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Warwick Economics Research Paper Series

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Jonathan de Quidty, Thiemo Fetzer and Maitreesh Ghatak

March, 2016
Series Number: 1119
ISSN 2059-4283 (online)
ISSN 0083-7350 (print)

This paper also appears as [CAGE Discussion Paper No: 272]

Commercialization and the Decline of Joint Liability Microcredit*

Jonathan de Quidt† Thiemo Fetzer‡ Maitreesh Ghatak§

February 29, 2016

Abstract

Numerous authors point to a decline in joint liability microcredit, and rise in individual liability lending. But empirical evidence is lacking, and there have been no rigorous analyses of possible causes. We first show using the well-known MIX Market dataset that there is evidence for a decline. Second, we show theoretically that *commercialization*–an increase in competition and a shift from non-profit to for-profit lending (both of which are present in the data)–drives lenders to reduce their use of joint liability loan contracts. Third, we test the model's key predictions, and find support for them in the data.

Keywords: microfinance; joint liability; commercialization; market structure

JEL Classification: G21, O12, O16

*We thank many seminar and conference audiences for helpful comments. All errors and omissions are our own.

†Institute for International Economic Studies. jonathan.dequidt@iies.su.se

‡University of Warwick. t.fetzer@warwick.ac.uk

§London School of Economics. M.Ghatak@lse.ac.uk

1 Introduction

Microfinance Institutions (MFIs), and in particular Muhammad Yunus' Grameen Bank, have long attracted the interest of economists for their success in lending to poor borrowers written off as uncreditworthy by traditional lenders. A large literature analyzes the innovative contractual tools used by MFIs to achieve this, of which the best known is joint liability lending (JL), whereby the borrower and one or more group members assume liability for one another's debts. Joint liability has been shown to be able to overcome problems of adverse selection, moral hazard and limited enforcement, leveraging social collateral that can substitute for the conventional collateral that the poor, by definition, lack.[1]

In the recent literature it has become common to see claims of a widespread decline in the use of JL.[2] Yet such claims are anecdotal, typically pointing to high-profile examples such as Grameen, BancoSol, and ASA who initially pioneered the use of joint liability credit yet have since moved to an individual liability (IL) lending model. Moreover, as yet we are aware of no satisfactory account of what has changed about the lending environment, if indeed there has been a change, to reverse the initial success of JL.

This paper makes two contributions. First, we use the best available data (the institution-level dataset collected by the MIX Market) to assess empirically whether there is evidence of a trend away from joint liability credit. Although our data on lending methodology are incomplete and span only the years 2008-2011, they do indicate a trend toward IL.

Second, we argue theoretically and empirically that the trend can be explained, at least in part, by commercialization. By commercialization, we refer to two forces. First, as we document below, the microcredit industry has shifted from being largely made up of non-profit and NGO lenders to an

[1]For a detailed review of both the theory and history of JL, see Ghatak and Guinnane (1999) and Armendáriz de Aghion and Morduch (2010).

[2]E.g. Hermes and Lensink (2007), Armendáriz de Aghion and Morduch (2010), Breza (2011), Giné, Krishnaswamy and Ponce (2011), Feigenberg, Field and Pande (2013), Carpena et al. (2013), Giné and Karlan (2014).

increasingly for-profit marketplace. Second, competition among lenders for borrowers has increased, leading to an expansion of the sector.[3]

We present a simple model that makes three empirical predictions. First, for-profit lenders are less likely to use JL than non-profits. Second, competition induces non-profits to switch from JL to IL. Third, interestingly and in contrast to the broad trend, competition induces for-profits to switch from IL to JL. While the three effects are not all in the same direction, the net effect is such that beginning from an uncompetitive, largely non-profit market, increasing competition and increasing the for-profit share in the market both lead to increases in the use of IL.

Intuitively, the main driving force in our model is that JL involves tighter incentive constraints than IL, since in some states of the world, it involves not only repaying one's own loan, but also helping a group-member repay her loan. At the same time, the advantage of JL is, because any given loan gets repaid with greater probability, the borrower gets to maintain access to credit from the lender, and depending on the market structure, the interest rate could go down. Non-profits choose whatever lending arrangement has higher borrower welfare, subject to the incentive constraints and a break-even constraint. Under non-profits, competition tends to reduce the use of JL as it improves the borrower's outside option, reduces the cost of losing her existing contract and thus tightening the more demanding incentive constraint, namely, that under JL. The non-profit offers JL whenever it breaks even, because JL maximizes borrower welfare. The for-profit also requires JL to break even, but additionally it must be more profitable than IL. Since this is a stricter condition, the for-profit ends up offering JL to fewer borrowers. Finally, as competition increases for-profits tend to use JL more (unlike non-profits) as revenue under JL is less sensitive to the borrower's outside option than under IL.

[3] In some cases the process of commercialization has not been without problems, which has often attracted attention to the sector for the wrong reasons. This is seen most dramatically in the credit crisis in Andhra Pradesh, India, that in 2010 led regulators to temporarily shut the industry down completely, and subsequently to the drafting of a proposed nationwide law regulating the industry.

We then test the implications of the model empirically. Exploiting within-region, within-country and within-MFI variation in market composition and proxies for competition, we find support for all three predictions. We find that for-profit lenders indeed tend to use JL less than non-profits. Both types of lenders change their offerings in the predicted directions when competition, measured with various proxies, increases. Although, given the data, we cannot perfectly resolve the issue of identification, our findings are robust to inclusion of a broad range of controls, interactions and fixed effects, and hold for two alternative measures of IL and JL usage intensity and four panel sampling frames.[4] We take further comfort from the fact that the model's prediction for for-profits' response to changes in competition–which is strongly supported in the data–is in the opposite direction to overall trends and therefore provides a particularly strong test of the theory.

Our theory fits into a branch of the literature that highlights the leverage of *social capital*, especially through JL lending, as a key feature of microcredit.[5] Our model explains changes in the use of JL via changes in the level social capital required for an MFI to be willing to offer JL. Since we cannot observe social capital, nor any reasonable proxies that we can match to our data, our main identifying assumption is that changes in the unobservable social environment are uncorrelated with changes in the market structure and competitive environment, conditional on our various controls and fixed effects. At least in the short run, we believe that this is a plausible assumption.

We are not in fact the first to note an *association* between commercializa-

[4]The results are however sensitive to the inclusion of data from one country, Peru, which we exclude from our main specifications. Appendix A.1 demonstrates the sensitivity and Table 12 presents the results including Peru for the three alternative measures of competition. The coefficient pattern is qualitatively consistent throughout, but the point estimates are much smaller in magnitude when Peru is included. The results are not sensitive to inclusion/exclusion of any other country or MFI. Our preferred competition measures, bank branch and ATM density, grew extremely rapidly in Peru over our four year time window (driven by the three largest cities) which may mean that our competition proxies are performing more poorly in Peru and will tend to depress the coefficients on these measures toward zero.

[5]E.g. Besley and Coate (1995), Ahlin and Townsend (2007), Ghatak and Guinnane (1999), Cassar and Wydick (2010), de Quidt, Fetzer and Ghatak (2016), de Quidt, Fetzer and Ghatak (forthcoming), Karlan (2005), Karlan (2007).

tion and the decline of JL. Karlan and Zinman (2009) write:[6]

> [T]he industrial organization of microcredit is trending toward something that looks more like the cash loan market: for-profit, more competitive delivery of untargeted, individual liability loans... This evolution is happening from both the bottom-up (non-profits converting to for- profits) and the top-down (for-profits expanding into subprime and consumer segments).

However to our knowledge we are the first to outline the theoretical and empirical case for a *causal* relationship from the former to the latter.

In related work, Cull, Demirgüç-kunt and Morduch (2009) use an early version of the MIX Market data to provide an extensive descriptive overview of the microcredit industry. Notably, they observe that non-profits are more likely than for-profits to use JL lending methods, as our model predicts and as we also observe in our chronologically later and larger sample. McIntosh, De Janvry and Sadoulet (2005) show empirically that increasing competition between lenders in Uganda harmed repayment performance, in line with the mechanism proposed in our paper (they put more weight on a multiple borrowing interpretation than weakened repayment incentives, though the latter must naturally go in hand with the former; our model features only the second channel). McIntosh and Wydick (2005) study theoretically the effects of competition on lenders' ability to cross-subsidize between clients who vary in their wealth. Baland, Somanathan and Wahhaj (2013) also study the choice between JL and IL contracts, focusing on the relationship with borrower wealth and arguing that wealthier borrowers are better served by JL. Our conceptualization of competition closely relates to Hoff and Stiglitz (1997) and Shapiro and Stiglitz (1984).

In this paper, we focus on the purely positive question of how and why the types of lending contracts used by MFIs are changing over time, analyzing the consequences of an exogenous increase in commercialization for the contracts

[6] See also Karlan and Zinman (2010).

offered in the market. Our goal is to provide structure and evidence to the discussions around the decline of joint liability. Elsewhere, de Quidt, Fetzer and Ghatak (2016), we focus on a different, normative question: the welfare consequences of different microcredit market structures. We use a restricted version of the model in that paper, specifically assuming that a) the borrower's outside option (if she defaults on her current loan) is completely determined by the loans available to her from competitor MFIs, and b), that the distribution of social capital is homogeneous. That additional structure provides us with the tractability to solve for welfare under three equilibria of interest: monopolistic non-profit or for-profit lending, and perfect competition. But it precludes the comparative static analysis on gradual changes to market structure we need for the questions of interest to this paper.[7]

Existing empirical work comparing IL and JL tends to focus on comparing the impact of credit under different contracts, or the relative performance of the two contract forms on repayment and other outcomes. Giné and Karlan (2014) show that converting joint liability groups to individual liability groups at an MFI in the Philippines did not affect average repayment rates (the average effect is a precisely-estimated zero). Carpena et al. (2013) study a natural experiment in which an Indian MFI switched from using IL to JL, exploiting variation in the switch date determined by the maturity of previous loans. They find a substantial *improvement* in repayment rates, in line with the model we use in this paper. Mahmud (2015) uses a similar strategy to study the decision by a Pakistan MFI to switch to JL, and again finds positive repayment effects. Attanasio et al. (2015) randomized Mongolian borrowers into either JL, IL or a control (no credit treatment). They find some positive economic impacts of access to JL credit, no significant impacts of IL credit, and no difference in repayment rates. Overall, the evidence seems consistent with JL (weakly) improving repayment rates, as it does in equilibrium in our

[7]Using a variant of the model, with only non-profit lenders, de Quidt, Fetzer and Ghatak (forthcoming) analyzes theoretically under what conditions individual liability can perform as well as joint liability in terms of repayment and borrower welfare, motivated in particular by the evidence in Giné and Karlan (2014). Allen (forthcoming) also works with a very similar model, studying structurally the optimal extent of "partial" joint liability.

model, though it should be noted that the two randomized studies do not find significant effects.

The paper is organized as follows. In section 2 we present the three stylized facts that motivate the theory. In section 3 we present the model and the theoretical analysis. In section 4 we present the empirical results. Section 5 concludes.

2 Three stylized facts

This section documents three simple stylized facts: 1) the share of for-profit MFIs and the microfinance industry as a whole have grown dramatically over time (the forces we term "commercialization"); 2) three plausible proxies for the competitiveness of the sector (capturing borrowers' outside options) have grown over our sampling period; and 3) the use of joint liability has declined. We defer a detailed description of the dataset for later. In addition to the later discussion in the text, Web Appendix A contains an extended discussion of figure construction and alternative approaches.

First we show a gradual increase in the share of for-profit MFIs over the last two decades. The top left panel of Figure 1 graphs a measure of the fraction of MFIs that lend for profit, over time. We reconstruct this time-series using data on for-profit/non-profit status from the MIX Market, as reported to the MIX in 2011. Combining this information with MFIs' founding dates, we can plot the evolution of for-profit and non-profit lending over time. We observe a gradual upward trend in the share of for-profit lenders over the period.[8]

[8] There are four potential biases in this figure. First, we cannot observe historical market shares, so we weight each MFI equally (weighting according to size in 2008-2011 does not affect the trend). If non-profit MFIs have increased lending significantly faster than for-profits (we suspect unlikely, since for-profits are more likely to raise commercial funds for lending), the true upward trend in for-profit market share would be lower. Second, survivor bias: MFIs that failed before data collection by MIX will not appear in the data. If for-profits fail more frequently than non-profits, it could be that the true for-profit share has not increased as much as it appears to have done. Third, we do not observe changes in profit status, only the status as of 2011. However, inspecting changes in *legal status* (e.g. NGO to non-bank financial intermediary) over 2008-2011, we suspect that these are relatively rare compared to new entries, and changes are more likely to be from NGO to other forms that

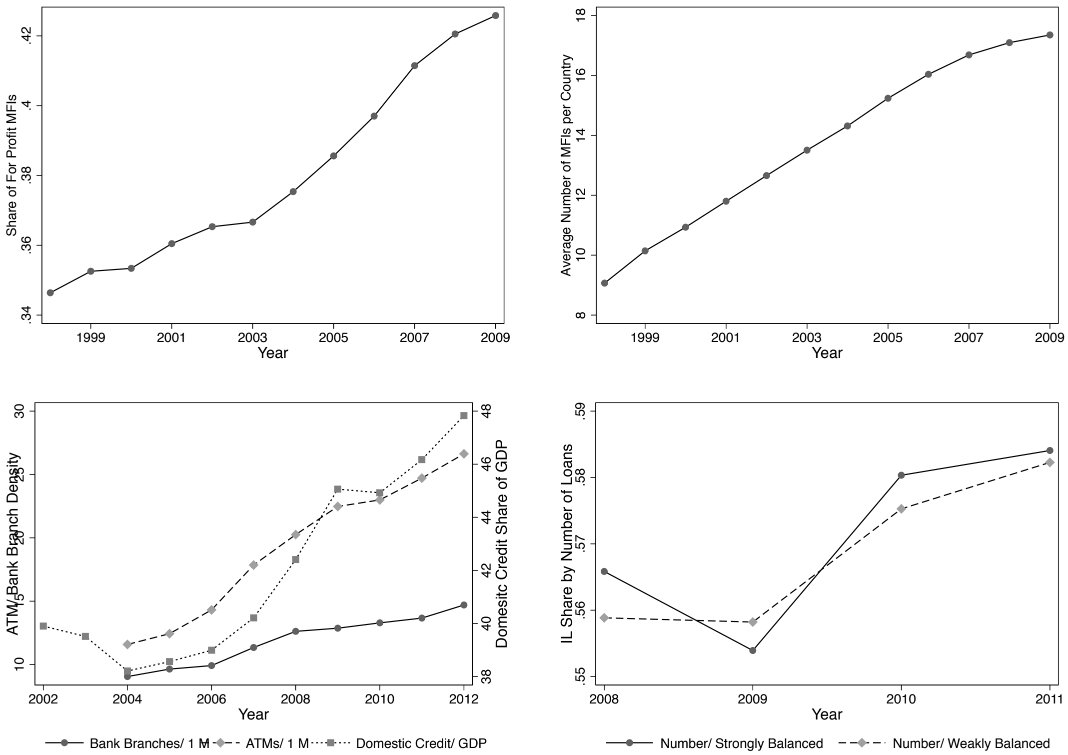


Figure 1: Three Stylized Facts. Top left and right: growth in the share of for-profit MFIs and the number of MFIs per country. Bottom Left: growth of proxies for competitiveness. Bottom right: growth of individual liability lending.

