effect, it is harder to characterize the time path of each borrower’s installments without making structural assumptions. Furthermore, the reduced form analysis does not pin down the absolute level effect of the peer channel. I introduce a dynamic discrete choice model to investigate the effect of peer repayment on MFI profits. In essence, this exercise compares the fragility of microlenders, which include social capital in the loan mechanics and repayment meetings, to more traditional, individual lenders.

6.1 A Simple Model of Loan Repayment

I model the default crisis as a breaking of the social contract between the borrowers and the MFI. The previously rigid repayment schedules became completely flexible following the District Collector’s statement. Since Spandana was happy to allow defaulters to recommence making payments at any time, borrowers were effectively given free options to delay indefinitely making further payments.

Borrowers face the following value function:

\[ V(w_i, x_{p(i)}), \epsilon_i(1) \]

Each period, borrowers decide whether or not to make one additional installment payment, denoted \( a_i \in \{0, 1\} \). Borrowers receive a per period utility of \( \pi_i(a_i, w_i, x_{p(i)}) \), which is a function of the action, \( a_i \), and the state variables \( (w_i, x_{p(i)}) \). The borrower’s continuation value is captured by \( \beta E \left[ V\left(w_i + a_i, x'_{p(i)}, \epsilon'_i(1)\right) | w_i, x_{p(i)}\right] \). The variable, \( w_i \in [0, 50] \) indexes the total number of loan installments previously paid by individual \( i \). This variable also advances deterministically as a function of the previous state and action variables, \( w'_i = w_i + a_i \). If \( w_i = 50 \), then the loan has been fully repaid. The vector \( x_{p(i)} \) contains state variables describing individual \( i \)’s peer group, \( p(i) \). In addition to the per period utility, borrowers also receive an additive, time varying, i.i.d. private utility shock \( \epsilon_i(a_i) \) where \( \epsilon_i(0) = 0 \overset{\text{WLOG}}{=} \) and \( E[\epsilon_i(1)] = 0 \). This cost \( \epsilon_i(1) \) can be thought of as a liquidity shock to the borrower if \( \epsilon_i(1) < 0 \). The additive error structure assumption follows \cite{Rust1987} and much of the subsequent dynamic discrete choice literature. I assume that all terms in the value function scale linearly with loan size, \( I_i \) and therefore omit loan size from the state.

\( WLOG, \epsilon_i(0) = 0 \) is a convenient normalization.
The per period utility function is assumed to take the following form:

\[
\pi_i (a_i, w_i, x_{p(i)}) = -\mathbf{1}(w_i < 50) \kappa a_i + \mathbf{1}(w_i = 50) V_{\text{new}} + E \left[ -\mathbf{1}(w_i < 50) \rho \left( w_i + a_i, x'_{p(i)} \right) + \mathbf{1}(w_i = 50) \left[ \Psi \left( x'_{p(i)} \right) \right] \right] | w_i, x_{p(i)} |
\]

If the borrower does make a payment \((a_i = 1, w_i < 50)\), then she pays a fixed amount \(\kappa\). If the loan was fully repaid last period \((w_i = 50)\), then the borrower receives a one-time continuation value of \(V_{\text{new}}\). This fixed value, \(V_{\text{new}}\), represents all of the benefits from borrowing from the MFI in the future. While Bulow and Rogoff (1989) show that the threat of credit denial alone is not sufficient to provide repayment incentives, \(V_{\text{new}}\) may also capture other perks from participating in microfinance.

The model also incorporates peer repayment into each individual’s value function. Every period, borrowers face a value (which could be positive or negative) \(E \left[ \rho \left( w_{it} + a_{it}, x'_{p(i)} \right) \right] | w_i, x_{p(i)} \) from differing from their peer groups. Since all borrowers in a peer group make repayment decisions simultaneously, individuals must take the expectation over the peer group’s actions when deciding whether or not to repay. To close the model, I also assume that borrowers receive a terminal utility payoff that depends on peer repayment actions. This peer-based terminal value is denoted \(\Psi \left( x_{p(i)} \right) \) and captures the continuation value of peer full loan repayment for the individual. For example, a small fraction of peers having completed their full loan cycles when individual \(i\) finishes her 50th repayment could make future borrowing from the MFI less valuable. For simplicity, I assume that the borrower doesn’t receive any additional utility after making the final loan payment and receiving the fixed continuation value payments.

For the estimation of the model, I make several functional form and error distribution assumptions. First, for tractability I assume that the peer state space can be approximated by three variables, \(x_{p(i)} = (w_{p(i)}, \sigma^2_{p(i)}, w_{50}^{50})\), where \(w_{p(i)}\) is the mean state for the peer group (excluding the individual), \(\sigma^2_{p(i)}\) is the variance of the peer state distribution and \(w_{50}^{50}\) is the fraction of peers who have already fully completed making their loan payments at each point in time. Second, I assume that the iid, privately observed utility shocks are distributed

\footnote{\(\kappa\) is owed for each unit of the loan.}
\footnote{Recall the discussion in Section 3.1.}
\footnote{The full state space of the model would ideally be \(\left( w_i, \{w_j\}_{j \in p(i)} \right) \) and would capture the number of payments made by every peer in the peer group each period. Since each borrower can advance by one payment}
such that \( \varepsilon_i(1) \sim N(0, 1) \). Note that the variance of the individual’s liquidity shock is not separately identified from the parameters of the model and is normalized to 1. Third, I model the per period peer value as a function of the distance between the individual’s own week in cycle and the average peer group week in cycle. Namely, 
\[
\rho \left( w_i, x_{p(i)} \right) = \rho_1 \left| w_i - w_{p(i)} \right| + \rho_2 \left( w_i - w_{p(i)} \right)^2.
\]
Fourth, I model the peer continuation value as a linear function of the fraction of peers who have also repaid their loans, 
\[
\Psi \left( x_{p(i)} \right) = \eta w_{50}^{p(i)}.
\]
These assumptions result in five structural parameters to be estimated, \( \theta = (\kappa, V_{\text{new}}, \rho_1, \rho_2, \Psi) \).

Finally, since the discount factor is not separately identified in this class of model, I calibrate \( \beta = 0.999 \) on a weekly basis, corresponding to an annual discount factor of approximately 0.95. Note that the structural model does not take into consideration the discontinuous nature of incentives between loan cycles. Because of the very large state space, the model classifies all individuals in the same week in cycle (regardless of the cycle) as having the same “own” incentives.

Thus, borrowers with \( w_i < 50 \) will choose to make an additional payment \( (a_i = 1) \) if the value is higher than from not repaying, i.e.

\[
\Delta V (w_i, x_p; \theta) = \pi_i (1, w_i, x_{p(i)}) + \beta E \left[ V \left( w_{i+1}, x'_{p(i)}, \varepsilon'_i(0), \varepsilon'_i(1) \right) \bigg| w_i, x_{p(i)} \right]
\]

\[
- \pi_i (0, w_i, x_{p(i)}) - \beta E \left[ V \left( w_{i}, x'_{p(i)}, \varepsilon'_i(0), \varepsilon'_i(1) \right) \bigg| w_i, x_{p(i)} \right]
\]

\[
> -\varepsilon_i (1)
\]

Since the distribution of \( \varepsilon(1) \) is assumed to be standard normal, the probability of making a payment can be expressed using the normal cdf:

\[
\Pr \left( a_i = 1 \big| w_i, x_p \right) = 1 - \Phi \left( \Delta V (w_i, x_p; \theta) \right)
\]

With \( \varepsilon_i(1) \) unbounded, there is always a strictly positive probability of an individual making a payment at any state in the state space. Thus, all borrowers will take action \( a_i = 1 \) in finite time. The structure of the model implies that every individual will eventually repay her loan. However, this repayment process may require an arbitrarily large number of periods.

It is important to note that this basic model leads to the possibility of multiple equilibria. As a much simplified example, suppose that there are only two members of each borrowing center. Let the payoffs of each borrower be \( \pi_i = a_i V + \rho S 1 (a_1 = a_2) - \rho D 1 (a_1 \neq a_2) \) so the payoffs in the four outcomes are as follows:

At each week, there are 51 possible states for each individual. The average peer group has approximately 30-50 borrowers, so a conservative estimate for the number of required states would be \( 51 \times 51^{29} \approx 9 \times 10^{50} \).
Note that if $\rho_S > V - \rho_D$ there are multiple equilibria in the stage game. This same logic carries forward to the full dynamic game.

### 6.2 Firm Profits

From the MFI’s perspective, the timing of the stream of repayments determines its revenues and profits. The actions of the District Collector extended the maturity of all outstanding debt with no increase in the size of the per installment payment, forcing the previously stipulated 27% annual interest rates toward zero.

Suppose that the MFI faces a weekly cost of capital, $r$. Then with no defaults and no delays, the expected revenues from a loan with weekly installment $I$ after $w$ regular payments are:

\[
\Pi_{ND}(w) = I \sum_{t=0}^{50-(w+1)} \frac{1}{1+r}
\]

Total profits for each loan are \(\frac{1}{1+r} \Pi_{ND}(0) - L\). However, with delays in payment, the profit function will depend on the likelihood of borrowers to repay each period. Note that the probability of a borrower paying an additional installment is a function of the state variables and is denoted $p\left(a_i = 1|w_i, x_{p(i)}\right)$. The action probabilities derive from the policy functions for the model described in equation 6.1. Thus, the expected revenues on a loan with the possibility of delay can be represented in the following recursive form:

\[
E\left[\Pi_D(I_i, w_i, x_p, P)\right] = p(a_i = 1|I_i, w_i, x_p) \left(I_i + \frac{1}{1+r} E\left[\Pi_D\left(w_i + 1, x_p', P\right) | I_i, w_i, x_p\right]\right) \\
+ (1 - p(a_i = 1|I_i, w_i, x_p)) \frac{1}{1+r} E\left[\Pi_D\left(w_i, x_p', P\right) | I_i, w_i, x_p\right]
\]

and the terminal value,

\[
E\left[\Pi_D(I_i, 50, x_p, P)\right] = 0, \forall x_p
\]

Thus, delay is costly to the MFI. It is easy to show that if for all possible state variable realizations, \((I_i, w_i, x_{p(i)}) \in \Omega_I \times \Omega_i \times \Omega_p\), $p\left(a_i = 1|I_i, w_i, x_{p(i)}\right) < 1$ then $\Pi_{ND}(j) > \Pi_D\left(j, x_{p(i)}\right) \forall j, x_{p(i)}$. 

\[\]
At the time of the defaults, the full expected revenues of the MFI, with \(N\) loans outstanding can be written:

\[
\sum_{k=1}^{N} E \left[ \Pi_D \left( I_i(k), w_i(k), x_{p(i)}(k), P \right) \right]
\]

compared with \(\sum_{k=1}^{N} \Pi_{ND}(I_i(k), w_i(k))\) in the no delay case.

### 6.3 Estimation

I solve and estimate the model assuming that individuals play a symmetric, Markov Perfect Equilibrium. All borrowers are ex ante identical and have the same probabilities of transitioning (or making a payment) conditional on the state variables. They each simultaneously choose the optimal action every period after calculating their full expected utility from each possible decision. Furthermore, I assume that borrowers have rational expectations about their peer’s actions (unbiased beliefs), and all borrowers select the same equilibrium if multiple equilibria exist. The strategies and resulting action probabilities associated with the MPE can thus be considered a fixed point of the best response mapping over the possible choice probabilities.

I follow the dynamic games techniques of Aguirregabiria and Mira (2007) to estimate the parameters of the model. I calculate the two-step PML estimator for the repayment model.

1. As a first stage, I estimate both peer and own repayment probabilities for each state in the state space. These estimated action probabilities serve as each individual’s beliefs about future peer actions.

2. Given these beliefs, I update each individual’s transition probabilities using the model. Then using maximum likelihood, I select the primitives of the model, \(\theta\), that best match the individual’s observed transition probabilities.

**Data** For the structural analysis, I take advantage of the high frequency repayment data also provided by Spandana. I use the highest quality parts of the data set, which includes weekly repayment indicators for a subset of borrowing centers from March 12, 2006 to September 30, 2006. The resulting data set contains approximately 1.7 million borrower by week observations. Note that I include all members of the borrowing center in the peer group definition, including the individual’s own borrowing group. Defining the peer group as such makes the implicit assumption that the size of the peer effect is fixed within the center, and that the identity of the repayer does not matter.
**Empirical States** To discretize the state space, I bin the possible values as follows: $w_i \in \{0, 1, ..., 50\}$, $w_p \in \{0, \frac{1}{3}, \frac{2}{3}, ..., 49\frac{2}{3}, 50\}$, $\sigma_p^2 \in \{\text{low, high}\}$, $w_{p0} \in \{0, \frac{1}{3}, \frac{2}{3}, 1\}$. This results in $151 \times 2 \times 4 = 1208$ possible values of $x_p$ and $1208 \times 51 = 61608$ total states. While this may still seem like a very large state space, the structure of the model puts severe restrictions on the allowed transitions from state to state. In terms of transitions, $w_i$ and $w_p$ are both only able to increase by at most 1 week or stay the same. This yields $2 \times 4 \times 2 \times 4 = 64$ admissible transitions for each state, greatly reducing the computational burden. For the remainder of the paper, I denote the full state space as $\Omega_i \times \Omega_p$.

**First Stage** For the first stage, I follow Aguirregabiria and Mira (2002) and use a multinomial sieve logit to estimate the probabilities of transitioning to one of the 2 possible own repayment states or 32 possible peer repayment states from any state in the state space. As an alternative, I could use the empirical distribution of transitions conditional on state. However, doing so would be very noisy. There are some transitions that are never observed in the data and others that are observed only once. The multinomial logit allows for smoothed transition probabilities, helping to fill in gaps present in the data. The logit to estimate the agent’s own repayment probability is:

$$\Pr (a_i = a|w_i, x_p) = \frac{\exp(\phi_a q(w_i, x_p))}{\sum_{a' \in \{0,1\}} \exp(\phi_{a'} q(w_i, x_p))}$$

where $q(w_i, x_p)$ is a vector of third degree polynomials of the state variables. $\phi_a$ is the vector of coefficients for action choice $a$. The logit to estimate the peer group’s state transitions is:

$$\Pr (x_p' = \chi|w_i, x_p) = \frac{\exp(\phi_{p,\chi} q(w_i, x_p)) 1(\chi \in B(x_p))}{\sum_{\chi' \in \Omega_p} \exp(\phi_{p,\chi'} q(w_i, x_p)) 1(\chi' \in B(x_p))}$$

where $\phi_{p,\chi}$ is a vector of coefficients for new state $\chi$ and $B(x_p)$ is the set of permissible transition states. Note that $\chi \in B(x_p)$ if $\chi = (\chi_1, \chi_2, \chi_3) : \chi_1 \leq x_p + 1, x_{p0} \leq \chi_3 \leq x_{p0} + 1$. $\hat{P}_0$ is the resulting vector of estimated transition probabilities evaluated at each state.

**Second Stage: Model Solution** Recall that the transition probabilities can be calculated given equation 6.2. This problem can be reformulated using the beliefs, $P$ estimated in the first stage, to evaluate all expectations. For $w_i < 50$:

$$\Psi_i (1|w_i, x_{p(i)}, P) = \Phi(\pi^P (1, w_i, x_{p(i)}) - \pi^P (0, w_i, x_{p(i)})) + \beta \sum_{x_{p(i)}' \in \Omega_p} \left[ \Gamma_i (w_i + 1, x_{p(i)}', P) - \Gamma_i (w_i, x_{p(i)}', P) \right] \pi^P (x_{p(i)}'|w_i, x_{p(i)})$$
where $\Gamma_i \left( w'_i, x'_{p(i)}, P \right)$ is the expected value function at state $\left( w'_i, x'_{p(i)} \right)$ where all beliefs and expectations are taken over the transition probabilities, $P$. The probability mass function $f^P \left( x'_{p(i)} | w_i, x_{p(i)} \right)$, gives the peer transition probabilities given state $\left( w_i, x_{p(i)} \right)$ according to $P$.