Second, in the top right figure we document that the average number of MFIs per country roughly doubled over the same period, using the same sampling frame and data on founding dates.

Third, in the bottom left figure we document growth in three country-level variables that arguably proxy for credit market competition and are commonly

are more likely to be for-profit, see further discussion below. Finally, we can only include data for MFIs that report to MIX, including their profit status and founding dates; if non-profits and for-profits' report at different rates *as a function of founding date*, the picture would change. In general, we expect each of these concerns to primarily affect the *level* of the for-profit share, rather than the qualitative trend.

referred to as proxies of financial access or financial depth (see e.g. Levine, 2005; Čihák et al., 2013).[9] We plot the growth of financial access, measured by the Commercial Bank Branch density and ATM density, and, the evolution of financial depth, measured as the domestic credit provided by the financial sector, relative to GDP. Using the set of countries that we observe in the MIX data between 2008-2011, we plot simple cross-country averages over time.[10] Financial access has expanded steadily over time: the number of bank branches per 1 million inhabitants has increased from 9.05 to 13.7 over our period. The prevalence of ATM follows a similar pattern. Financial depth, as measured by domestic credit, has expanded by around 26% over the sample period. Our empirical strategy relies on these variables forming a valid proxy for competition. For the formal banking sector, Beck, Demirgüç-Kunt and Maksimovic (2004) is one of several papers that suggests that financial access and depth are positively associated with competition. Unfortunately, we were not able to find any reliable direct measures of the competitiveness of the microfinance sector: in particular, the selection of MFIs into and out of the MIX Market data that we discuss in detail make it impossible in our view to construct useful competitiveness measures from these data.

The bottom right figure attempts to illustrate the change in MFI lending methodologies over time. This is a challenge. Primarily, our panel is short, while we are interested in long-run trends. Second, as we explain below, reporting limitations constrain us to examining within-MFI trends. We do the best we can given the data limitations, and find evidence of a trend toward IL in the 2008-2011 period.

For each MFI we compute, for each year it is available, the fraction of IL loans by number (i.e. ignoring loan size. Weighting by size gives a very similar picture). Only around a quarter of MFIs report this variable in every year of

[9]These are available from the World Bank Development Indicators and have been collected mainly through the Financial Access Surveys, maintained by the International Monetary Fund. This data has been used in the past to study outreach of the financial sector, e.g. by Beck (2007) or Ahlin, Lin and Maio (2011).

[10]The picture is very similar if we weight by size of MFIs or number of MFIs in the relevant country, i.e. assigning more weight to countries with larger MFI sectors.

our data, and two thirds report in at least two years. Therefore looking at cross-sectional means over time risks confounding changes in actual lending practices with selection into and out of the sample. We instead plot only *within-MFI* changes. In other words, we show the evolution of the average MFI's IL share over time, taking out changes in the composition of that average. We regress IL shares on year and MFI fixed effects, then plot the year fixed effects. We use both a "strongly balanced" panel of 348 (340) MFIs that report every year by Number of Loans (Gross Loan Portfolio), and a "weakly balanced" panel of 879 (832) MFIs that report at least twice by Number of Loans (Gross Loan Portfolio). Both indicate a roughly 2 percentage point increase in the share of IL loans over the period.[11] [12]

3 Model

Our starting point is a model of credit under weak enforcement, as in Besley and Coate (1995). There is a population of atomistic, risk neutral borrowers. Borrowers are homogeneous and each period have access to a productive technology that requires one unit of capital and produces $R > 1$ units of output with probability $p > 0$ (success), and nothing otherwise (failure). Borrowers do not have access to a saving technology so must borrow one unit of capital each period if they wish to invest.[13] Borrowers' liability is limited to their cash

[11] Giné and Karlan (2014) report similar figures for 2007-2009, also using the MIX data. However, in 2007 just 31 institutions reported their lending methodology, hence our focus on 2008-2011.

[12] An alternative approach to constructing the figure would be to weight by MFI size, to account for relative growth of lenders according to their methodology (e.g. predominantly IL lenders growing, or predominantly JL lenders shrinking). This is only possible in the strongly balanced panel. We find that the picture is less clear than for the within-MFI changes, with the caveat that it is unclear to us how one should best weight MFIs in this calculation. Finally, ideally we would like to also account for entry/exit of lenders according to lending methodology. Given our data this is simply not possible, as we only observe founding dates up to 2009 and essentially all entry into or exit from our sample is driven by reporting, not MFI founding or closure.

[13] This is a common assumption in the literature, and some form of saving constraint is required to avoid a Bulow and Rogoff (1989) unravelling of the dynamic repayment incentives used by the lender. It does not appear unreasonable in the microcredit context, see e.g. Dupas and Robinson (2013*a*,*b*).

on hand, so they cannot repay if unsuccessful. They discount exponentially with discount factor δ.[14]

There are one or more lenders, who each face a gross opportunity cost of funds equal to ρ. If the borrower is successful in obtaining a loan, she borrows 1 each period and repays gross interest rate r. If she defaults, her contract is terminated and she receives no future loans from that lender. In the equilibria we focus on she will repay with some probability π (i.e. paying πr in expectation each period), and her contract will be renewed with probability π. If it is terminated, she becomes "unmatched" and receives continuation value U (e.g. the option value of waiting for a new lender to offer her a contract). The value function of a borrower who has received a loan is therefore

$$V = pR - \pi r + \delta \pi V + \delta(1-\pi)U = \frac{pR - \pi r}{1-\delta\pi} + \frac{\delta(1-\pi)U}{1-\delta\pi}.$$

Lenders can offer either IL or JL contracts. An IL contract requires a borrower to repay her loan, otherwise her contract is terminated. She faces one choice: to repay when successful. If the contract makes her better off repaying, she repays whenever successful, i.e. with probability $\pi^{IL} = p$.

A JL contract binds together a pair of borrowers and requires both loans to be repaid, otherwise both contracts will be terminated. This gives borrowers an incentive to repay on behalf of an unsuccessful partner, an incentive that can be strengthened by the use of social sanctions.[15] However it might also induce a successful borrower to default rather than repay on behalf of her unsuccessful partner. In the latter case it is straightforward to show that IL can earn both higher profits and higher borrower welfare than JL, so JL will

[14] The benchmark model assumes the borrower wants to borrow every period, but easily extends to the possibility that with some probability x she discovers at the beginning of the period that she will never want to borrow again (e.g. because she loses access to the investment technology, or because of a positive wealth shock). In this case, her effective discount factor becomes $\delta' = \delta(1-x)$ because with probability x the continuation value of the loan contract falls to zero. A similar modification can allow for the case where she only wants to borrow infrequently.

[15] A possibility that we do not consider in this paper (because it does not arise in equilibrium under our assumptions) but analyze extensively in de Quidt, Fetzer and Ghatak (forthcoming) is that IL borrowers might also assist one another with repayment.

not be offered. In the former, both loans are repaid whenever at least one borrower succeeds, with probability $\pi^{JL} = p(2-p)$.[16] We define

$$q \equiv p(2-p).$$

Borrower welfare under IL and JL therefore equals:

$$V^{IL} = \frac{pR - pr}{1-\delta p} + \frac{\delta(1-p)U}{1-\delta p} \tag{1}$$

$$V^{JL} = \frac{pR - qr}{1-\delta q} + \frac{\delta(1-q)U}{1-\delta q}. \tag{2}$$

The first incentive constraint, IC1, is identical under IL or JL: the borrower must be willing to repay her own loan (under JL: when her partner is also repaying). If she does, she renews her contract and receives continuation value V, if she does not, she becomes unmatched and receives U. The condition is thus $\delta V - r \geq \delta U$, which simplifies to:

$$r \leq \delta pR - \delta(1-\delta)U \equiv r_{IC1}(U). \tag{3}$$

Under JL there is a second constraint, IC2: the borrower must be willing and able to repay on behalf of her unsuccessful partner. Her choice is to either repay two loans and renew her contract, receiving V, or default. If she defaults, her contract is terminated and she faces a social sanction of size S, so she receives $U - S$.[17] Thus the condition is $\delta V - 2r \geq \delta(U - S)$, or:

$$r \leq \frac{\delta pR - \delta(1-\delta)U + \delta(1-\delta q)S}{2-\delta q} = \frac{r_{IC1}(U) + \delta(1-\delta q)S}{2-\delta q} \equiv r_{IC2}(U,S). \tag{4}$$

[16] For simplicity, we assume throughout the symmetric equilibrium such that successful borrowers always repay their own loan when their partner was successful, and repay both when their partner was unsuccessful. This maximizes expected borrower welfare and has the weakest incentive compatibility conditions over all (time-invariant) repayment rules.

[17] An obvious question is why the JL version of IC1 does not include an S term, i.e. why does a JL borrower's partner not sanction her for defaulting? The reason is that under JL, the partner has no reason to threaten a social sanction in this case: if IC1 is violated it is optimal for both borrowers to default.

Only one of IC1 or IC2 can bind, depending on the level of S. IC2 is tighter if:

$$S \leq pR - (1 - \delta)U = \bar{S}(U). \tag{5}$$

We take social capital, S, to be a measure of all the informal means borrowers can use to persuade one another to assist with repayment. These can include loss of reputation, loss of a friendship, shame, non-pecuniary punishments, et cetera.[18] We assume that S is symmetric within borrowing groups, is observable to the lender (so the lender can base his contract offer on S), and distributed in the population with cumulative density $F(S)$.

For IC1 to hold it must be that $V > U$: alternative sources of credit cannot be so freely available that the borrower is always better off defaulting on her current loan and taking her outside option. We therefore assume there is excess demand for credit (credit rationing), ensuring that a) lenders are free to set the interest rate and b) lenders can always costlessly replace a terminated borrower.[19]

Finally, we must check whether the borrower is *able* to repay, i.e. check the relevant limited liability constraint(s) (LLC). IC1 implies $r < R$, so the borrower can always repay at least one loan. Under JL the borrower must sometimes repay two loans, requiring $2r < R$.[20] For simplicity we impose a parameter restriction that ensures that the LLC never binds, but note that our qualitative results do not depend upon this and that the equivalent restriction would become weaker if we allowed for larger borrowing groups or for borrower output to take intermediate values between 0 and R. In equilibrium, IC1 ensures that r can never exceed δpR, so we assume $\delta pR < \frac{R}{2}$ or:

[18] For further discussion, see de Quidt, Fetzer and Ghatak (forthcoming) and de Quidt, Fetzer and Ghatak (2016).

[19] If the borrower's outside option derives exclusively from access to alternative MFI lenders, credit rationing is guaranteed in equilibrium (de Quidt, Fetzer and Ghatak, 2016).

[20] Obviously this is a somewhat restrictive condition: the borrower's income when successful must exceed the full repayment of two loans. Its restrictiveness stems from two of our key simplifying assumptions: groups of size two and the Bernoulli income distribution. A smoother income process (such that the unsuccessful partner can contribute to her repayment) and bigger groups (so the repayment burden can be split across more successful partners) relax the LLC. See, for example, the simulation results in de Quidt, Fetzer and Ghatak (forthcoming).

Assumption 1 $\delta p < \frac{1}{2}$.

3.1 Non-profit lender

The non-profit chooses the contract that maximizes borrower welfare, subject to IC1, IC2 and a zero-profit condition: $\pi r \geq \rho$, where π is the repayment probability. We denote equilibrium values (for example, utilities, interest rates) under non-profit lending with a "hat" (e.g. $\hat{x}$). The non-profit interest rates under IL and JL are:

$$\hat{r}^{IL} \equiv \frac{\rho}{p} \qquad \hat{r}^{JL} \equiv \frac{\rho}{q}. \tag{6}$$

To focus on the choice between IL and JL, we assume that the lender is always able to at least break even under an IL contract. We define a maximum value for U, $\bar{U}$ such that IC1 binds at the zero-profit rate $\hat{r}^{IL}$ (and therefore IC1 is satisfied at $\hat{r}^{JL}$ since $\hat{r}^{JL} < \hat{r}^{IL}$).

Assumption 2 $U \leq \bar{U} \equiv \frac{\rho - \delta p^2 R}{\delta p(1-\delta)}$.