Since $\pi^P \left( a_i, w_i, x_{p(i)} \right)$ is linear in the model’s parameters, it can be rewritten

$$\pi^P \left( a_i, w_i, x_{p(i)} \right) = z^P_i \left( a_i, w_i, x_{p(i)} \right) \theta$$

similarly, the expected value functions can be decomposed into both observable and stochastic components:

$$\Gamma_i \left( w'_i, x'_{p(i)}, P \right) = \Gamma^Z_i \left( w'_i, x'_{p(i)}, P \right) \theta + \Gamma^\lambda_i \left( w'_i, x'_{p(i)}, P \right)$$

Finally, combining:

$$\Psi_i \left( 1 | w_i, x_{p(i)}, P \right) = \Phi \left( \bar{z}^P \left( w_i, x_{p(i)} \right) \theta + \bar{\lambda}^P \left( w_i, x_{p(i)} \right) \right)$$

where

$$\bar{z}^P \left( w_i, x_{p(i)} \right) = z^P_i \left( 1, w_i, x_{p(i)} \right) - z^P_i \left( 0, w_i, x_{p(i)} \right)$$

$$\bar{\lambda}^P \left( w_i, x_{p(i)} \right) = \beta \sum_{x'_{p(i)} \in \Omega_p} \Gamma^Z_i \left( w_i + 1, x'_{p(i)}, P \right) - \Gamma^Z_i \left( w_i, x'_{p(i)}, P \right) f^P \left( x'_{p(i)} | w_i, x_{p(i)} \right)$$

Second Stage: Pseudo-Likelihood Maximization [Aguirregabiria and Mira (2007)] demonstrate that the vector of equilibrium transition probabilities, $P^*$ represents a fixed point of $\Psi_i \left( 1 | w_i, x_{p(i)}, P \right)$, thus given a consistent estimate $\hat{P}^0$ from the first stage, the two step estimator is $\hat{\theta}_{2S} = \arg \max_\theta Q_M \left( \theta, \hat{P}^0 \right)$:

$$Q_M \left( \theta, P \right) = \sum_{t=1}^T \sum_{i=1}^{N(g)} \ln \Psi_i \left( a_{it} | w_{it}, x_{i,t}, P; \theta \right)$$

where $i$ indexes individual borrowers and $t$ indexes weeks.
6.4 Counterfactual Model

The goal of the structural exercise is to determine how much more or less costly the Krishna crisis was for the MFI as a result of the peer repayment dependencies. In other words, what would have happened to firm profits if the peer terms in the model could have been “turned off”? Restricting $\kappa$ and $V_{new}$ to take the same values as in the model specified in equation 6.1, the relevant model without peer effects is:

$$ V(w_i, \varepsilon(1)) = \max_{a_i \in \{0,1\}} \{1 (w_i < 50) (\kappa a_i + a_i \varepsilon (1) + \beta E[V(w_i + a_i, \varepsilon'(1))] + 1 (w_i = 50) V_{new} \} $$

Since the peer decision does not enter the model, all peer variables can be eliminated from the state space.

I then solve the model for the transition probabilities when $\hat{\theta}_{NP} = (-\hat{\kappa}, \hat{V}_{new} + \hat{\Psi}, 0, 0, 0)$. Note that the two-step pseudo maximum likelihood estimator cannot be used to evaluate the resulting action probability vector, $P_{NP}$. That method requires rational beliefs about the transition probabilities, based on the observed state transitions in the data. The observed own transitions as a function of the state variables is not consistent with $\hat{\theta}_{NP}$ by construction. I estimate the expected value functions of the model and $P_{NP}$ using backward induction. Since the model without peer effects has a single equilibrium, this is quite straightforward.

The resulting action probabilities of this model, $P_{NP}$, can be used to calculate expected revenues under the no peer effect counterfactual:

$$ \sum_{k=1}^{N} E \left[ \Pi_D \left( I_i(k), w_i(k), x_{p(i)}(k), P_{NP} \right) \right] $$

6.5 Results

Model Estimates Table 11 shows the estimated parameters from the model. As predicted, $-\kappa < 0$, representing a cost of making each additional payment. Furthermore, $V$, the terminal value of repaying is positive. While these parameters are only identified to scale, they indicate that repayment is costly, but has some sort of final reward such as receiving a new loan.

The peer effect parameters show an interesting pattern. First $\Psi > 0$, indicating that the expectation of peer full repayment positively influences an individual’s own repayment behavior. Second, both of the flow peer value parameters $\rho_1, \rho_2 > 0$, which implies that there are actually flow benefits from differing from one’s peers. This benefit cuts in the opposite direction as $\Psi > 0$. Taken together, these parameter values imply that the costs
of differing from one’s peers are concave. If the peer group is likely to finish making all 50 payments quickly, borrowers respond by accelerating their own repayment. However, for borrowers ahead of the pack, it may not be worth it to wait for their peers to catch up; these individuals may prefer to quickly finish repaying and to be rematched with a new borrowing group.\footnote{During the defaults, borrowers who repaid and had peers who remained in default were rematched with new groups when new loans were disbursed. The $\Psi$ term captures the fact that there may be continuation costs from finishing ahead of the peer group.}

Figure 7 shows the individual action probabilities by both own and average peer weeks. These curves are the value functions for individuals in week 15, 30 and 45 respectively. I use the weights given in the empirical distribution to project the full state space onto these two variables. The dashed lines plot the smooth data underlying the structural estimation. The solid lines plot the transition probabilities under the model with peer effects. Finally, the finely dotted lines plot the transition probabilities under the counterfactual model with no peer effects. The x-axes in all three plots correspond to the average number of weeks already paid by the center peer group, while the y-axes correspond to the probability of the individual borrower making one additional payment. Note that under the counterfactual model, the repayment probability does not depend on the fraction of peers repaying. It is simply a monotone increasing function in the number of individual weeks already paid.

Panel A details the relationship between peer weeks and the repayment likelihood for individuals in week 15 of their loan cycles. If the peer group is on average farther ahead of the individual borrower, then there is a virtuous peer effect. Individuals try to catch up to their peers and make payments with higher probabilities. They are motivated by receiving $\Psi$ after paying off the loan. However, a higher payment likelihood also arises when the peer group is significantly behind the individual borrower. For these own week variables, the $\rho$ function dominates and a borrower who is ahead of the pack prefers to repay quickly and surge ahead of the peer group. Panel B shows a similar relationship for individuals in week 30 of their loan cycles. The bowl shaped repayment pattern is again present.

Finally, Panel C captures the relationship between own and peer repayment for individuals in week 45. These individuals are very close to getting a new loan. In contrast to Panels A and B, the model with peer effects is roughly monotone increasing in peer incentives. Having peers with poor repayment incentives only slows down an individual’s repayment progress. This is for two reasons. First, there is very little chance that the week 45 borrower will receive the peer bonus $\Psi$ at the end of the loan. Second, there is some value to stalling for the week 45 individual with low incentive peers. These types of borrowers actually receive
a repeated flow benefit from $\rho$ as long as they still have payments outstanding. However, once the loan has been completed, the borrower no longer receives these flow benefits and also does not receive $\Psi$.

**Counterfactual Results** To estimate the net costs or benefits of peer effects under the model, I simulate 200 192-week paths for each borrower. At each week in the simulation, I update each borrower’s own and peer states using the simulated actions of all individuals in the borrowing center. First, the model with peer effects does a better job coaxing individuals with low incentives to repay than the model without peer mechanisms. The opposite is true for those with already high incentives. Since the average peer week is bounded between 0 and 50, those individuals with low incentives face peers with incentives that are at least as good. In contrast, individuals at week 49 must have weakly better incentives than the rest of their center. I use the firm profit equation and the simulated repayment paths to calculate this expected revenue for each repayment week. Assuming a cost of capital of 10%, figure 8 plots the expected revenues under two regimes: the model with no peer effects and the full model with peer effects. Note that the greatest revenue differences come from the slight probability increases among borrowers with otherwise low repayment incentives. The expected revenues from individuals in weeks 0-5 are on aggregate 38.2% higher under the peer effects regime. The peer effect benefit is 17.3% for borrowers in weeks 10-15. The revenues are approximately equivalent for individuals in weeks 30-35, while the net peer effect is slightly negative (-1.4%) for those individuals in weeks 45-50. I also compare Spandana’s expected revenues under each model as of 2006. For its 115,000 loans included in the analysis sample, Spandana’s aggregate expected revenues are 10% higher in a world with peer effects than in a world without a peer mechanism.

Finally, the peer effects estimates allow me to investigate how different initial loan disbursement policies would have fared in encouraging timely repayment according to the model. I do this by assuming that each borrowing center consists of 4 groups of 10 individuals each, and that groups are always fully synchronized. However, the MFI can choose how to space the disbursements between groups within a borrowing center. I then simulate the model for different timing arrangements. Because crises generally occur unexpectedly, I calculate the expected value for each spacing arrangement by averaging over each possible timing of the shock. Note that this exercise implicitly requires that individuals play the same equilibrium in these various spacing counterfactuals that is observed in the actual data.

I investigate three types of spacing regimes, full synchronization, partial synchronization and full separation. Full synchronization is characterized by simultaneous loan disbursement for all members of a borrowing center. In partial synchronization, 2 groups of borrowers
are disbursed loans together while the remaining groups wait some number of weeks before receiving their disbursements. In full separation, each group takes turns receiving loan disbursements over time. Within the partial synchronization and full separation strategies, I also vary the number of weeks between each group’s loan disbursements.

The patterns in the simulated repayment results are clear. Full synchronization performs the worst out of all of the spacing arrangements. As a rule, putting as much space as possible between groups yields the best outcomes. The full separation strategy with the maximal number of weeks (12-13) between groups yields the highest expected profits for the MFI. The revenue gain from full spacing over full synchronization is very large, on the order of 25%. While there may be reasons outside of the model for keeping groups closer together in terms of loan timing, this spacing exercise shows that any number of weeks between borrowers is preferable to full synchronization.

7 Mechanisms

There are five classes of candidate mechanisms that could be driving the repayment peer effect:

1. Information about future credit prospects from MFI
2. Borrower’s availability of funds for repayment
3. MFI collections practices
4. Peer mimicry
5. Social capital from functional repayment groups

A first plausible mechanism driving the observed effects could be borrowers learning from peers about the availability of future credit. Learning models are common mechanisms that yield S-shaped adoption patterns and peer effects in many contexts (see (See Foster and Rosenzweig (1995), Conley and Udry (2010), Banerjee et al. (2010)). Naturally, borrowers at the beginning of the crisis could have been concerned that there would be severe punishment for defaulting or that Spandana would not be able to disburse loans in the future. The MFI could have decided to leave Krishna district after the crisis. Moreover, had Spandana not had extensive loan operations in other districts in India, the crisis could have created
serious liquidity problems. These mechanisms would make learning a potential driver of the observed effects.

It is unlikely that learning fully drives the estimated effects. MFI field officers made a habit of visiting all villages on a regular basis regardless of repayment status. They frequently referred to the ongoing loan availability for borrowers in other villages who had already repaid their loans. Further, all information sessions were held at the village level, not the center level. In microfinance more generally, outside observers often keep track of new loan disbursements, so news of new loans being made most likely traveled even across villages and neighborhoods without the aid of the credit officers. Similarly, during the crisis, the credit officers were under intense local scrutiny and often drew crowds of bystanders. The fact that any village peer effect is small, information probably cannot explain the full magnitude of the results. Finally, the offer of refinancing plans in late 2007 should have sent a strong signal to borrowers and uniformly increased trust across the entire district. In these plans, defaulters could receive new loans before completing the previous loan cycle.

A second explanation is that after the collector’s announcement, individuals became liquidity constrained. If the lowest cost repayers repaid first, then those individuals could have lent the proceeds of the subsequent loan to other peers, facilitating repayment and generating a peer effect. Similarly, the liquidity mechanism is probably not driving the results, either. The full roll out of refinancing plans completely removed the liquidity cost of repayment. Borrowers actually received loan disbursements before having to make any significant repayment inroads.

The third mechanism, MFI behavior, could pose problems for the identification strategy previously outlined. If the credit officers had an effective means of making borrowers repay as a function of some cost (maybe a time cost) spent on each borrower, then the MFI could have decided to focus collections efforts on centers with high concentrations of borrowers already close to full repayment. This would generate the patterns observed in the data without there actually being a peer effect. However, this is probably not the case. Assuming that the main fixed cost of making collections is the cost of traveling to a village (which is likely to be true), then it is rational for a credit officer to visit all week 49 borrowers in a

33 These sorts of liquidity problems have pervaded Indian microfinance in the wake of the November 2010 crisis in Andhra Pradesh.

34 Robberies of MFI staff are not uncommon. Individuals know when field staff carry large sums of money.

35 If learning is driving the effect, then we would expect the majority of the peer effect to come from the period before the refinancing plans were introduced. There is no evidence that this is the case. When I run the peer effect regressions for repayment as of October 2006, the peer effect is smaller than the peer effect as of November 2009, but very noisy.
village before attempting to encourage repayment from individuals with weaker incentives to repay. If the credit officer is looking for easy repayers, then it would not be rational to focus on those with weak incentives within an above average center without some sort of strong peer enforcement component. All of these facts would suggest that the MFI strategy would be a far larger component of a village level peer effect. However, almost the full village peer effect can be attributed to the borrowing center, ruling out credit officer effort as a likely explanation.

A fourth possible explanation for peer effects could be social mimicry, whereby individuals copy the actions of others. The asymmetric peer effects and concave costs of differing from peers makes this explanation unlikely. Peers seem to only influence repayment decisions in positive ways, not negative ways. However, it is impossible to rule out all possible mimicry functions due to the binary nature of the outcome variable.

The last class of possible drivers, social capital from being a member of a functional microfinance center, builds on the idea that there is more to the group structure of microfinance than just joint liability. The repayment decision could provide information about each peer group member’s repayment type, for example. In a separating equilibrium, borrowers who default could be labeled as bad credit risks in informal financial relationships. Borrowers may also have strong preferences for resuming the social components of borrowing from Spandana. The MFI suspended all regular center meetings until borrowers fully finished paying off their defaulted loans. Only upon full repayment were the weekly meetings and other social capital-intensive activities resumed. The relationship between own and peer incentives in the structural exercise suggests that individuals display the highest repayment rates when the peer group is likely to finish paying off the defaulted loan and resume future borrowing quickly. Additionally, recall that if the borrower’s own peer group is unlikely to repay, there are some cases when the borrower prefers to jump ahead of the peer group and to finish making all of the loan installments before the peer group. This pattern is compatible with peers preferring to join a new borrowing center rather than to remain in default and wait a very long time for the original peer group to finally finish repaying. Under this interpretation, borrowers find value in the social aspect of microfinance.

8 Conclusion

I analyze repayment data following the universal default of Spandana borrowers during the 2006 Krishna District crisis. Using a novel identification strategy that exploits the dynamic incentives embedded in microfinance contracts, I find strong evidence of repayment peer
effects. Even without joint liability, the decision of a peer group to repay does significantly impact an individual's own repayment likelihood. In terms of incentives, the entire peer group switching from default to repayment is equivalent to writing off 10 weeks of a borrower's loan. These peer effects seem to be driven by social connections within the borrowing center, not the village, and are likely cultivated by regular MFI practices themselves. Estimates from a dynamic discrete choice model of repayment indicate that the asymmetric nature of the peer effect implies that the net value of social effects is actually positive from an MFI revenues perspective.