If $U > \bar{U}$, both lender types offer JL when JL at least breaks even, and shut down if it does not, so there is no variation in contracts offered.

Substituting for $\hat{r}^{IL}$ and $\hat{r}^{JL}$, inspection of (1) and (2) reveals that $\hat{V}^{JL} > \hat{V}^{IL}$. When the JL contract is incentive-compatible, borrowers are able to repay more frequently, lowering their interest rate and increasing their contract renewal probability. Therefore, the lender will always offer JL provided IC2 is satisfied at $\hat{r}^{JL}$. This can be written as $\rho \leq q \min\{r_{IC1}(U), r_{IC2}(U, S)\}$ or, since we know IC1 holds,

$$S \geq \max\left\{0, \frac{(2-\delta q)\rho - \delta q[pR - (1-\delta)U]}{\delta q(1-\delta q)}\right\} \equiv \hat{S}(U). \tag{7}$$

If $S < \hat{S}$, IL is offered.[21] Given Assumption 2, a sufficient condition for $\hat{S} < 0$

[21] Note that Assumption 2 implies $\hat{S}(U) < \bar{S}(U)$.

is that JL is always more profitable than IL:

$$p < \delta q. \tag{8}$$

Our first result relates the non-profit's use of JL to the level of competition. Increasing competition is captured by an increase in the borrower's outside option, U. If she defaults on a loan from her current lender, she can go on to obtain a loan elsewhere. This tightens both IC1 and IC2, since the maximum interest rate at which repayment is incentive compatible under either contract decreases.

Proposition 1 $\hat{S}'(U) > 0$. *In other words, the minimum amount of social capital needed for JL to break even is increasing in the level of competition. Thus, competition reduces joint liability lending by non-profits.*

Competition improves the borrower's outside option, reducing the cost of losing her existing contract. As a result, for a given interest rate the minimum level of social capital for a borrower to be willing to repay her partner's loan is increasing in competition.

3.2 For-profit lender

The for-profit lender, unsurprisingly, maximizes profits. Since he can always costlessly replace a terminated borrower next period, he does not discount future profits from a given borrower, instead maximizing only per-period profit $\Pi = \pi\tilde{r} - \rho$. We denote equilibrium quantities under for-profit lending by a tilde ($\tilde{x}$). Profits are maximized at the maximum incentive-compatible interest rate, which under IL is $\tilde{r}^{IL}(U) = r_{IC1}(U)$. Under JL the maximum rate is the minimum of $r_{IC1}(U)$ and $r_{IC2}(U, S)$, so $\tilde{r}^{JL}(U, S) = \min\{r_{IC1}(U), r_{IC2}(U, S)\}$.[22]

[22] If the lender sets the JL interest rate higher than $r_{IC2}(U, S)$, then the borrowers repay only when both are successful, with probability p^2, and he cannot earn more than under IL. If he sets $r > r_{IC1}(U, S)$ the borrowers always default.

The lender offers JL when $q\tilde{r}^{JL}(U,S) > p\tilde{r}^{IL}(U)$, or

$$S \geq \max\left\{0, \frac{p(p-\delta q)[pR-(1-\delta)U]}{q(1-\delta q)}\right\} \equiv \tilde{S}(U).$$

Condition (8) is now necessary and sufficient for the lender to always offer JL. It is easy to check that $\tilde{S}(U) \geq \hat{S}(U)$, and hence the for-profit is always (weakly) less likely to offer JL than the non-profit.

Proposition 2 *For a given level of competition, U, a non-profit lender is more likely to offer JL than a for-profit: $\tilde{S}(U) \geq \hat{S}(U)$.*

The intuition for the proposition is straightforward. The non-profit offers JL whenever it breaks even, because JL maximizes borrower welfare. The for-profit also requires JL to break even, but additionally it must be more profitable than IL. Since this is a stricter condition, the for-profit ends up offering JL to fewer borrowers. It is easily verified that the expressions for $\hat{S}$ and $\tilde{S}$ coincide at $U = \bar{U}$, i.e. when U is so high that IL is just breaking even.

We have assumed that the for-profit is myopic, ignoring the impact on future profits of retaining a borrower for longer. The motivation for this assumption is that lenders have limited capacity relative to demand, so the lender can easily replace a defaulting borrower next period. However, it is easy to see that the result also holds for a patient for-profit, who discounts the future with discount factor $\beta \in [0,1]$. Now the net present value of profits from a given borrower are $\frac{\pi\tilde{r}-\rho}{1-\beta\pi}$. The non-profit offers JL provided it is possible to break even with a JL contract, which is equivalent to checking $q\tilde{r}^{JL}(U,S) - \rho \geq 0$. The for-profit offers JL whenever it is more profitable than IL, i.e. when $\frac{q\tilde{r}^{JL}(U,S)}{1-\beta q} \geq \max\left\{0, \frac{p\tilde{r}^{IL}(U)-\rho}{1-\delta p}\right\}$, which is a more restrictive condition for all β.

Next we consider the impact of competition on the for-profit's use of JL.

Proposition 3 *For-profit lenders become* more *likely to offer JL as competition increases: $\tilde{S}'(U) < 0$.*

The result follows from the fact that revenue under JL is less sensitive to U than under IL. Under IL the relevant incentive constraint (IC1) determines the maximum single payment the borrower is willing to make, $\delta(V - U) = r$, so increases in U are passed through to decreases in r. Under JL, the relevant incentive constraint (IC2) determines the maximum *double* payment the borrower will make, $\delta(V - U + S) = 2r$, so for a given decrease in the left-hand-side, the interest rate r falls by half as much.[23] Therefore, profits decrease faster under IL than JL, can make JL more profitable when U is sufficiently high.

Collecting results, we see that competition decreases JL usage by non-profits. Conversion to for-profit also decreases JL usage, but competition increases JL usage by for-profits. Finally, an observation:

Observation 1 *For a given level of social capital, S, an increase in U cannot induce both the non-profit to switch from JL to IL and the for-profit to switch from IL to JL.*

The observation follows formally from Proposition 2, which shows that for profits always have a higher threshold than non-profits for offering JL. Intuitively, if the non-profit switches to IL it is because JL can no longer break even, thus the for-profit will not switch to JL.

3.3 Joint liability over time

Now we use the assumed heterogeneity of S in the population to study changes in the aggregate level of IL and JL lending. We first derive the steady state share of borrowers receiving IL loans for a given share of for-profit lenders in the market, which we denote by f, and a given level of the borrowers' outside option U. Then we analyze comparative statics on these variables. We deliberately take f and U as exogenous since these are our measures of commercialization that we will attempt to study in the data.

We assume that lenders are atomistic with a fixed capacity of two borrowers per period, enabling them to each serve either two IL borrowers or one JL

[23]Note that V also depends on both U and r, with different slopes under IL and JL, complicating the relation between U and r. Inspection of r_{IC1} and r_{IC2} reveals that $\frac{\frac{dr_{IC1}(U)}{dU}}{\frac{dr_{IC2}(U,S)}{dU}} = \frac{1}{2-\delta q} \in (0.5, 1)$.

group. At the end of each period, lenders terminate all defaulting IL borrowers or JL groups. We then make two technical assumptions for simplicity. First, because IL defaults can leave lenders with a single vacancy, we assume that surviving IL borrowers are reshuffled to fill vacancies in other equivalent IL branches. This ensures that (with the exception of a zero measure of "remainder" borrowers when there is an odd number of defaults) branches either have two or zero vacancies at the beginning of the next period, and can therefore freely offer IL or JL. Second, a borrower whose contract is terminated rejoins the pool of unmatched borrowers and draws a new potential borrowing partner and value of S from F. This ensures that S is always distributed according to F in the pool. Atomistic lenders imply that borrowers' histories do not matter since they will never re-match with a previous lender.

Borrowers without a current loan contract receive utility U. At the beginning of a period, branches with vacant spaces fill them by drawing a pair of borrowers at random from the pool of unmatched borrowers. They observe the pair's value of S, and offer them either an IL or JL contract which determines their value for V. Non-profits offer IL when $S < \hat{S}(U)$, and for-profits offer IL when $S < \tilde{S}(U)$, i.e. with probability $F(\tilde{S}(U))$. If a borrower rejects, she goes back to the pool until next period. Since the lender will always offer a contract such that $V > U$ (otherwise the incentive conditions are violated), borrowers always accept.

Denote by $\hat{\eta}(U)$ ($\tilde{\eta}(U)$) the steady-state fraction of non-profit (for-profit) lenders offering IL. When filling a vacancy at a non-profit (for-profit) lender, a borrower receives an IL contracts with probability $F(\hat{S}(U))$ ($F(\tilde{S}(U))$), since we assumed she her value of S was drawn anew from F. However, IL and JL borrowers default and re-enter the pool at different rates ($1-p$, and $1-q$ respectively), so JL groups survive for longer. As a result in steady state, where the flows into and out of IL/JL are equalized, the fraction of IL borrowers will be smaller than $F(S)$ and the fraction of JL borrowers larger than $1-F(S)$.

Solving for the steady states, we obtain $\hat{\eta}(U) = \frac{F(\hat{S}(U))(1-p)}{1-F(\hat{S}(U))p} < F(\hat{S}(U))$ and $\tilde{\eta}(U) = \frac{F(\tilde{S}(U))(1-p)}{1-F(\tilde{S}(U))p} < F(\tilde{S}(U))$. The steady state JL shares are $1-\hat{\eta}(U) = \frac{1-F(\hat{S}(U))}{1-F(\hat{S}(U))p}$ and $1-\tilde{\eta}(U) = \frac{1-F(\tilde{S}(U))}{1-F(\tilde{S}(U))p}$. Derivations are given in the Appendix.

With these objects in hand, the steady state IL share in the market is $\eta(U) = f\tilde{\eta}(U) + (1-f)\hat{\eta}(U)$. How does the IL share change over time? It depends on the change in U and the change in f. We can write it as:

$$\frac{d\eta}{dt} = \frac{df}{dt}\underbrace{[\tilde{\eta}(U) - \hat{\eta}(U)]}_{\geq 0}$$
$$+ \frac{dU}{dt}(1-p)\left[f \underbrace{\frac{F'(\tilde{S}(U))\tilde{S}'(U)}{(1-pF(\tilde{S}(U)))^2}}_{\leq 0} + (1-f) \underbrace{\frac{F'(\hat{S}(U))\hat{S}'(U)}{(1-pF(\hat{S}(U)))^2}}_{\geq 0} \right].$$

An increase in the share of for-profits increases the share of IL lending, as for-profits demand more social capital to offer JL. The effect of an increase in the borrowers' outside option (for example, because of an increase in competitiveness) is ambiguous, as it increases IL lending by non-profits and JL lending by for-profits. However when the initial share of for-profits is low (f close to zero), the effect of increasing U will also be to increase η.

Observation 2 *Provided the initial share of for-profits in the market is sufficiently low, concurrent growth in for-profit lending and competition lead to an overall increase in IL lending.*

3.4 Endogenizing U

Ideally, we would like to endogenize U as a function of the scale of lending relative to the borrower population (since this determines how long an unmatched borrower must wait for a loan) and the share of for-profits (since for-profits charge higher interest rates and so are a less attractive outside option). It is straightforward to do so in competitive equilibrium with homogeneous S (i.e. F is degenerate), and we do so in de Quidt, Fetzer and Ghatak (2016) in order to make statements about aggregate welfare. When S is homogeneous a given lender type (non-profit/for-profit) either offers only IL or JL loans. In competitive equilibrium the lender's motivation does not matter: there is just one feasible contract that breaks even. We show that the level of social capital required for the competitive market to offer JL is higher than a monopolist non-profit, and lower than a monopolist for-profit. In other words, transition from an uncompetitive, not-for-profit industry to a competitive one increases the likelihood that IL is used.

However, the model in this paper necessarily focuses on behavior out of competitive (i.e. zero-profit) equilibrium, to analyze the effect of changing lender motivation and market competitiveness on the contracts offered. Solving for the equilibrium value of U and deriving comparative statics is much more complex in this setting. For this reason, we use our "reduced form" analysis which takes U as given to motivate the below empirical work, in which we test the model's three main predictions: that for-profits are more likely to use IL, that increasing competitiveness increases IL use by non-profits, and decreases it by for-profits. Appendix B.2 outlines the procedure for deriving an implicit function the equilibrium value of U when U is assumed to capture only the possibility of obtaining a loan from a competitor lender in future.

3.5 Ex-ante competition

So far we have modeled the effects of competition only through the borrower's outside option upon default, i.e. competition is *ex-post*, only affecting behavior after the contract is accepted. This is natural because we assumed throughout that credit is scarce relative to the number of potential borrowers, such that lenders have market power in setting prices but must pay attention to borrowers' ex-post incentive to repay. However the model does allow us to think in a simple way about *ex-ante* competition, whereby increased competition constrains the prices lenders can charge or face losing their clients.

There are three natural ways to model ex-ante competition. The first is that competition acts as a simple cap on the interest rate that lenders can charge under either contract, $r \leq \bar{r}$. This has no effect on the contract offering of non-profits, but may cause them to shut down entirely, while it predicts that for-profits increase their use of JL, as in Proposition 3. Non-profits already earn zero profits, so if the cap is binding they must shut down.[24] For-profits offer the profit maximizing contract, and charge higher interest rates under IL than JL. Therefore, the cap binds first on IL, reducing its profitability and increasing the attractiveness of JL. If it binds on both contracts, the lender will offer JL for sure since the interest rates are equalized but the repayment rate is higher under JL.

Second, ex-ante competition might manifest as a floor on borrower welfare that the contract must meet or exceed. Call this value $\underline{V}$. Since the non-profit maximizes borrower welfare, once again this constraint either has no effect or puts it out of business. Turning to the for-profits, we require $\tilde{V}^{IL} \geq \underline{V}$ and $\tilde{V}^{JL} \geq \underline{V}$. Using expressions (1) and (2), we obtain the implied bounds on revenue under IL and JL:

$$\overline{Revenue}^{IL} = pr^{IL} \leq pR + \delta(1-p)U - (1-\delta p)\underline{V}$$
$$\overline{Revenue}^{JL} = qr^{JL} \leq pR + \delta(1-q)U - (1-\delta q)\underline{V}.$$

Taking the difference, we obtain $\overline{Revenue}^{JL} - \overline{Revenue}^{IL} = \delta p(1-p)(\underline{V} - U)$. Noting that IC1 requires $V > U$, so the constraint can only bind when $\underline{V} > U$, we learn that the constraint is tighter on IL revenue than JL revenue, and therefore, to the extent that it is binding, will also push the lender toward offering JL, again in line with Proposition 3.

Finally, we could conceptualize ex-ante competition as putting an upper bound on profits, i.e. $\Pi = \pi r - \rho \leq \bar{\Pi}$. Assuming $\bar{\Pi} \geq 0$, for the non-profit this is never binding, since it earns zero profits, so once again there is no effect. For the for-profit it either has no effect or makes it indifferent between the contracts. It maximizes profits, $\pi r - \rho$, so this constraint only affects the profitability of the most profitable contract, not their (strict) ordering.

We sum up the findings with the following observation:

Observation 3 *Ex-ante competition that increases with commercialization*

[24]Notably, the cap doesn't induce switching between contract types. If they were offering IL before the cap we know that JL is not profitable, while because IL rates are higher, if the cap is binding on JL it already rendered IL unprofitable.

weakly reinforces the qualitative predictions of our main theory. The non-profit's contract choices are unaffected, while the for-profit is either unaffected or increases his use of JL in line with Proposition 3.

4 Empirical analysis

4.1 Data

The dataset we work with come from MIXMarket.org (henceforth MIX), an organization that collects, validates and publishes financial performance data of MFIs around the world. The MIX is the largest and most comprehensive source of data on microfinance institutions. For example, in 2011, 1,375 MFIs reported data on loan portfolio value and loans outstanding to the MIX. Their combined gross loan portfolio had a value of USD 71.5 billion across 151 million loans. Our estimating sample contains financial data for 1,000 MFIs, which provide some lending methodology data across a total of 3,479 observations, for the period from 2008 to 2011.[25] Our focus in this paper is to highlight trends in lending methodology. The MIX is the only data source of which we are aware that has collected this data systematically over time. Lending methodology, according to the MIX, is categorized into three categories: Individual, Solidarity Group and Village Banking/Self Help Group. The MIX is not explicit about whether joint liability is used; its definition reads "loans are considered to be of the Solidarity Group methodology when some aspect of loan consideration depends on the group, including credit analysis, liability, guarantee, collateral, and loan size and conditions." We follow other authors in treating such loans as JL. We also classify village-banking/self help groups as JL lending, though this is not important for our results.[26] Using these data we construct MFI-level IL portfolio shares, "IL shares."

[25] This is a significant subset of the 1,932 MFIs that report a total of 5,219 observations to the MIX in this four year period.

[26] Self-help groups are particularly common in India. Typically they take the form of small groups organized by an NGO, who take joint loans from a bank and distribute them among their members.

Lending methodology information is provided by MFIs in the Gross Loan Portfolio report and/or in the Number of Loans Outstanding report. In the paper we mostly focus on regressions based on the fraction of the number of loans under IL lending, and provide the (very similar) results based on the fraction of the gross loan portfolio in the appendix.

The main weakness of the MIX data is selection: the MFIs who report methodology data may not be representative of the population of MFIs, either because of missing observations (an MFI does not report in a given year) or missing variables (the MFI does not report one of our key measures in a given year). Because of these concerns, we work throughout with different sources of "within" variation (within region, country, MFI), based on two panel sampling frames. We study a "strongly balanced" panel of 348 (340), which report lending method by number of loans (gross loan portfolio) for all four years. We also present results from a "weakly balanced" panel of 878 (831), who report lending methodology by number of loans (gross loan portfolio) at least twice.[27] Because of the potentially non-representative sample we are less interested in the raw levels of IL/JL in our sample, instead focusing on changes. We must simply assume for external validity that (at least qualitatively) any trends or comparative statics we observe net of the relevant controls and fixed effects would also be observed in the population.

In view of selection concerns, we note that the MFIs that report lending methodology comprise a significant share of all loans in the MIX market dataset. The strongly balanced panels accounts between 24.7-34.4 percent of all loans in a given year (24.4-32.5 percent of all lending by Gross Loan Portfolio), while the weakly balanced panels account for between 52.0 -78.1 percent of all loans (50.8.7-71.4 percent of Gross Loan Portfolio). We are able to check whether our two panel datasets appear representative of the full dataset of

[27]In addition, sometimes there are discrepancies in the data. For example, the number of loans reported by each lending methodology might not add up to the total number of loans outstanding. We assume that such errors are not systematically over- or under-reporting the IL share, so for example an MFI reporting 100 IL and 100 JL loans but a total portfolio of 250, would be coded as 50 percent IL. Our results are robust to dropping observations with discrepancies.

MFIs. Table 1 presents summary statistics for the full sample, the weakly balanced and the strongly balanced sample.[28] We perform t-tests to compare the means of key observables between the MFIs included in the refined samples, and those excluded. Overall the two panel datasets look fairly representative of the full dataset, in particular on our key IL share and profit status variables, though we do find significant differences in some other variables.

For-profit/non-profit status ("profit status") is recorded as a static variable, reported in the 2011 data snapshot. One concern might be that MFIs have changed status over time without us knowing. We do have data on transitions of legal status and legal status and profit status are very tightly related. Most (84 percent) non-profit MFIs have either Credit Union/Cooperative or NGO as legal status (see Appendix Table 4). In our sample period, out of the 1,000 MFIs, only 13 have changed their legal status. Out of those, 7 transitions were from NGO to Non-Bank Financial Institution, mostly associated with for-profits. The low frequency of legal status changes suggests that profit status changes are unlikely to endanger our results, and removing institutions that changed legal status does not change our results.

We use three proxies for the extent of credit market competition which enters the borrowers' outside options, U in the model.[29] These data come from the Financial Access Survey collected by the International Monetary Fund. They have been used in the past to study outreach of the financial sector, for example, by Beck (2007), Ahlin, Lin and Maio (2011), Levine (2005), and Čihák et al. (2013). They are incorporated in the World Development Indicators. We mostly focus on the variable measuring the number of commercial bank branches per million people; in addition, we obtain similar results using

[28]This table includes MFIs reporting IL shares by number of loans. Table 5 reports the equivalent figures for the sample defined by GLP IL share data. Because not every MFI is observed every year, we report the 2009 values where available (since 2009 has the greatest data availability), otherwise we take the closest available datapoint (averaging 2008 and 2010 when both are available).

[29]An obvious alternative to the proxy variables would be to try to construct competition measures from the MIX data, e.g. computing concentration indices. We do not pursue this because such measures are highly sensitive to the selection issues discussed above, and we suspect most of the cross- and within-country variation would be spurious.

two other indicators of financial development: the density of ATMs per million people and the overall measure of domestic credit provided by the financial sector as a share of GDP. We exploit the differential effect of changes in these measures of financial development on the choice of lending methodology by MFIs. In our regressions, we standardize these variables to mean zero, standard deviation one, to ease interpretation and comparison of their coefficients. Our country-level observables are summarized in Table 2.

4.2 Empirical Specification

We test three predictions of the model, that (1) non-profits use JL relatively more than for-profits; (2) that competition increases JL use by for-profits via a general equilibrium effect; and (3) competition decreases JL use by non-profits.

To test these predictions, we estimate the following main specification:

$$IL_{icrt} = \alpha\, NP_i + \eta\, C_{ct} + \gamma NP_i \times C_{ct} + \mathbf{X}'_{ict}\beta + a_{icr} + b_t + \epsilon_{icrt}. \tag{9}$$

Here, IL_{icrt} measures the share of individual liability loans, measured either based on Number of Loans or based on the Gross Loan Portfolio of an MFI i in country c, region r, and year t. NP_i is an indicator variable for whether MFI i is a non-profit, while C_{ct} is a country-year level measure of competition. a_{icr} is an MFI, country, or region fixed effect, and b_t is a year fixed effect. For robustness checks, we also control for further covariates that vary at the country level or the MFI level and are included in $\mathbf{X}_{ict}$; these are discussed further below.

Mapping the tested predictions into parameter estimates: (1) non-profits have lower IL shares ($\alpha < 0$); (2) competition decreases the use of IL by for-profits ($\eta < 0$); (3) competition increases the use of IL by non-profits ($\eta + \gamma > 0$). We additionally test whether the effect of competition on non-profit IL shares is more positive than on for-profits ($\gamma > 0$).

We exploit variation at two levels. First, we exploit variation across MFIs within a region or country in order to estimate the coefficient α, since the non-profit indicator does not vary within MFI. For these specifications, we control for region or country fixed effects and year fixed effects. Secondly, we exploit variation within MFIs over time, in order to more cleanly identify how changes in competition C_{ct} affect for-profit MFIs differently from non-profit MFIs. In these specifications we cannot estimate α for obvious reasons.

4.3 Main Results

The main results are presented in Table 3. We present results for both the strongly and weakly balanced panels, and for both measures of IL share.

The results support the model. Each of the three coefficient sign predictions consistently holds across specifications, though not all point estimates are statistically significantly different from zero. On average, we estimate that non-profits have lower IL shares, and this coefficient is quite stable across specifications (around 10–20 percentage points). An increase in bank branch density induces for-profits to lower their IL share (these point estimates vary, from 1.7 to 10.0 percentage points per one standard deviation change in bank branch density), while non-profits raise theirs (all but one coefficient positive, ranging from -0.5 to $+4$ percentage points per standard deviation change).

The main concerns with this empirical analysis fall into three categories. First, the expansion of commercial bank branches may just capture some other macroeconomic trends which are non-causally correlated with changes in lending methodology. Second, the expansion of commercial bank branches may be a poor proxy for competition. Third, non-profit status or our competition measures could be confounded with other MFI-level characteristics (though this is somewhat addressed by our fixed effects strategy). We will address each of these concerns in turn.

4.3.1 Robustness to additional controls

An obvious concern with our identification strategy is that we proxy for competition with country-level variables that may capture other within-region differences or within-country trends. For example, if individual loans are difficult to administer in rural areas, differences in urbanization might be driving the effects we see. Or perhaps the shift towards IL lending reflects the growth of mobile banking, which can substitute for the transaction cost-lowering benefits of group lending. Lastly, as our sample period covers the period following the financial crisis, we may be concerned about the regulatory changes, which may have affected MFIs differentially.

We perform several checks. First, we interact the non-profit indicator with additional country level covariates (also taken from the World Development Indicators) to highlight the extent to which these concerns apply.[30]

Results are presented in Appendix Tables 6 and 7. The signs, magnitudes and the precision of our main coefficients are highly robust, and if anything the results are somewhat strengthened.

Appendix Table 8 checks robustness to inclusion of further control variables that vary at the country and MFI level. We control for non-linear country-specific trends (using country-year fixed effects). This of course precludes estimation of the direct effect of the competition proxies (so we cannot test $\eta < 0$ or $\eta + \gamma > 0$), but we can still exploit within-country variation to analyze the differences in behavior of non-profits and for-profits, testing whether $\alpha < 0$ and $\gamma > 0$. We also control for some MFI-level indicators (and/or fixed effects): a static measure capturing the MIX Market's assessment of the sustainability of an MFI's operations ("Diamonds"), and time-varying measures (namely, Capital to Asset Ratio, Debt to equity ratio, Average loan balance per borrower, Return on assets, Financial revenue/Assets, Yield on gross portfolio, Financial expense/assets ratio, and Operating expense/assets ratio). We lose some observations as not all variables are available for all MFIs. The coefficients remain stable relative to the main specifications, consistently estimating a lower IL share for non-profits and a more positive effect of competition on IL lending by non-profits than for-profits.

While our model abstracts from loan size, for a given level of social capital S, growth in loan sizes (perhaps driven by income growth) also predicts a shift toward IL. This is because the larger the loan, the more social capital

[30]We include the urban population share, mobile phones per 100 people, GDP per capita, agriculture/industry shares in GDP, and foreign aid.

is required for a JL borrower to be willing to assist her partner, making low social capital JL groups no longer viable. It is therefore encouraging that our coefficient estimates are robust to inclusion of controls for GDP and loan size, because this gives confidence that the trend we observe is not simply capturing by other changes in lending behavior.

4.3.2 Robustness to other proxies for competition

In this section, we show that our results are robust to using two other proxy variables for the extent of competition. Results can be found in Appendix Tables 9 and 10. First, we focus on the density of ATMs (measured per million inhabitants, then standardized by us). This measure has been previously used as a proxy variable for financial access in the literature. As with the bank branch density, we believe this is a variable that is correlated with borrowers' outside option at a given MFI, while not directly measuring competition between MFIs. The coefficient pattern is very similar to our previous results, though the point estimates are less precise, see Appendix Table 9.

Our third proxy variable is commonly referred to as Financial Depth and measures the overall size of the domestic credit market: the share of loans given by domestic financial institutions relative to GDP. The pattern of coefficients is again similar to our baseline results using this alternative proxy of competition. While some of the point estimates are implausibly large, it is to be noted that by imposing linearity our specification permits estimates of changes in portfolio shares that exceed 100 percent.

Overall, the evidence is broadly consistent with the theoretical predictions.

4.3.3 Regulation shocks

One concern is that the patterns we observe might be driven by regulatory changes during our sample period which happen to correlate with our proxy variables. We attempt to address such concerns in Appendix Table 13.