In light of these results, several policy implications emerge. With respect to these types of default episodes, continuing to foster peer effects through the format of frequent group meetings has positive effects on the value of assets following widespread defaults. Lenders could also improve the value of their loan portfolios following a crisis by staggering the disbursements of loans within the peer lending center, as demonstrated by the spacing exercise. In terms of collections practices following defaults, the results suggest two policies. First, convincing one person in a local peer group to repay has disproportionately large spillover effects, as demonstrated by the non-linear peer effect shape. Therefore, collections practices that give special incentives to the first repayer could have large repayment spillovers. Second, in settings like the Krishna defaults, eliminating joint liability is probably a good decision. In the aftermath of the crisis, joint liability would have made it much more costly for individuals with low incentive peers to jump ahead and repay.

In sum, the social capital that MFIs work so hard to nurture does play a role in preserving asset values in the aftermath of crises. The Krishna District experience has shown that while in good times, microfinance can boast nearly perfect repayment rates, when problems arise, the system can become quite fragile. This study provides some of the first evidence that, against this backdrop, peer effects may actually improve repayment rates and act as a stabilizing force.
References


Appendix A: Figures

Figure 1: Stylized Repayment Incentives and Actual Repayment Over the Loan Cycle

The dotted lines represent stylized repayment incentives across the borrowing relationship. They are derived from simple net present value calculations. The units are in terms of NPV per Rs 1,000 in loan principal initially borrowed and are displayed on the y-axis to the right. The dots represent actual, observed average repayment rates.

Figure 2: Differential Repayment Incentives Across the Loan Cycle
The solid line plots the local linear approximation of the number of borrowers in each week of their borrowing relationship with the MFI. The curves are estimated separately for individuals in cycles 1, 2 and 3. The dashed lines are point-wise 95% confidence intervals.

Figure 3: Number of Borrowers by Week with MFI
Panel A: Village Repayment

Panel B: Center Repayment

Figure 4: Kernel Density Estimates of Full Repayment by Village and Center
Figure 5: Individual Repayment by Peer Group Incentives

Figure 6: Non-Linear Effects of Peer Repayment on Individual Repayment
**Panel A: Own Week = 15**

**Panel B: Own Week = 30**

**Panel C: Own Week = 45**

Figure 7: Model and Actual Transition Probabilities by Average Peer Weeks for Individuals at 15, 30, and 45 “Own” Weeks
Figure 8: Expected Loan Value Calibration by Weeks Completed when the Defaults Occurred
### Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>As of 3/9/2006</strong></td>
<td></td>
</tr>
<tr>
<td>Mean Loan Size (Rs)</td>
<td>7,644</td>
</tr>
<tr>
<td>Mean Loan Outstanding (Rs)</td>
<td>3,621</td>
</tr>
<tr>
<td>Mean Date of Disbursement</td>
<td>9/24/2005</td>
</tr>
<tr>
<td>Mean Date of Disbursement</td>
<td>111 days</td>
</tr>
<tr>
<td>Number of Loans</td>
<td>114,943</td>
</tr>
<tr>
<td>Number of Groups</td>
<td>13,437</td>
</tr>
<tr>
<td>Number of Centers</td>
<td>5,340</td>
</tr>
<tr>
<td>Number of Villages/Slums</td>
<td>574</td>
</tr>
<tr>
<td><strong>As of 11/20/2009</strong></td>
<td></td>
</tr>
<tr>
<td>Percent of Loans Still in Arrears</td>
<td>56.89%</td>
</tr>
<tr>
<td><strong>Most Common Stated Loan Purposes</strong></td>
<td></td>
</tr>
<tr>
<td>Livestock</td>
<td>26.33%</td>
</tr>
<tr>
<td>Textiles</td>
<td>16.81%</td>
</tr>
<tr>
<td>Retail Shop</td>
<td>11.43%</td>
</tr>
<tr>
<td>Agriculture</td>
<td>8.75%</td>
</tr>
<tr>
<td>Household and Family Expenses</td>
<td>8.27%</td>
</tr>
</tbody>
</table>
Table 2: Average Village Characteristics by Average Borrower Week

<table>
<thead>
<tr>
<th></th>
<th>Average Week in Cycle</th>
<th>Fraction in First 5 Weeks of Cycle</th>
<th>Fraction in Last 5 Weeks of Cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>-56.86** <em>(25.87)</em></td>
<td>2167</td>
<td>-1100</td>
</tr>
<tr>
<td>Cultivation Area per Capita</td>
<td>0.00195 <em>(0.00125)</em></td>
<td>-0.0380</td>
<td>0.0474</td>
</tr>
<tr>
<td>Irrigated Area per Capita</td>
<td>0.00189 <em>(0.001121)</em></td>
<td>-0.0919</td>
<td>0.0304</td>
</tr>
<tr>
<td>Distance to Town</td>
<td>-0.152* <em>(0.0911)</em></td>
<td>14.72*** <em>(4.694)</em></td>
<td>8.199** <em>(3.678)</em></td>
</tr>
<tr>
<td>Education Facilities</td>
<td>0.000551 <em>(0.000366)</em></td>
<td>0.0128</td>
<td>0.0123</td>
</tr>
<tr>
<td>Primary Schools per Capita</td>
<td>1.26e-05** <em>(5.65e-06)</em></td>
<td>-0.000101</td>
<td>0.000499** <em>(0.000233)</em></td>
</tr>
<tr>
<td>Medical Facilities</td>
<td>-0.00148 <em>(0.00225)</em></td>
<td>0.0698</td>
<td>-0.0491</td>
</tr>
<tr>
<td>Health Centers per Capita</td>
<td>3.18e-07 <em>(3.35e-07)</em></td>
<td>1.45e-05</td>
<td>-7.65e-06</td>
</tr>
<tr>
<td>Health SubCenters per Capita</td>
<td>8.62e-07 <em>(1.16e-06)</em></td>
<td>4.47e-05</td>
<td>4.48e-05</td>
</tr>
<tr>
<td>Number of Banks per Capita</td>
<td>-8.99e-07 <em>(6.31e-07)</em></td>
<td>1.24e-05</td>
<td>-2.03e-05</td>
</tr>
<tr>
<td>Railway</td>
<td>-0.000363 <em>(0.00129)</em></td>
<td>-0.0753</td>
<td>-0.0233</td>
</tr>
<tr>
<td>Paved Roads</td>
<td>0.000324 <em>(0.00138)</em></td>
<td>0.0561</td>
<td>0.0440</td>
</tr>
</tbody>
</table>

Notes: Each row represents a separate regression, where the dependent variables are indicated by the row titles. Column 1 represents a set of regressions where the independent variable is the average week in the loan cycle at the village level. Columns 2 and 3 show results from a second set of regressions, where the independent variables are the fraction of individuals in the first 5 weeks of their loan cycles and the fraction of individuals in the last 5 weeks of their loan cycles. Standard errors are clustered at the village level. *** significant at 1%, ** significant at 5%, * significant at 10%.
### Table 3: OLS Regressions of Own Repayment on Peer Repayment

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Village Repayment ex Group</td>
<td>0.813***</td>
<td>0.302***</td>
<td>0.556***</td>
</tr>
<tr>
<td></td>
<td>(0.0232)</td>
<td>(0.0221)</td>
<td>(0.0158)</td>
</tr>
<tr>
<td>Village Repayment ex Center</td>
<td></td>
<td></td>
<td>0.636***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0156)</td>
</tr>
<tr>
<td>Center Repayment ex Group</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual and Peer Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Branch</td>
<td>Branch</td>
<td>Branch</td>
</tr>
<tr>
<td>Observations</td>
<td>107734</td>
<td>107734</td>
<td>107734</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.345</td>
<td>0.401</td>
<td>0.394</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is an indicator for whether an individual fully repaid her loan by November, 2009. The regressors of interest represent the average repayment in the peer group. Standard errors are clustered at the village level. *** significant at 1%, ** significant at 5%, * significant at 10%.

### Table 4: Individual Determinants of Loan Repayment

<table>
<thead>
<tr>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week in Cycle</td>
<td>0.0119***</td>
<td>0.0111***</td>
<td>0.0106***</td>
<td>0.0107***</td>
</tr>
<tr>
<td></td>
<td>(0.000430)</td>
<td>(0.000434)</td>
<td>(0.000412)</td>
<td>(0.000395)</td>
</tr>
<tr>
<td>Number of Weeks with MFI</td>
<td>-0.00265***</td>
<td>-7.82e-05</td>
<td>0.000219</td>
<td>-0.000977***</td>
</tr>
<tr>
<td></td>
<td>(0.000254)</td>
<td>(0.000148)</td>
<td>(0.000154)</td>
<td>(0.000483)</td>
</tr>
<tr>
<td>Number of Weeks with MFI Squared</td>
<td>9.44e-06**</td>
<td>4.00e-06</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Loan Amount (Rs 1000s)</td>
<td>-0.00536*</td>
<td>0.00167</td>
<td>0.00229</td>
<td>-0.00797</td>
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<tr>
<td></td>
<td>(0.00281)</td>
<td>(0.00230)</td>
<td>(0.00221)</td>
<td>(0.00882)</td>
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<tr>
<td>Loan Amount (Rs 1000s) Squared</td>
<td></td>
<td></td>
<td>0.000674</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000524)</td>
<td></td>
</tr>
<tr>
<td>Village Peer Controls</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Fixed Effects</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>114943</td>
<td>114943</td>
<td>114943</td>
<td>114943</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.170</td>
<td>0.213</td>
<td>0.283</td>
<td>0.289</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is an indicator for whether an individual fully repaid her loan by November, 2009. Village peer controls include the following average village level variables: loan size, loan size squared, and second order polynomials of number of weeks with the MFI. Standard errors are clustered at the village level. *** significant at 1%, ** significant at 5%, * significant at 10%.
Table 5: Aggregate First Stage and Reduced form: Average Weeks Instruments

<table>
<thead>
<tr>
<th></th>
<th>Aggregate First Stage: Peer Group Repayment</th>
<th>Reduced Form: Individual Repayment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Village (1)</td>
<td>Village (2)</td>
</tr>
<tr>
<td>Village Average Week in Cycle ex Group</td>
<td>0.0110*** (0.00107)</td>
<td>0.00122 (0.00112)</td>
</tr>
<tr>
<td>Village Average Week in Cycle ex Center</td>
<td>0.0112*** (0.000946)</td>
<td>0.000357 (0.00101)</td>
</tr>
<tr>
<td>Center Average Week in Cycle ex Group</td>
<td>-0.000141 (0.000196)</td>
<td>0.0112*** (0.000428)</td>
</tr>
<tr>
<td>Week in Cycle</td>
<td>0.000141 (0.000196)</td>
<td>0.0107*** (0.000385)</td>
</tr>
<tr>
<td>Individual and Peer Controls</td>
<td>Yes Branch</td>
<td>Yes Branch</td>
</tr>
<tr>
<td>Observations</td>
<td>107734</td>
<td>107734</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.673</td>
<td>0.656</td>
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</tbody>
</table>

Notes: Columns 1-4 present aggregate first stage regressions, where the dependent variable is the fraction of individuals in the relevant peer group who fully repaid their loans by November, 2009. Columns 5-7 present reduced form regressions, where the dependent variable is an indicator for whether an individual fully repaid her loan by November, 2009. In these regressions, the instrument is peer-group-level average weeks in the loan cycle. Note that columns 1 and 5 define the peer group as the village ex group. Columns 2, 3 and 6 analyze two levels, of the peer group: village ex center and center ex group. Since there are two endogenous regressors of interest, I use two separate instruments in these regressions. Column 2 shows the first stage regression for the village ex center peer group, while column 3 shows the first stage regression for the center ex group peer group. Columns 4 and 7 focus on only the center ex group peer group. All specifications include the following individual-level controls: loan size, loan size squared, and fifth order polynomials of weeks with the MFI. Peer controls are defined at the relevant level and include: average loan size and loan size squared, fifth order polynomials of the average number of weeks with the MFI, and the minimum and maximum values for weeks with MFI within the peer group. Standard errors are clustered at the village level. *** significant at 1%, ** significant at 5%, * significant at 10%.
Table 6: Aggregate First Stage and Reduced form: Extreme Weeks Instruments

<table>
<thead>
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<th></th>
<th>Aggregate First Stage:</th>
<th>Reduced Form:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Peer Group Repayment</td>
<td>Individual Repayment</td>
</tr>
<tr>
<td></td>
<td>Village (1)</td>
<td>Village (5)</td>
</tr>
<tr>
<td>Fraction of Village (ex g) in <strong>First</strong> 5 Weeks</td>
<td>-0.268*** (0.0499)</td>
<td>-0.0229 (0.0520)</td>
</tr>
<tr>
<td>Fraction of Village (ex g) in <strong>Last</strong> 5 Weeks</td>
<td>0.244*** (0.0446)</td>
<td>0.0492 (0.0468)</td>
</tr>
<tr>
<td>Fraction of Village (ex c) in <strong>First</strong> 5 Weeks</td>
<td>-0.270*** (0.0423) -0.0694 (0.0449)</td>
<td>-0.0162 (0.0467)</td>
</tr>
<tr>
<td>Fraction of Village (ex c) in <strong>Last</strong> 5 Weeks</td>
<td>0.269*** (0.0379) 0.0446 (0.0397)</td>
<td>0.0106 (0.0416)</td>
</tr>
<tr>
<td>Fraction of Center (ex g) in <strong>First</strong> 5 Weeks</td>
<td>-0.00505 (0.00747) -0.237*** (0.0151) -0.245*** (0.0167)</td>
<td>0.00327 (0.0138) -0.00577 (0.0160)</td>
</tr>
<tr>
<td>Fraction of Center (ex g) in <strong>Last</strong> 5 Weeks</td>
<td>0.000244 (0.00685) 0.212*** (0.0167) 0.205*** (0.0176)</td>
<td>0.0428*** (0.0138) 0.0392*** (0.0149)</td>
</tr>
</tbody>
</table>

| Week in Cycle             | 0.0107*** (0.000401) 0.0105*** (0.000405) 0.0106*** (0.000413) |
| Individual and Peer Controls | Yes       | Yes       | Yes       | Yes       | Yes       | Yes       |
| Fixed Effects             | Branch    | Branch    | Branch    | Branch    | Branch    | Branch    |
| Observations              | 107734    | 107734    | 107734    | 107734    | 107734    | 107734    |
| R-squared                 | 0.647     | 0.622     | 0.438     | 0.429     | 0.292     | 0.296     | 0.289     |

Notes: Columns 1-4 present aggregate first stage regressions, where the dependent variable is the fraction of individuals in the relevant peer group who fully repaid their loans by November, 2009. Columns 5-7 present reduced form regressions, where the dependent variable is an indicator for whether an individual fully repaid her loan by November, 2009. In these regressions, the instruments are the fraction of individuals in the relevant peer group who are in the first 5 weeks of their loan cycles and the fraction of the peer group in the last 5 weeks of their loan cycles. Note that columns 1 and 5 define the peer group as the village ex group. Columns, 2,3 and 6 analyze two levels, of the peer group: village ex center and center ex group. Since there are two endogenous regressors of interest, I use two separate instruments in these regressions. Column 2 shows the first stage regression for the village ex center peer group, while column 3 shows the first stage regression for the center ex group peer group. Columns 4 and 7 focus on only the center ex group peer group. All specifications include the following individual-level controls: loan size, loan size squared, and fifth order polynomials of weeks with the MFI. Peer controls are defined at the relevant level and include: average loan size and loan size squared, fifth order polynomials of the average number of weeks with the MFI, and the minimum and maximum values for weeks with MFI within the peer group. Standard errors are clustered at the village level. *** significant at 1%, ** significant at 5%, * significant at 10%.
### Table 7: IV Regressions of Own Repayment on Peer Repayment