First, we drop India from the main regression specification. India is an important country for microfinance, as it has given rise, over just a short time period, to some of the biggest institutions. However, over our sample period it experienced a major repayment crisis (in the state of Andhra Pradesh), which triggered regulatory changes in that state (essentially shutting down the industry) as well as leading the drafting of the "Microfinance Bill," which is presently in the pipeline through the Parliamentary process.[31] Our results, if anything, are stronger when India is dropped.

In a further specification we control flexibly for time-varying regulatory shocks, using Region by Legal Status by Year fixed effects (legal status and for-profit status are correlated but not collinear). Under the assumption that regulation varies according to legal status and not profit status, this specification controls for time-varying regulatory shifts, albeit at the regional and not country level. Our results, if anything, get stronger.

5 Conclusion

While it often claimed that joint liability is in decline, there is little analysis beyond some allusions to JL being inconvenient for borrowers, who dislike having their social capital leveraged in this way. For this taste-based argument to have bite in explaining the trend, there must be a change in tastes over time, which is very difficult to test (in particular because we are aware of no dataset that even attempts to measure such preferences).

We show that even with stable tastes, commercialization predicts the decline. Our paper is the first rigorous attempt to examine the trend empirically, and to analyze its cause. We show that MFIs do indeed appear to be reducing the share of JL in their portfolios, albeit over a short panel. We argue theoretically that a key mechanism underlying the decline of JL is commercialization: a hand-in-hand increase in competition alongside a shift from non-profit to for-profit lending, and show that both trends are present in the data. Finally, we test the model under a variety of sampling frames and with an increasingly stringent set of fixed effects and controls. Overall, we find the data are largely qualitatively consistent with the theory: non-profits do use JL more

[31] See de Quidt, Fetzer and Ghatak (2012) for further background.

than for-profits; competition increases the use of JL by for-profits and (in most specifications) reduces its use by non-profits. Unfortunately, though we use the best-available data, they are imperfect. In particular we do not have a fully balanced and representative panel and our competition measures are proxies rather than direct measures and so we avoid making quantitative claims based on our results. Also, while we control for a number of observables and fixed effects, in the absence of a natural experiment, we do not have a way of causally identifying the effect of changes in market structure on the switch from JL to IL. We hope our analysis can be complemented with more micro-level evidence that can test some of the mechanisms highlighted in the paper.

References

Ahlin, Christian, and R M Townsend. 2007. "Using Repayment Data to Test Across Models of Joint Liability Lending." *The Economic Journal*, 117(517): F11–F51.

Ahlin, Christian, Jocelyn Lin, and Michael Maio. 2011. "Where does microfinance flourish? Microfinance institution performance in macroeconomic context." *Journal of Development Economics*, 95(2): 105–120.

Allen, Treb. forthcoming. "Optimal (Partial) Group Liability in Microfinance Lending." *Journal Of Development Economics.*

Armendáriz de Aghion, Beatriz, and Jonathan Morduch. 2010. *The Economics of Microfinance, Second Edition. MIT Press Books*, Cambridge, MA:The MIT Press.

Attanasio, Orazio, Britta Augsburg, Ralph De Haas, Emla Fitzsimons, and Heike Harmgart. 2015. "The impacts of microfinance: Evidence from joint-liability lending in Mongolia." *American Economic Journal: Applied Economics*, 7(1): 90–122.

Baland, Jean-Marie, Rohini Somanathan, and Zaki Wahhaj. 2013. "Repayment incentives and the distribution of gains from group lending." *Journal of Development Economics*, 105: 131–139.

Beck, Thorsten. 2007. "Reaching out: Access to and use of banking services across countries." *Journal of Financial Economics*, 85(1): 234–266.

Beck, Thorsten, Asli Demirgüç-Kunt, and Vojislav Maksimovic. 2004. "Bank Competition and Access to Finance: International Evidence." *Journal of Money, Credit, and Banking*, 36(3b): 627–648.

Besley, Timothy, and Stephen Coate. 1995. "Group lending, repayment incentives and social collateral." *Journal of Development Economics*, 46(1): 1–18.

Breza, Emily. 2011. "Peer Effects and Loan Repayment: Evidence from the Krishna Default Crisis." *mimeo*, 1–60.

Bulow, Jeremy, and Kenneth Rogoff. 1989. "Sovereign Debt: Is to Forgive to Forget?" *The American Economic Review*, 79(1): 43–50.

Carpena, Fenella, Shawn Cole, Jeremy Shapiro, and Bilal Zia. 2013. "Liability Structure in Small-Scale Finance: Evidence from a Natural Experiment." *The World Bank Economic Review*, 27(3): 437–469.

Cassar, Alessandra, and Bruce Wydick. 2010. "Does social capital matter? Evidence from a five-country group lending experiment." *Oxford Economic Papers*, 62(4): 715–739.

Čihák, Martin, Asli Demirgüč-Kunt, Erik Feyen, and Ross Levine. 2013. "Financial Development in 205 Economies, 1960 to 2010." *Journal of Financial Perspectives*, 1(2): 17–36.

Cull, Robert, Asli Demirgüç-kunt, and Jonathan Morduch. 2009. "Microfinance meets the market." *Journal of Economic Perspectives*, 23(1): 167–192.

de Quidt, Jonathan, Thiemo Fetzer, and Maitreesh Ghatak. 2016. "Market Structure and Borrower Welfare in Microfinance." *mimeo.*

de Quidt, Jonathan, Thiemo René Fetzer, and Maitreesh Ghatak. 2012. "Microfinance, Market Structure, and Borrower Welfare: Regulatory Lessons from the Indian Crisis." *mimeo.*

de Quidt, Jonathan, Thiemo René Fetzer, and Maitreesh Ghatak. forthcoming. "Group Lending Without Joint Liability." *Journal Of Development Economics.*

Dupas, Pascaline, and Jonathan Robinson. 2013*a*. "Savings Constraints and Microenterprise Development: Evidence from a Field Experiment in Kenya." *American Economic Journal: Applied Economics*, 5(1): 163–192.

Dupas, Pascaline, and Jonathan Robinson. 2013*b*. "Why Don't the Poor Save More? Evidence from Health Savings Experiments." *American Economic Review*, 103(4): 1138–1171.

Feigenberg, B., E. Field, and R. Pande. 2013. "The Economic Returns to Social Interaction: Experimental Evidence from Microfinance." *The Review of Economic Studies*, 80(4): 1459–1483.

Ghatak, Maitreesh, and Timothy W. Guinnane. 1999. "The economics of lending with joint liability: theory and practice." *Journal of Development Economics*, 60(1): 195–228.

Giné, Xavier, and Dean S. Karlan. 2014. "Group versus individual liability: Short and long term evidence from Philippine microcredit lending groups." *Journal of Development Economics*, 107: 65–83.

Giné, Xavier, Karuna Krishnaswamy, and Alejandro Ponce. 2011. "Strategic Default in joint liability groups: Evidence from a natural experiment in India." *mimeo.*

Hermes, Niels, and Robert Lensink. 2007. "The empirics of microfinance: what do we know?" *The Economic Journal*, 117(517): F1–F10.

Hoff, Karla, and J Stiglitz. 1997. "Moneylenders and bankers: price-increasing subsidies in a monopolistically competitive market." *Journal of Development Economics*, 52(2): 429–462.

Karlan, Dean, and Jonathan Zinman. 2009. "Expanding Credit Access: Using Randomized Supply Decisions to Estimate the Impacts." *Review of Financial Studies*, 23(1): 433–464.

Karlan, Dean S. 2005. "Using Experimental Economics to Measure Social Capital and Predict Financial Decisions." *The American Economic Review*, 95(5): 1688–1699.

Karlan, Dean S. 2007. "Social connections and group banking." *Economic Journal*, 117(517): F52–F84.

Karlan, Dean S, and J Zinman. 2010. "Expanding microenterprise credit access: Using randomized supply decisions to estimate the impacts in Manila." *Working paper.*

Levine, Ross. 2005. "Finance and Growth: Theory and Evidence." *Handbook of Economic Growth*, , ed. Durlauf Steven and Philippe Aghion Vol. 1, Chapter 12, 865–934. North Holland.

Mahmud, Mahreen. 2015. "Repaying Microcredit Loans: A Natural Experiment on Liability Structure." *Kent Discussion Paper in Economics 1509.*

McIntosh, Craig, Alain De Janvry, and Elisabeth Sadoulet. 2005. "How rising competition among microfinance institutions affects incumbent lenders." *Economic Journal*, 115(506): 987–1004.

McIntosh, Craig, and Bruce Wydick. 2005. "Competition and microfinance." *Journal of Development Economics*, 78(2): 271–298.

Shapiro, Carl, and Joseph E. Stiglitz. 1984. "Equilibrium unemployment as a worker discipline device." *American Economic Review*, 74(3): 433–444.

6 Tables and figures

Table 1: MFI Characteristics for MFIs reporting IL share by Number of Loans

	Full Sample		Weakly Balanced			Strongly Balanced		
	Mean	N	Mean	N	p	Mean	N	p
IL Share by Number of Loans	0.60	1538.00	0.58	932.00	0.35	0.58	378.00	0.72
IL Share by Loan Value	0.64	1476.00	0.64	894.00	0.87	0.64	365.00	0.99
Non Profit	0.60	1408.00	0.60	932.00	0.94	0.66	378.00	0.19
Non-Regulated	0.33	1768.00	0.39	932.00	$<$0.01	0.46	378.00	$<$0.01
NGO	0.32	1898.00	0.36	932.00	0.01	0.44	378.00	$<$0.01
Portfolio at Risk 90 days	6.43	1732.00	5.71	930.00	0.26	4.86	378.00	$<$0.01
Return on Assets	-0.25	1657.00	0.62	930.00	$<$0.01	1.56	378.00	0.01
Profit Margin	-4.88	1741.00	0.45	931.00	$<$0.01	4.85	378.00	$<$0.01
MFI Risk Rating (1-5)	2.65	1920.00	2.95	932.00	$<$0.01	3.57	378.00	$<$0.01
Capital to Asset Ratio	36.77	1813.00	31.90	931.00	0.11	29.98	378.00	0.78
Debt to Equity Ratio	8.47	1772.00	4.84	931.00	0.16	7.10	378.00	0.08
Average Loan Balance	6405.76	1906.00	1448.17	932.00	0.66	1273.97	378.00	0.20
Cost per Borrower	304.37	1514.00	241.57	923.00	0.10	197.31	378.00	$<$0.01
Write Offs/ Assets	2.36	1623.00	2.21	929.00	0.31	2.21	378.00	0.58

Notes: Comparison of sample means across different samples used in the main table. Weakly balanced refers to MFIs reporting lending method by number of loans at least twice from 2008 - 2011, while strongly balanced only includes MFIs that report data on lending method by number of loans in each year between 2008-2011. We report the 2009 values where available (since 2009 has the greatest data availability), otherwise we take the closest available datapoint (averaging 2008 and 2010 when both are available). The number of MFIs changes as not all institutions report data on all the characteristics explored. "Mean" reports the average of the characteristic, "N" reports the number of MFIs included in the sample, while "p-value" reports the significance of the difference in means between the respective sample and the remainder of the full sample.

Table 2: Country characteristics

	Full Sample		Weakly Balanced			Strongly Balanced		
	Mean	N	Mean	N	p	Mean	N	p
Urban population share	0.47	113.00	0.47	100.00	0.57	0.51	64.00	0.03
Mobile Phones/100 people	74.16	112.00	73.13	99.00	0.39	82.21	63.00	0.01
Agriculture share in GDP	18.18	103.00	18.52	92.00	0.63	15.64	61.00	0.02
Industrial sector share in GDP	29.06	103.00	28.27	92.00	0.27	28.93	61.00	0.97
Service sector share in GDP	53.21	104.00	53.71	93.00	0.25	56.14	62.00	<0.01
Development Aid as share of GDP	6.72	107.00	6.19	95.00	0.51	5.31	61.00	0.17
GDP Growth Rate	3.87	111.00	3.99	98.00	0.17	3.82	64.00	0.99
GDP per capita	3.68	111.00	3.33	98.00	0.06	3.78	64.00	0.72
Domestic Credit / GDP	4.52	105.00	4.34	93.00	0.60	4.70	61.00	0.37
Commercial bank density	1.30	112.00	1.29	100.00	0.82	1.65	64.00	<0.01
ATM Density	2.26	110.00	2.16	98.00	0.21	2.61	63.00	0.07

Notes: "Full sample" contains country-level characteristics for the countries represented in the full MIX sample, while "weakly balanced" and "strongly balanced" restrict to the countries that appear in the respective panels (the "number of loans" samples). We report unweighted averages, i.e. each country is given equal weight irrespective of the number or scale of MFIs in that country. We report 2009 values where available, otherwise we take the closest available datapoint (averaging 2008 and 2010 when both are available). The number of countries changes as not all countries have data for all characteristics. "Mean" reports the average of the characteristic, "N" reports the number of countries included in the sample, while "p-value" reports the significance of the difference in means between the respective sample and the remainder of the full sample.