<table>
<thead>
<tr>
<th></th>
<th>Average Weeks</th>
<th>Extreme Weeks</th>
<th></th>
<th></th>
<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
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<tr>
<td>Village Repayment ex Group</td>
<td>0.111</td>
<td>0.0327</td>
<td>0.0967***</td>
<td>0.0107***</td>
<td>0.114943</td>
<td>0.107734</td>
</tr>
<tr>
<td></td>
<td>(0.0929)</td>
<td>(0.0800)</td>
<td>(0.0298)</td>
<td>(0.000383)</td>
<td>(0.0506)</td>
<td>(0.000569)</td>
</tr>
<tr>
<td>Village Repayment ex Center</td>
<td>0.159</td>
<td>0.112***</td>
<td>0.112***</td>
<td>0.0102***</td>
<td>0.136***</td>
<td>0.0106***</td>
</tr>
<tr>
<td></td>
<td>(0.110)</td>
<td>(0.0329)</td>
<td>(0.0329)</td>
<td>(0.000386)</td>
<td>(0.0491)</td>
<td>(0.000569)</td>
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<tr>
<td>Center Repayment ex Group</td>
<td>0.0471</td>
<td>0.141***</td>
<td>0.141***</td>
<td>0.0106***</td>
<td>0.143***</td>
<td>0.0111***</td>
</tr>
<tr>
<td></td>
<td>(0.0937)</td>
<td>(0.0473)</td>
<td>(0.0473)</td>
<td>(0.000414)</td>
<td>(0.0552)</td>
<td>(0.000661)</td>
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<tr>
<td>Week in Cycle</td>
<td>0.0109***</td>
<td>0.0109***</td>
<td>0.0109***</td>
<td>0.0106***</td>
<td>0.00997***</td>
<td>0.0101***</td>
</tr>
<tr>
<td></td>
<td>(0.000383)</td>
<td>(0.000386)</td>
<td>(0.000386)</td>
<td>(0.000414)</td>
<td>(0.000458)</td>
<td>(0.000459)</td>
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<tr>
<td>Individual and Peer Controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
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<td>Branch</td>
<td>Branch</td>
<td>Branch</td>
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<td>Branch</td>
</tr>
<tr>
<td>Observations</td>
<td>114943</td>
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<td>107734</td>
<td>114943</td>
<td>107734</td>
<td>107734</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.360</td>
<td>0.328</td>
<td>0.323</td>
<td>0.311</td>
<td>0.341</td>
<td>0.332</td>
</tr>
</tbody>
</table>

Notes: In all specifications, the dependent variable is an indicator for whether an individual fully repaid her loan by November, 2009. In columns 1-3, the instrument is the average week in the loan cycle for the relevant peer group definition. In columns 4-6, the instruments are the fraction of individuals in the relevant peer group who are in the first 5 weeks of their loan cycles and the fraction of the peer group in the last 5 weeks of their loan cycles. All specifications include the following individual-level controls: loan size, loan size squared, and fifth order polynomials of weeks with the MFI. Peer controls are defined at the relevant level and include: average loan size and loan size squared, fifth order polynomials of the average number of weeks with the MFI, and the minimum and maximum values for weeks with MFI within the peer group. Standard errors are clustered at the village level. ** significant at 1%, ** significant at 5%, * significant at 10%.

### Table 8: IV Regressions of Own Repayment on Peer Repayment: Restricted Sample

<table>
<thead>
<tr>
<th></th>
<th>Sample Restriction:</th>
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<th></th>
<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>± 5 weeks around Discontinuities</td>
<td>Mode</td>
<td>&gt; 50%</td>
<td>&gt; 75%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Center Repayment ex Group</td>
<td>0.143***</td>
<td>0.136***</td>
<td>0.143***</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.0506)</td>
<td>(0.0491)</td>
<td>(0.0552)</td>
<td></td>
<td></td>
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<tr>
<td>Week in Cycle</td>
<td>0.0107***</td>
<td>0.0106***</td>
<td>0.0111***</td>
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<tr>
<td></td>
<td>(0.000569)</td>
<td>(0.000569)</td>
<td>(0.000661)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual and Peer Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Branch</td>
<td>Branch</td>
<td>Branch</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>28757</td>
<td>30646</td>
<td>21892</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.433</td>
<td>0.403</td>
<td>0.418</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: In all specifications, the dependent variable is an indicator for whether an individual fully repaid her loan by November, 2009. The specifications are restricted versions of column 3 in Table 7. Column 1 restricts the sample to peer groups where the mode week with MFI is close to a discontinuity. Columns 2 and 3 restrict the sample based on the fraction of individuals in the peer group close to the discontinuity. All specifications include the following individual-level controls: loan size, loan size squared, and fifth order polynomials of weeks with the MFI. Peer controls are defined at the center level and include: average loan size and loan size squared, fifth order polynomials of the average number of weeks with the MFI, and the minimum and maximum values for weeks with MFI within the peer group. Standard errors are clustered at the village level. ** significant at 1%, ** significant at 5%, * significant at 10%.
Table 9: Center Peer Effects: Fuzzy RD

<table>
<thead>
<tr>
<th>Fraction of Peers in Extreme Weeks</th>
<th>0.75</th>
<th>0.80</th>
<th>0.85</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
</tbody>
</table>

**A. Reduced Form**

<table>
<thead>
<tr>
<th>Peer Group Has High Repayment Incentive</th>
<th>0.0705**</th>
<th>0.0631**</th>
<th>0.0551*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0306)</td>
<td>(0.0308)</td>
<td>(0.0321)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Week in Cycle</th>
<th>0.0114***</th>
<th>0.0117***</th>
<th>0.0119***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.000641)</td>
<td>(0.000661)</td>
<td>(0.000677)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Individual and Peer Controls</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Effects</td>
<td>Branch</td>
<td>Branch</td>
<td>Branch</td>
</tr>
<tr>
<td>Observations</td>
<td>21188</td>
<td>20561</td>
<td>19857</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.378</td>
<td>0.380</td>
<td>0.378</td>
</tr>
</tbody>
</table>

**B. Instrumental Variables**

<table>
<thead>
<tr>
<th>Center Repayment ex Group</th>
<th>0.144**</th>
<th>0.127**</th>
<th>0.111*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0585)</td>
<td>(0.0586)</td>
<td>(0.0616)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Week in Cycle</th>
<th>0.0112***</th>
<th>0.0115***</th>
<th>0.0117***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.000662)</td>
<td>(0.000684)</td>
<td>(0.000710)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Individual and Peer Controls</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Effects</td>
<td>Branch</td>
<td>Branch</td>
<td>Branch</td>
</tr>
<tr>
<td>Observations</td>
<td>21188</td>
<td>20561</td>
<td>19857</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.424</td>
<td>0.422</td>
<td>0.416</td>
</tr>
</tbody>
</table>

Notes: In all specifications, the dependent variable is an indicator for whether an individual fully repaid her loan by November, 2009. All regressions restrict the sample to those individuals whose peer groups either have very high or very low repayment incentives. The instrument used is an indicator for whether the peer group has very high repayment incentives. Panel A presents the reduced form estimates, while Panel B presents the instrumental variables results. All specifications include the following individual-level controls: loan size, loan size squared, and fifth order polynomials of weeks with the MFI. Peer controls are defined at the relevant level and include: average loan size and loan size squared, fifth order polynomials of the average number of weeks with the MFI, and the minimum and maximum values for weeks with MFI within the peer group. Standard errors are clustered at the village level. *** significant at 1%, ** significant at 5%, * significant at 10%.
### Table 10: IV Regressions of Partial Repayment on Peer Partial Repayment

<table>
<thead>
<tr>
<th>Partial Repayment ex Group</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Village Repayment ex Group</td>
<td>0.356**</td>
<td>(0.165)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Village Repayment ex Center</td>
<td>0.174</td>
<td>(0.140)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Center Repayment ex Group</td>
<td>0.222***</td>
<td>(0.0708)</td>
<td>0.301***</td>
<td>(0.0722)</td>
</tr>
<tr>
<td>Week in Cycle</td>
<td>0.00466***</td>
<td>(0.000378)</td>
<td>0.00420***</td>
<td>(0.000386)</td>
</tr>
<tr>
<td>Individual and Peer Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Branch</td>
<td>Branch</td>
<td>Branch</td>
<td>Branch</td>
</tr>
<tr>
<td>Observations</td>
<td>107734</td>
<td>107734</td>
<td>107734</td>
<td>107734</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.249</td>
<td>0.299</td>
<td>0.296</td>
<td>0.317</td>
</tr>
</tbody>
</table>

Notes: In columns 1-3, the dependent variable is an indicator for whether an individual partially repaid her loan by November, 2009. The endogenous regressors of interest are partial repayment rates of the peer groups. In column 4, the dependent variable is full repayment by November 2009, and the endogenous regressors are the number of peers who have fully repayed by November 2009. In all specifications, the instrument is average peer group weeks in the cycle. All specifications include the following individual-level controls: loan size, loan size squared, and fifth order polynomials of weeks with the MFI. Peer controls are defined at the relevant level and include: average loan size and loan size squared, fifth order polynomials of the average number of weeks with the MFI, and the minimum and maximum values for weeks with MFI within the peer group. Standard errors are clustered at the village level. *** significant at 1%, ** significant at 5%, * significant at 10%.

### Table 11: Structural Parameter Estimates

<table>
<thead>
<tr>
<th>Description</th>
<th>$\theta$</th>
<th>Estimate</th>
<th>Counterfactual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow Values</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repayment Amount</td>
<td>$-\kappa$</td>
<td>-2.52</td>
<td>-2.52</td>
</tr>
<tr>
<td>Peer - Linear</td>
<td>$\rho_1$</td>
<td>0.04</td>
<td>0</td>
</tr>
<tr>
<td>Peer - Squared</td>
<td>$\rho_2$</td>
<td>0.00005</td>
<td>0</td>
</tr>
<tr>
<td>Continuation Values</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual</td>
<td>$V_{\text{new}}$</td>
<td>65.02</td>
<td>65.02+2.42</td>
</tr>
<tr>
<td>Peer</td>
<td>$\psi$</td>
<td>2.42</td>
<td>0</td>
</tr>
</tbody>
</table>

Standard Errors are calculated by bootstrapping the second stage of the estimation procedure. Standard errors bootstrapped over the full procedure are forthcoming.
Appendix C: The Reflection Problem

Suppose that all peer groups are of size $n$ and that the peer effect operates through the average repayment in the peer group. Then the key structural parameter to identify is $\alpha_2$. Note that the problem is symmetric for all individuals in the same peer group, so

$$repay_1 = \alpha_0 + \alpha_1 date_1 + \alpha_2 \sum_{j \neq 1} \frac{repay_j}{n-1} + \epsilon_1$$

$$repay_2 = \alpha_0 + \alpha_1 date_2 + \alpha_2 \sum_{j \neq 2} \frac{repay_j}{n-1} + \epsilon_2$$

$$...$$

$$repay_n = \alpha_0 + \alpha_1 date_n + \alpha_2 \sum_{j \neq n} \frac{repay_j}{n-1} + \epsilon_n$$

So, first sum equations 2 through $n$

$$\sum_{j \neq 1} \frac{repay_j}{n-1} = \frac{n}{n-1} \alpha_0 + \alpha_1 \sum_{j \neq 1} \frac{date_j}{n-1} + \alpha_2 \frac{1}{n-1} \sum_{i=2}^{n} \sum_{j \neq i} \frac{repay_j}{n-1} + \sum_{j \neq 1} \frac{\epsilon_j}{n-1}$$

where

$$\alpha_2 \frac{1}{(n-1)^2} \sum_{i=2}^{n} \sum_{j \neq i} repay_j$$

$$= \alpha_2 \left[ \frac{repay_1}{n-1} + \frac{(n-2)}{(n-1)} \sum_{j \neq 1} \frac{repay_j}{n-1} \right]$$

So

$$\sum_{j \neq 1} \frac{repay_j}{n-1} = \frac{1}{1 - \alpha_2 \frac{(n-2)}{(n-1)}} \left( \frac{n}{n-1} \alpha_0 + \alpha_1 \sum_{j \neq 1} \frac{date_j}{n-1} + \alpha_2 \frac{repay_1}{n-1} + \sum_{j \neq 1} \frac{\epsilon_j}{n-1} \right)$$

Plugging this back into the first equation gives:

$$repay_1 = \alpha_0 + \alpha_1 date_1 + \frac{\alpha_2}{1 - \alpha_2 \frac{(n-2)}{(n-1)}} \left( \frac{n}{n-1} \alpha_0 + \alpha_1 \sum_{j \neq 1} \frac{date_j}{n-1} + \alpha_2 \frac{repay_1}{n-1} + \sum_{j \neq 1} \frac{\epsilon_j}{n-1} \right) + \epsilon_1$$

$$= \tilde{\alpha}_0 + \frac{1}{1 - \frac{\alpha_1 \alpha_2}{(n-1) - \alpha_2 (n-2)}} \left( \alpha_1 date_1 + \frac{\alpha_1 \alpha_2}{1 - \alpha_2 \frac{(n-2)}{(n-1)}} \sum_{j \neq 1} \frac{date_j}{n-1} \right) + \tilde{\epsilon}$$

Now, let’s go back and look at the average peer repayment equation, since this is in...
essence, the first stage of my regressions

\[ \sum_{j \neq 1} \frac{\text{repay}_j}{n - 1} = \frac{1}{1 - \alpha_2 \frac{(n-2)}{(n-1)}} \left( \frac{n}{n - 1} \alpha_0 + \alpha_1 \sum_{j \neq 1} \frac{\text{date}_j}{n - 1} + \alpha_2 \frac{\text{repay}_1}{n - 1} + \sum_{j \neq 1} \frac{\varepsilon_j}{n - 1} \right) \]

\[ = \phi + \frac{1}{1 - \alpha_2 \frac{(n-2)}{(n-1)}} \left( \alpha_1 + \frac{\alpha_2^2}{n - 1} \right) \sum_{j \neq 1} \text{date}_j \]

where \( \phi \) includes all of the other terms. So the coefficient on average date in this regression (excluding \( \text{date}_1 \) which is orthogonal to the other date variable) is

\[ \frac{1}{1 - \alpha_2 \frac{(n-2)}{(n-1)}} \left( \alpha_1 + \frac{\alpha_2^2}{n - 1} \right) \]

So the ratio of the reduced form coefficient over the first stage coefficient is what IV gives us, so

\[ \frac{\alpha_1 \alpha_2}{1 - \alpha_2 \frac{(n-2)}{(n-1)}} \left( \alpha_1 + \frac{\alpha_2^2}{n - 1} \right) = \frac{\alpha_1 \alpha_2}{\alpha_1 + \frac{\alpha_2^2}{n - 1}} \]

\[ = \frac{\alpha_2}{1 + \frac{\alpha_2^2}{\alpha_1(n-1)}} \approx \alpha_2 \]

If anything, the small sample bias makes this estimate too low. IV gives a consistent estimate of the peer effect.
Appendix D: Supplemental Figures and Tables

Figure 9: Distribution of Average Weeks in Cycle Across Centers