Table 3: Non Profit Status, Competition and IL Lending

Panel A: IL Share by Number of Loans

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.059	-0.088*	-0.023	-0.058	-0.047	-0.021
	(0.065)	(0.052)	(0.017)	(0.036)	(0.029)	(0.014)
Non Profit	-0.139**	-0.179**		-0.098*	-0.169***	
	(0.059)	(0.077)		(0.050)	(0.046)	
Non-Profit x Bank Branch Density	0.067	0.113*	0.031	0.069**	0.067**	0.024*
	(0.052)	(0.060)	(0.020)	(0.029)	(0.033)	(0.014)
Joint test:						
Comp + Non-Profit x Comp = 0?	.008	.024*	.008	.011	.02**	.003
	(.0415)	(.0132)	(.0116)	(.0253)	(.00864)	(.00621)
MFIs	348	348	348	878	878	878
Countries	64	64	64	94	94	94
Observations	1392	1392	1392	2756	2756	2756

Panel B: IL Share by Gross Loan Portfolio

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.090	-0.100**	-0.017	-0.075**	-0.066**	-0.018
	(0.064)	(0.043)	(0.012)	(0.033)	(0.026)	(0.011)
Non Profit	-0.151***	-0.182***		-0.119***	-0.170***	
	(0.051)	(0.062)		(0.043)	(0.041)	
Non-Profit x Bank Branch Density	0.086*	0.140**	0.032	0.080***	0.092***	0.029
	(0.049)	(0.054)	(0.023)	(0.028)	(0.032)	(0.018)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.005	.04**	.015	.005	.026**	.011
	(.04)	(.0156)	(.017)	(.024)	(.0122)	(.0116)
MFIs	340	340	340	831	831	831
Countries	60	60	60	92	92	92
Observations	1360	1360	1360	2605	2605	2605
Year FE	X	X	X	X	X	X
Region FE	X			X		
Country FE		X			X	
MFI FE			X			X

Notes: The dependent variable is the share of individual liability loans provided by an MFI as measured by Number of Loans (Panel A) or by Value of Loan Portfolio (Panel B). Strongly balanced refers to a balanced dataset for which lending methodology data is available for the period 2008-2011, while weakly balanced includes only MFIs that report this information at least twice. Standard errors in parentheses are clustered at the country level, with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix to "Commercialization and the Decline of Joint Liability Microcredit"

For Online Publication

Jonathan de Quidt Thiemo Fetzer Maitreesh Ghatak

February 29, 2016

A Data Appendix

We combine three different data sets from the MIX Market and data from the World Bank's World Development Indicators. This note will outline the process by which we combine these different data sources to arrive at the data set we use in our paper.

Global Data Download The MIX provides a global data download of basic portfolio information that is constantly updated. This data can be downloaded from `http://www.mixmarket.org/crossmarket-analysis-report/download`. This contains basic profile information, such as the MFI name, the respective MIX Market identification number, Profit status, Legal status as well as the basic portfolio report, detailing the Number of Loans Outstanding, Portfolio At Risk and other measures of performance that vary at the MFI level over time. We drop MFIs for which the Profit Status information is missing. We match the various financial years to the nearest calendar years. Unfortunately this comprehensive data download does not provide a detailed breakdown of lending methodology.

Further, we map the country names into 16 world regions: Central Africa, Central America, Central Asia, East Asia, Eastern Africa, Indian Ocean, Northern Africa, Northern Asia, South America, South Asia, South East Asia, South East Europe, South West Asia, Southern Africa, West Indies, Western

Africa. This region definition is finer than the one used by the MIX market, which only distinguishes continent.

This is our basic MFI-level panel, which we augment with auxiliary data obtained from detailed portfolio reports to obtain information about lending methodology.

Detailed Portfolio Reports For every MFI, a detailed portfolio report can be constructed through the MIX Market's reporting facility. We downloaded this information in July 2014. We proceed as follows. We take all the MFI names contained in the global data download, and download each MFI's detailed portfolio report individually. For example, for the MFI "Brac", this data is available from `http://reports.mixmarket.org/mfi/brac`. We collect methodology data from the Balance Sheet and/or the Products and Clients report and then match to the data from the Global Data Download. We use this information to construct the share of IL lending. Lending methodology is reported across three categories: individual, solidarity group or village banking/self help group.

We assign an MFI as reporting lending methodology by number of loans if any of these lending method numbers is non missing or non-zero. For example, if an MFI reports zero individual, zero solidarity group and zero village banking/self help group loans, then we would record this MFI as having missing lending methodology data. If the MFI reports a strictly positive number of loans in any of these categories then we code the MFI as reporting lending methodology. We compute the share of IL loans as simply the number of individual divided by the total of individual, solidarity group and village banking/self help group loans. We proceed similarly in the construction of the share of individual liability loans as measured by the loan portfolio value. Our weakly balanced panel includes on MFIs that report data on lending methodology at least twice between 2008 and 2011, while our strongly balanced panel includes those that report in all four years.

For village banks the lending method is less clear than for pure individual liability lenders. Our main analysis treats them as JL lenders. In a robustness check, regression Table 11 exclude all MFIs that, at some point, reported positive village lending.

In some cases, the total sum of individual, solidarity group and village banking/self help group loans does not add up to the total number of loans outstanding. For three MFIs, we remove obvious errors that are due to data entry, which resulted in dramatic discrepancies. Especially for IL shares measured by Gross Loan Portfolio, small discrepancies arise due to rounding errors. In Table 11, we remove all MFI-year observations with any discrepancy for the Panel A (IL Share measured by Number of Loans), while in Panel B, we remove all MFI-year observations where the discrepancy between the Gross Loan Portfolio and the implied Gross Loan Portfolio when adding up the portfolio by lending methods is larger than 10%.

Incorporation Date and Profit Status In order to construct the top left panel of Figure 1, we obtain data on the incorporation dates of the MFIs. Unfortunately, this information is not contained in the main data download. We make use of an older data download which provides this information for the set of MFIs that reported some data to the MIX market prior to February 2011. This data is available from `http://www.mixmarket.org/sites/default/files/mfi_profile_information_02.24.11.xls`. We merge the date established to the global data download to construct the share of for-profit MFIs by incorporation dates. Obviously, this can only be constructed for the set of MFIs for which we know the incorporation date, in order to illustrate the global trend the figure also includes MFIs that do not disclose data on lending methodology. The figure looks very similar when weighting by MFI size in 2009 or by including e.g. only on the MFIs from the weakly balanced sample.

In addition, the 2011 data snapshot provides us with an additional record of the For-profit/non-profit status ("profit status") as of February 2011. One concern might be that some MFIs changed status prior to February 2011 (or between February 2011 and the end of 2011). Since legal status and non profit status are likely closely related (see Appendix Table 4), we remove MFIs that switched legal status during our sample period. The results are presented in Table 11.

Competition Proxies Lastly, we obtain proxy variables for the extent of competition from the development indicators. These can be obtained from the World Bank Website, available at `http://data.worldbank.org/data-catalog/world-development-indicators`.

We use these data as proxies for the borrowers' outside options, the availability of alternative sources of credit. The top right Figure 1 plots the simple cross-country averages over time (unbalanced, i.e. including countries that do not have data for every year) in these measures for the set of countries that appear in the full MIX dataset. Again, the trends look similar when focusing only on the countries which are present in our weakly balanced sample.

A.1 Peru

Our main analysis excludes Peruvian MFIs. As discussed in footnote 4 it turns out that the results are highly sensitive to inclusion of Peru, but not to any other country. To demonstrate this, Figure 2 Panel A presents box plots of our three main coefficient estimates,[1] where we re-run the main Strongly Balanced panel regression dropping each country in turn. In other words, we have one set of point estimates for all countries excluding Nicaragua, one set excluding Pakistan, etc. The main lesson is that the two point estimates related to bank branch density are tightly distributed and close to zero whenever Peru is included, then increase dramatically in magnitude when Peru is dropped. Put the other way, including Peru shrinks the point estimates dramatically toward zero. Peru is also a moderate outlier in the non-profit coefficient (this coefficient is more sensitive to Nepal and India, which are also moderate outliers for the other coefficients, but note that although we do not drop Nepal and India, doing so would only strengthen our results).

[1] For "Commercial bank density" (competition effect on for-profits), "Commercial bank density + Non-profit x Bank Branch Density" (competition effect on non-profits), and "Non profit" (difference in IL share between non-profit and for-profit).

Figure 2 Panel B then repeats the exercise, now excluding Peru, i.e. we always drop Peru, then run the regressions dropping each other country in turn. The results are not notably sensitive to any other country, and our conclusions are not sensitive to their inclusion.

B Theory Appendix

B.1 Derivation of steady-state IL/JL shares

The non-profit IL share in period t is as follows:

$$\hat{\eta}_t = \hat{\eta}_{t-1}p + \hat{\eta}_{t-1}(1-p)F(\hat{S}(U)) + (1-\hat{\eta}_{t-1})(1-q)F(\hat{S}(U))$$

The first term on the right-hand side corresponds to the non-defaulting IL borrowers (fraction p of the $\hat{\eta}_{t-1}$ IL borrowers), who retain their IL contracts. The second term corresponds to the vacancies at formerly IL branches which are filled by new IL borrowers (fraction $1-p$ of the $\hat{\eta}_{t-1}$ borrowers default creating vacancies, and then new borrowers are drawn of whom fraction $F(\hat{S})$ receive IL and $1-F(\hat{S})$ receive JL). The third term corresponds to the vacancies at formerly JL branches which are now filled by IL borrowers (fraction $1-q=(1-p)^2$ JL borrowers default creating vacancies, and then new borrowers are drawn of whom fraction $F(\hat{S})$ receive IL and $1-F(\hat{S})$ receive JL).

Solving this equation for the steady state by setting $\hat{\eta}_t = \hat{\eta}_{t-1}$ we obtain:

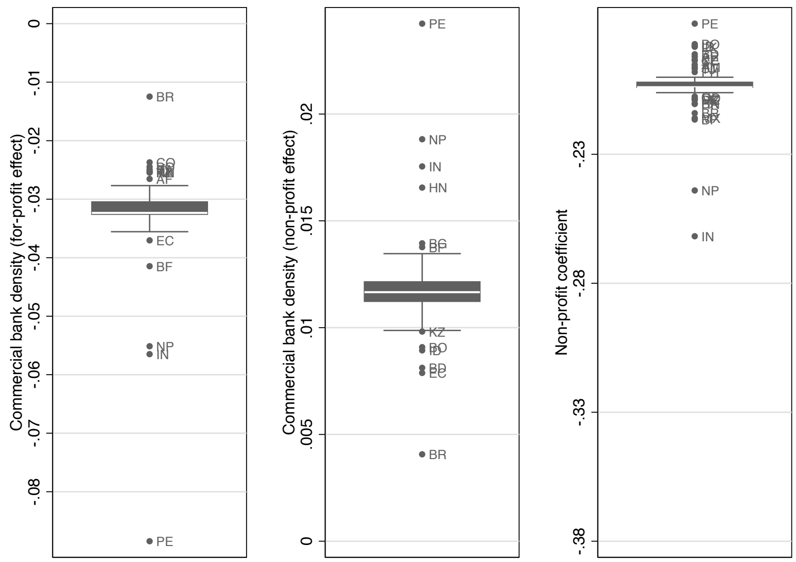
$$\hat{\eta}(U) = \frac{F(\hat{S}(U))(1-p)}{1-F(\hat{S}(U))p}$$

The steady state JL share is equal to $1-\hat{\eta}(U)$. The for-profit derivations are identical.

B.2 Endogenizing U

We take the simplest case, where social capital is homogeneous and equal to S for all borrowers. The population of borrowers has measure 2, but it is simpler

Panel A: Dropping each country in turn



Panel B: Excluding Peru and dropping each country in turn

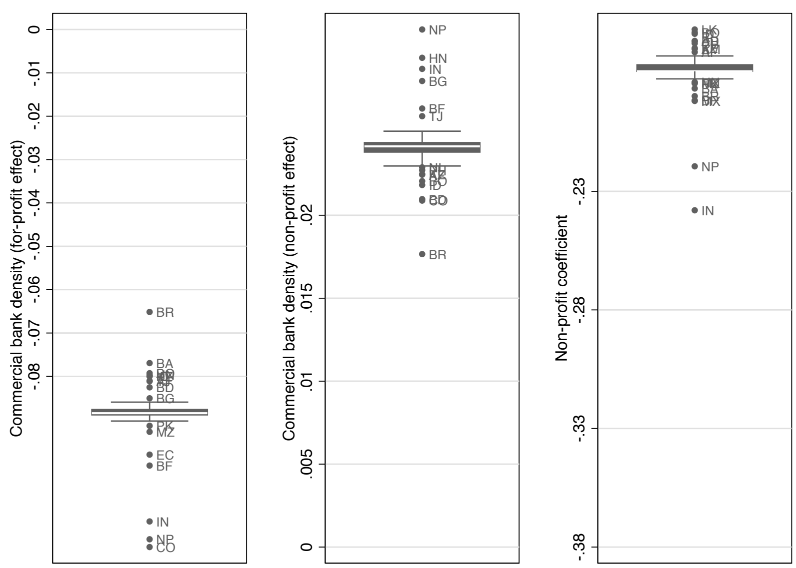


Figure 2: Sensitivity of regression coefficients to inclusion of Peru (balanced panel, IL share by number)

to work in terms of the measure of pairs of borrowers, which has measure 1. The measure of lenders is $l < 1$ (recall that each lender can serve two borrowers, and that if $l > 1$ then all borrowers can guarantee they receive a loan every period, so have no incentive to repay their current loan). Since there is excess demand for credit, l borrower pairs are served each period. Thus there are lf for-profits and $l(1-f)$ non-profits.

Each period some borrowers default, leaving vacancies at their branches. We allow for the possibility that some lenders offer IL and some offer JL, and since borrowers are homogeneous we assume that their probability of receiving a given contract equals their probability of matching to a lender offering that contract. Thus $lf\tilde{\eta}(U)(1-p)$ for-profit IL vacancies, $lf(1-\tilde{\eta})(1-q)$ for-profit JL vacancies, $l(1-f)\hat{\eta}(U)(1-p)$ non-profit IL vacancies and $l(1-f)(1-\hat{\eta})(1-q)$ non-profit JL vacancies open each period. The total measure of unmatched borrowers, which we define as $D(U)$, is the number of defaulters last period plus the excess demand, $1-l$, equalling:

$$\begin{aligned} D(U) = 1 - l + l[&f\tilde{\eta}(U)(1-p) + (1-f)\hat{\eta}(U)(1-p) \\ &+ f(1-\tilde{\eta}(U))(1-q) + (1-f)(1-\hat{\eta}(U))(1-q)]. \end{aligned}$$

Hence, an unmatched borrower can expect to receive:

$$\begin{aligned} U = \frac{1}{D(U)}[&lf\tilde{\eta}(U)(1-p)\tilde{V}^{IL}(U,S) + l(1-f)\hat{\eta}(U)(1-p)\hat{V}^{IL}(U) \\ &+ lf(1-\tilde{\eta}(U))(1-q)\tilde{V}^{JL}(U) + l(1-f)(1-\hat{\eta}(U))(1-q)\hat{V}^{JL}(U) \\ &+ (1-l)\delta U]. \end{aligned}$$

Substituting for the Vs (note, using $(1-p)^2 = (1-q)$):

$$U = \frac{1}{D(U)} \Bigg[lf\tilde{\eta}(U)(1-p)\frac{pR - p\tilde{r}^{IL}(U)}{1-\delta p} + l(1-f)\hat{\eta}(U)(1-p)\frac{pR-\rho}{1-\delta p}$$
$$+ l\left(f\tilde{\eta}(U) + (1-f)\hat{\eta}(U)\right)\frac{\delta(1-q)U}{1-\delta p}$$
$$+ lf(1-\tilde{\eta}(U))(1-q)\frac{pR - q\tilde{r}^{JL}(U,S)}{1-\delta q} + l(1-f)(1-\hat{\eta}(U))(1-q)\frac{pR-\rho}{1-\delta q}$$
$$+ l\left[f(1-\tilde{\eta}(U)) + (1-f)(1-\hat{\eta}(U))\right]\frac{\delta(1-q)^2 U}{1-\delta q} + (1-l)\delta U \Bigg].$$

Finally, substitute for the $\tilde{r}$s:

$$U = \frac{1}{D(U)} \Bigg[lf\tilde{\eta}(U)(1-p)pR + l(1-f)\hat{\eta}(U)(1-p)\frac{pR-\rho}{1-\delta p}$$
$$+ lf\tilde{\eta}(U)(1-p)\frac{\delta(1-\delta)U}{1-\delta p}$$
$$+ l\left(f\tilde{\eta}(U) + (1-f)\hat{\eta}(U)\right)\frac{\delta(1-q)U}{1-\delta p}$$
$$+ lf(1-\tilde{\eta}(U))(1-q)\frac{pR - q\frac{\delta pR + \delta(1-\delta q)S}{2-\delta q}}{1-\delta q} + l(1-f)(1-\hat{\eta}(U))(1-q)\frac{pR-\rho}{1-\delta q}$$
$$+ lf(1-\tilde{\eta}(U))(1-q)\frac{q\frac{\delta(1-\delta)}{2-\delta q}U}{1-\delta q}$$
$$+ l\left[f(1-\tilde{\eta}(U)) + (1-f)(1-\hat{\eta}(U))\right]\frac{\delta(1-q)^2 U}{1-\delta q} + (1-l)\delta U \Bigg].$$

Clearly this remains a complex implicit function in U. An equilibrium obtains at a fixed point whereby lenders do not want to change their contract offerings given the value of U. We do not proceed with an in-depth analysis, but we note that there at least exist all-IL ($\tilde{\eta} = \hat{\eta} = 1$) and all-JL ($\tilde{\eta} = \hat{\eta} = 0$) equilibria. This follows from the analysis of competitive equilibrium in de Quidt, Fetzer and Ghatak (2016), where we derive as a function of S the value of l such that all lenders earn zero profits. Except for a unique value for S (at which both contracts break even) the equilibrium involves either all lenders offering IL (when S is low) or all lenders offering JL (when S is high).

C Additional tables

Table 4: Non Profit Status and Legal Status

	For-Profit	Non-Profit	Total
Legal Status			
Unknown	6	0	6
Bank	103	8	111
Credit Union / Cooper	4	248	252
NBFI	350	114	464
NGO	8	464	472
Other	6	9	15
Rural Bank	86	2	88
	563	845	1,408

Notes: MFIs by legal status and profit status in our sample.

Table 5: MFI Characteristics for MFIs reporting IL share by Gross Loan Portfolio

	Full Sample		Weakly Balanced			Strongly Balanced		
	Mean	N	Mean	N	p	Mean	N	p
IL Share by Number of Loans	0.60	1538.00	0.58	881.00	0.59	0.58	368.00	0.71
IL Share by Loan Value	0.64	1476.00	0.64	883.00	0.80	0.64	368.00	0.94
Non Profit	0.60	1408.00	0.61	883.00	0.44	0.63	368.00	0.45
Non-Regulated	0.33	1768.00	0.37	883.00	0.33	0.45	368.00	0.02
NGO	0.32	1898.00	0.37	883.00	$<$0.01	0.44	368.00	0.01
Portfolio at Risk 90 days	6.43	1732.00	5.64	881.00	0.18	4.77	368.00	$<$0.01
Return on Assets	-0.25	1657.00	0.54	881.00	0.04	1.69	368.00	$<$0.01
Profit Margin	-4.88	1741.00	0.11	882.00	0.01	5.12	368.00	$<$0.01
MFI Risk Rating (1-5)	2.65	1920.00	2.97	883.00	$<$0.01	3.58	368.00	$<$0.01
Capital to Asset Ratio	36.77	1813.00	31.93	882.00	0.13	29.75	368.00	0.68
Debt to Equity Ratio	8.47	1772.00	4.94	882.00	0.11	7.18	368.00	0.07
Average Loan Balance	6405.76	1906.00	1415.59	883.00	0.37	1323.51	368.00	0.34
Cost per Borrower	304.37	1514.00	237.52	874.00	0.06	202.35	368.00	$<$0.01
Write Offs/ Assets	2.36	1623.00	2.20	880.00	0.30	2.19	368.00	0.53

Notes: Comparison of sample means across different samples used in the main table. Weakly balanced refers to MFIs reporting lending method by gross loan portfolio at least twice from 2008 - 2011, while strongly balanced only includes MFIs that report data on lending method by gross loan portfolio in each year between 2008-2011. We report the 2009 values where available (since 2009 has the greatest data availability), otherwise we take the closest available datapoint (averaging 2008 and 2010 when both are available). The number of MFIs changes as not all institutions report data on all the characteristics explored. "Mean" reports the average of the characteristic, "N" reports the number of MFIs included in the relevant sample, while "p-value" reports the significance of the difference in means between the respective sample and the remainder of the full sample.

Table 6: Additional country-level controls, IL shares by number of loans

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.110	-0.151***	-0.032	-0.073*	-0.062*	-0.026
	(0.075)	(0.053)	(0.020)	(0.039)	(0.034)	(0.017)
Non Profit	-0.166***	-0.200***		-0.124***	-0.184***	
	(0.050)	(0.052)		(0.038)	(0.041)	
Non-Profit x Bank Branch Density	0.134**	0.197***	0.048**	0.103**	0.102**	0.038**
	(0.065)	(0.066)	(0.020)	(0.041)	(0.039)	(0.016)
Further Interactions:						
Urban population share	-0.026	-0.056	-0.990	-0.253	1.615	-0.322
	(0.452)	(1.283)	(1.383)	(0.266)	(1.418)	(0.883)
Non Profit x Urban population share	0.129	-0.085	-0.207	0.094	-0.220	-0.288
	(0.487)	(0.526)	(1.844)	(0.358)	(0.386)	(1.812)
Mobile Phones/100 people	-0.002	-0.001	-0.000	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Non Profit x Mobile Phones/100 people	-0.006***	-0.004**	0.001	-0.007***	-0.004***	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
GDP per capita	-0.006	-0.004	-0.013**	-0.020*	-0.006	-0.013**
	(0.017)	(0.008)	(0.005)	(0.012)	(0.007)	(0.005)
Non Profit x GDP per capita	0.018	0.007	-0.021**	0.019	0.005	-0.008
	(0.026)	(0.028)	(0.009)	(0.022)	(0.023)	(0.011)
Joint test:						
Comp + Non-Profit x Comp = 0?	.024	.046**	.016	.03	.039***	.013*
	(.0524)	(.0179)	(.0111)	(.0379)	(.0148)	(.00711)
MFIs	334	334	334	792	792	792
Countries	58	58	58	82	82	82
Observations	1335	1335	1335	2517	2517	2517
Year FE	X	X	X	X	X	X
Region FE	X			X		
Country FE		X			X	
MFI FE			X			X

Notes: The dependent variable is the share of individual liability loans provided by an MFI. Strongly balanced refers to a balanced dataset for which lending methodology data is available for the period 2008-2011, while weakly balanced includes only MFIs that report this information at least twice. All regressions control in addition for the Share of Agriculture in GDP, Share of Industry in GDP, Development Assistance received and their respective interactions with the non-profit indicator. Standard errors in parentheses are clustered at the country level, with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Additional country-level controls, IL shares by Gross Loan Portfolio

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.122	-0.135**	-0.022*	-0.085**	-0.081*	-0.027**
	(0.079)	(0.059)	(0.012)	(0.038)	(0.042)	(0.011)
Non Profit	-0.180***	-0.197***		-0.141***	-0.178***	
	(0.050)	(0.053)		(0.039)	(0.041)	
Non-Profit x Bank Branch Density	0.151**	0.201**	0.052**	0.123***	0.131**	0.052***
	(0.073)	(0.077)	(0.022)	(0.044)	(0.051)	(0.018)
Further Interactions:						
Urban population share	0.096	0.607	0.218	-0.175	1.440	-0.195
	(0.425)	(1.238)	(1.210)	(0.263)	(1.765)	(0.824)
Non Profit x Urban population share	0.341	0.220	0.381	0.203	-0.043	0.284
	(0.379)	(0.452)	(2.028)	(0.324)	(0.345)	(2.090)
Mobile Phones/100 people	-0.002	-0.000	-0.000	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Non Profit x Mobile Phones/100 people	-0.004***	-0.001	0.001	-0.006***	-0.003**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GDP per capita	-0.009	-0.010*	-0.014***	-0.021**	-0.009	-0.013***
	(0.018)	(0.006)	(0.005)	(0.011)	(0.009)	(0.005)
Non Profit x GDP per capita	0.010	-0.006	-0.028***	0.006	-0.003	-0.032***
	(0.026)	(0.030)	(0.008)	(0.021)	(0.023)	(0.008)
Joint test:						
Comp + Non-Profit x Comp = 0?	.028	.065***	.03*	.038	.05**	.025**
	(.0522)	(.0211)	(.0148)	(.0328)	(.0196)	(.0112)
MFIs	327	327	327	753	753	753
Countries	54	54	54	81	81	81
Observations	1307	1307	1307	2392	2392	2392
Year FE	X	X	X	X	X	X
Region FE	X			X		
Country FE		X			X	
MFI FE			X			X

Notes: The dependent variable is the share by value of the gross loan portfolio that is under individual liability. Strongly balanced refers to a balanced dataset for which lending methodology data is available for the period 2008-2011, while weakly balanced includes only MFIs that report this information at least twice. All regressions control in addition for the Share of Agriculture in GDP, Share of Industry in GDP, Development Assistance received and their respective interactions with the non-profit indicator. Standard errors in parentheses are clustered at the country level, with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Additional fixed effects and MFI-level controls

Panel A: IL Share by Number of Loans

	Strongly Balanced				Weakly Balanced			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non Profit	-0.179**		-0.104		-0.170***		-0.133***	
	(0.083)		(0.074)		(0.049)		(0.042)	
Non-Profit x Bank Branch Density	0.112*	0.016	0.117*	0.020*	0.067*	0.017**	0.076**	0.015*
	(0.066)	(0.010)	(0.070)	(0.010)	(0.034)	(0.008)	(0.032)	(0.008)
MFIs	348	348	348	348	878	878	874	874
Countries	64	64	64	64	94	94	94	94
Observations	1392	1392	1347	1347	2756	2756	2611	2611

Panel B: IL Share by Gross Loan Portfolio

	Strongly Balanced				Weakly Balanced			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non Profit	-0.182***		-0.101		-0.173***		-0.138***	
	(0.066)		(0.070)		(0.044)		(0.040)	
Non-Profit x Bank Branch Density	0.139**	0.015	0.131**	0.014	0.093***	0.019	0.091***	0.015
	(0.059)	(0.015)	(0.058)	(0.017)	(0.034)	(0.013)	(0.031)	(0.013)
MFIs	340	340	340	340	831	831	827	827
Countries	60	60	60	60	92	92	92	92
Observations	1360	1360	1318	1318	2605	2605	2467	2467
Country x Year FE	X	X	X	X	X	X	X	X
MFI FE		X		X		X		X
Controls			X	X			X	X

Notes: The dependent variable is the share of individual liability loans provided by an MFI as measured by Number of Loans (Panel A) or by Value of Loan Portfolio (Panel B). Strongly balanced refers to a balanced dataset for which lending methodology data is available for the period 2008-2011, while weakly balanced includes only MFIs that report this information at least twice. Controls include Diamonds, Capital to Asset Ratio, Debt to equity ratio, Average loan balance per borrower, Return on assets, Financial revenue/Assets , Yield on gross portfolio (nominal), Financial expense/assets, Operating expense/assets. Standard errors in parentheses are clustered at the country level, with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: IL Share by Number of Loans: Robustness to Other Competition Proxy Variables

	Strongly Balanced			Weakly Balanced		
Panel A:	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.059	-0.088*	-0.023	-0.058	-0.047	-0.021
	(0.065)	(0.052)	(0.017)	(0.036)	(0.029)	(0.014)
Non Profit	-0.139**	-0.179**		-0.098*	-0.169***	
	(0.059)	(0.077)		(0.050)	(0.046)	
Non-Profit x Bank Branch Density	0.067	0.113*	0.031	0.069**	0.067**	0.024*
	(0.052)	(0.060)	(0.020)	(0.029)	(0.033)	(0.014)
Joint test:						
Comp + Non-Profit x Comp = 0?	.008	.024*	.008	.011	.02**	.003
	(.0415)	(.0132)	(.0116)	(.0253)	(.00864)	(.00621)
MFIs	348	348	348	878	878	878
Countries	64	64	64	94	94	94
Observations	1392	1392	1392	2756	2756	2756
Panel B:	(1)	(2)	(3)	(4)	(5)	(6)
ATM Density	-0.057	-0.050	-0.014	-0.055	-0.023	-0.010
	(0.055)	(0.047)	(0.031)	(0.044)	(0.037)	(0.020)
Non Profit	-0.157**	-0.209***		-0.109**	-0.187***	
	(0.059)	(0.076)		(0.051)	(0.047)	
Non-Profit x ATM Density	0.042	0.057	0.006	0.028	0.026	0.013
	(0.045)	(0.055)	(0.036)	(0.042)	(0.038)	(0.020)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.015	.008	-.008	-.027	.003	.003
	(.0311)	(.0286)	(.0289)	(.0223)	(.0114)	(.00823)
MFIs	346	346	346	864	864	864
Countries	63	63	63	91	91	91
Observations	1348	1348	1348	2667	2667	2667
Panel C:	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Credit Share	-0.130**	-0.189***	-0.112***	-0.097**	-0.086*	-0.110***
	(0.054)	(0.058)	(0.037)	(0.038)	(0.049)	(0.038)
Non Profit	-0.153***	-0.227***		-0.113**	-0.193***	
	(0.051)	(0.061)		(0.049)	(0.043)	
Non-Profit x Domestic Credit Share	0.109*	0.174**	0.066	0.077*	0.086	0.094**
	(0.057)	(0.075)	(0.041)	(0.040)	(0.054)	(0.036)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.021	-.015	-.045	-.02	.001	-.016
	(.0293)	(.0343)	(.0309)	(.0219)	(.0367)	(.0208)
MFIs	338	338	338	833	833	833
Countries	61	61	61	88	88	88
Observations	1352	1352	1352	2640	2640	2640
Year FE	X	X	X	X	X	X
Region FE	X			X		
Country FE		X			X	
MFI FE			X			X

Notes: The dependent variable is the share of individual liability loans provided by an MFI by Number of Loans. Strongly balanced refers to a balanced dataset for which lending methodology data is available for the period 2008-2011, while weakly balanced includes only MFIs that report this information at least twice. Standard errors in parentheses are clustered at the country level, with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: IL Share by Gross Loan Portfolio: Robustness to Other Competition Proxy Variables

	Strongly Balanced			Weakly Balanced		
Panel A:	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.090	-0.100**	-0.017	-0.075**	-0.066**	-0.018
	(0.064)	(0.043)	(0.012)	(0.033)	(0.026)	(0.011)
Non Profit	-0.151***	-0.182***		-0.119***	-0.170***	
	(0.051)	(0.062)		(0.043)	(0.041)	
Non-Profit x Bank Branch Density	0.086*	0.140**	0.032	0.080***	0.092***	0.029
	(0.049)	(0.054)	(0.023)	(0.028)	(0.032)	(0.018)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.005	.04**	.015	.005	.026**	.011
	(.04)	(.0156)	(.017)	(.024)	(.0122)	(.0116)
MFIs	340	340	340	831	831	831
Countries	60	60	60	92	92	92
Observations	1360	1360	1360	2605	2605	2605
Panel B:	(1)	(2)	(3)	(4)	(5)	(6)
ATM Density	-0.096**	-0.039	-0.005	-0.066*	-0.046	-0.017
	(0.037)	(0.039)	(0.032)	(0.035)	(0.031)	(0.022)
Non Profit	-0.168***	-0.201***		-0.133***	-0.189***	
	(0.049)	(0.056)		(0.044)	(0.043)	
Non-Profit x ATM Density	0.066**	0.089**	0.040	0.030	0.043	0.007
	(0.032)	(0.034)	(0.041)	(0.035)	(0.030)	(0.024)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.03	.05	.035	-.036*	-.003	-.011
	(.024)	(.0332)	(.0372)	(.0184)	(.0133)	(.0102)
MFIs	338	338	338	818	818	818
Countries	59	59	59	90	90	90
Observations	1318	1318	1318	2512	2512	2512
Panel C:	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Credit Share	-0.128***	-0.139**	-0.123***	-0.118***	-0.064	-0.103**
	(0.048)	(0.058)	(0.040)	(0.033)	(0.044)	(0.040)
Non Profit	-0.158***	-0.203***		-0.137***	-0.195***	
	(0.043)	(0.060)		(0.039)	(0.041)	
Non-Profit x Domestic Credit Share	0.075	0.123	0.101**	0.078**	0.078	0.092**
	(0.052)	(0.076)	(0.042)	(0.035)	(0.048)	(0.037)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.053*	-.016	-.022	-.04*	.013	-.011
	(.0305)	(.033)	(.0251)	(.0227)	(.0368)	(.026)
MFIs	333	333	333	789	789	789
Countries	58	58	58	87	87	87
Observations	1329	1329	1329	2499	2499	2499
Year FE	X	X	X	X	X	X
Region FE	X			X		
Country FE		X			X	
MFI FE			X			X

Notes: The dependent variable is the share of individual liability loans provided by an MFI by Value of Loan Portfolio. Strongly balanced refers to a balanced dataset for which lending methodology data is available for the period 2008-2011, while weakly balanced includes only MFIs that report this information at least twice. Standard errors in parentheses are clustered at the country level, with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Restricting the Analysis to Non-Village Banks, Institutions that did not switch Legal Status and have no Discrepancy in IL Shares reporting: Profit Status, Competition and IL Lending

Panel A: IL Share by Number of Loans

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.055	-0.066	-0.019	-0.074**	-0.042	-0.020
	(0.038)	(0.042)	(0.014)	(0.032)	(0.038)	(0.013)
Non Profit	-0.178***	-0.199***		-0.090	-0.170***	
	(0.062)	(0.074)		(0.055)	(0.047)	
Non-Profit x Bank Branch Density	0.063	0.084	0.024	0.071**	0.065	0.023*
	(0.047)	(0.052)	(0.016)	(0.035)	(0.041)	(0.013)
Joint test:						
Comp + Non-Profit x Comp = 0?	.009	.017	.005	-.003	.023**	.004
	(.032)	(.0142)	(.00935)	(.022)	(.00922)	(.00513)
MFIs	252	252	252	681	681	681
Countries	59	59	59	92	92	92
Observations	993	993	993	2060	2060	2060

Panel B: IL Share by Gross Loan Portfolio

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.049	-0.050	-0.009	-0.078**	-0.063	-0.010
	(0.034)	(0.035)	(0.008)	(0.030)	(0.038)	(0.009)
Non Profit	-0.177***	-0.183**		-0.125**	-0.186***	
	(0.064)	(0.074)		(0.050)	(0.049)	
Non-Profit x Bank Branch Density	0.062	0.063	0.030	0.081**	0.083*	0.026*
	(0.048)	(0.048)	(0.018)	(0.036)	(0.042)	(0.014)
Joint test:						
Comp + Non-Profit x Comp = 0?	.013	.014	.021	.002	.021*	.016**
	(.0339)	(.0166)	(.0131)	(.0227)	(.0118)	(.00791)
MFIs	243	243	243	639	639	639
Countries	54	54	54	91	91	91
Observations	925	925	925	1880	1880	1880
Year FE	X	X	X	X	X	X
Region FE	X			X		
Country FE		X			X	
MFI FE			X			X

Notes: The dependent variable is the share of individual liability loans provided by an MFI as measured by Number of Loans (Panel A) or by Value of Loan Portfolio (Panel B). Strongly balanced refers to a balanced dataset for which lending methodology data is available for the period 2008-2011, while weakly balanced includes only MFIs that report this information at least twice. The analysis only includes non-village banks, institutions that did not switch legal status and have no discrepancy in IL shares reported. Standard errors in parentheses are clustered at the country level, with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Including Peru with IL Share by Number of Loans: Robustness to Other Competition Proxy Variables

	Strongly Balanced			Weakly Balanced		
Panel A:	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.023	-0.032	-0.009	-0.028	-0.029	-0.010
	(0.048)	(0.052)	(0.012)	(0.037)	(0.027)	(0.009)
Non Profit	-0.156**	-0.202**		-0.112**	-0.182***	
	(0.059)	(0.077)		(0.050)	(0.046)	
Non-Profit x Bank Branch Density	0.021	0.044	0.013	0.035	0.034	0.010
	(0.051)	(0.066)	(0.013)	(0.036)	(0.037)	(0.010)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.002	.012	.004	.006	.005	0
	(.0342)	(.0171)	(.00987)	(.0233)	(.0157)	(.00574)
MFIs	378	378	378	932	932	932
Countries	65	65	65	95	95	95
Observations	1512	1512	1512	2934	2934	2934
Panel B:	(1)	(2)	(3)	(4)	(5)	(6)
ATM Density	-0.052	-0.049	-0.012	-0.054	-0.023	-0.009
	(0.054)	(0.047)	(0.030)	(0.043)	(0.036)	(0.019)
Non Profit	-0.173***	-0.226***		-0.120**	-0.194***	
	(0.057)	(0.070)		(0.049)	(0.044)	
Non-Profit x ATM Density	0.041	0.056	0.002	0.027	0.025	0.011
	(0.046)	(0.056)	(0.034)	(0.041)	(0.038)	(0.019)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.01	.007	-.009	-.027	.002	.003
	(.0281)	(.0281)	(.0279)	(.0204)	(.0117)	(.00824)
MFIs	376	376	376	918	918	918
Countries	64	64	64	92	92	92
Observations	1468	1468	1468	2845	2845	2845
Panel C:	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Credit Share	-0.125**	-0.180***	-0.110***	-0.100***	-0.079*	-0.108***
	(0.049)	(0.049)	(0.036)	(0.034)	(0.045)	(0.037)
Non Profit	-0.166***	-0.227***		-0.123***	-0.196***	
	(0.046)	(0.050)		(0.046)	(0.038)	
Non-Profit x Domestic Credit Share	0.113**	0.165***	0.067	0.083**	0.085*	0.094**
	(0.051)	(0.060)	(0.040)	(0.037)	(0.047)	(0.036)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.012	-.015	-.043	-.017	.006	-.014
	(.0299)	(.0306)	(.0299)	(.0214)	(.0352)	(.0201)
MFIs	368	368	368	887	887	887
Countries	62	62	62	89	89	89
Observations	1472	1472	1472	2818	2818	2818
Year FE	X	X	X	X	X	X
Region FE	X			X		
Country FE		X			X	
MFI FE			X			X

Notes: The dependent variable is the share of individual liability loans provided by an MFI by Number of Loans. Strongly balanced refers to a balanced dataset for which lending methodology data is available for the period 2008-2011, while weakly balanced includes only MFIs that report this information at least twice. Standard errors in parentheses are clustered at the country level, with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Ruling out Time Varying Regulatory Shocks and Sensitivity to India: Profit Status, Competition and IL Lending

Panel A: IL Share by Number of Loans

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.113**	-0.138***	-0.149***	-0.059**	-0.056	-0.059
	(0.054)	(0.043)	(0.045)	(0.029)	(0.037)	(0.037)
Non Profit	-0.238***	-0.073	-0.093	-0.203***	-0.116**	-0.125**
	(0.077)	(0.059)	(0.076)	(0.042)	(0.046)	(0.056)
Non-Profit x Bank Branch Density	0.142**	0.198***	0.213***	0.081**	0.091**	0.095**
	(0.064)	(0.062)	(0.064)	(0.033)	(0.043)	(0.044)
Joint test:						
Comp + Non-Profit x Comp = 0?	.029**	.06***	.064***	.022**	.036**	.036**
	(.0144)	(.0226)	(.023)	(.00835)	(.0173)	(.0174)
MFIs	310	348	310	803	878	803
Countries	63	64	63	93	94	93
Observations	1240	1392	1240	2506	2756	2506

Panel B: IL Share by Gross Loan Portfolio

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.115**	-0.091***	-0.098***	-0.074***	-0.063**	-0.063**
	(0.046)	(0.031)	(0.032)	(0.026)	(0.026)	(0.026)
Non Profit	-0.214***	-0.053	-0.057	-0.196***	-0.104**	-0.102*
	(0.069)	(0.056)	(0.065)	(0.041)	(0.045)	(0.055)
Non-Profit x Bank Branch Density	0.156**	0.131**	0.141***	0.101***	0.089**	0.089**
	(0.059)	(0.050)	(0.050)	(0.033)	(0.035)	(0.036)
Joint test:						
Comp + Non-Profit x Comp = 0?	.041**	.04	.042	.027**	.027	.026
	.0163	.0257	.0259	.0117	.0191	.0192
MFIs	305	340	305	757	831	757
Countries	59	60	59	91	92	91
Observations	1220	1360	1220	2362	2605	2362
India included?	No		No	No		No
Country FE	X	X	X	X	X	X
Year FE	X			X		
Region x Legal Status x Year FE		X	X		X	X

Notes: The dependent variable is the share of individual liability loans provided by an MFI as measured by Number of Loans (Panel A) or by Value of Loan Portfolio (Panel B). Strongly balanced refers to a balanced dataset for which lending methodology data is available for the period 2008-2011, while weakly balanced includes only MFIs that report this information at least twice. The analysis focuses on the sensitivity of results to India and controls for time varying regulatory shocks that affect MFIs by different legal status differentially across regions. Standard errors in parentheses are clustered at the country level, with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.