Commercialization and the Decline of Joint Liability Microcredit

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Abstract

Numerous authors point to an apparent 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. In this paper, we first show using the well-known MIX Market dataset that there is indeed evidence for a decline. Second, we show theoretically that a plausible cause is *commercialization*: an increase in competition and a shift from non-profit to for-profit lending, both of which are present in the data, drive 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. Commercialization does indeed seem to be a contributor to the decline of joint liability.

Keywords: microfinance; joint liability; commercialization; market structure

JEL Classification: G21, O12, O16

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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 by 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 unfortunately our data on lending methodology are incomplete and span only the years 2008-2011, they do point to a trend toward IL.

Second, we argue using a simple theoretical model 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

[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).

an increasingly for-profit marketplace. Second, competition for borrowers has increased, as seen most dramatically by the credit crisis in Andhra Pradesh, India, that ultimately led regulators to shut the industry down completely.

Our simple model 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, 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.

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 lender change their offerings in the predicted directions when competition, proxied for example by the density of bank branches, increases. We show that our findings, particularly with respect to the three competition proxies we explore, 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.[3] Our theory fits into a branch of the literature that points to the leverage of *social capital*, especially through JL lending, as a key feature of microcredit.[4] 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

[3]The results are however sensitive to the inclusion of data from one country, Peru, which we exclude from our main specifications. No other individual country or MFI is important for the robustness of the results.

[4]E.g. Besley and Coate (1995), Ahlin and Townsend (2007), Ghatak and Guinnane (1999), Cassar and Wydick (2010), de Quidt, Fetzer and Ghatak (2013), de Quidt, Fetzer and Ghatak (forthcoming), Karlan (2005), Karlan (2007).

short run, we believe that this is a plausible assumption.

We are not in fact the first to note the association between commercialization and the decline of JL, however to our knowledge we are the first to outline the theoretical case and empirical evidence for a causal relationship from the former to the latter. Karlan and Zinman (2009) write:[5]

> [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 (nonprofits converting to for- profits) and the top-down (for-profits expanding into subprime and consumer segments).

The existing paper that comes closest to arguing for an explanation for the decline in JL is Giné and Karlan (2014), who show that converting joint liability groups to individual liability groups in the Philippines did not affect average repayment rates (the average effect is a precisely-estimated zero). This could be interpreted as showing that JL is actually unnecessary or ineffective, hence the decline in its use, though we think this is hard to square with the early and lasting success of JL-based lending.[6]

Three other papers compare IL and JL in a field setting, 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

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

[6] One possibility is that the social environment has changed, in particular social capital has strengthened such that JL is *no longer* necessary, as in the model of de Quidt, Fetzer and Ghatak (forthcoming), or it has weakened such that JL is no longer effective.

consistent with JL (weakly) improving repayment rates, as it does in equilibrium in our model, though it should be noted that the randomized studies do not find significant effects.

Finally, a number of other authors have worked with the MIX Market data. Cull, Demirgüç-kunt and Morduch (2009) use an early dataset to provide an extensive overview of the microcredit industry. In particular for our purposes, they also observe that non-profits are more likely than for-profits to use JL lending methods, as do we in our chronologically later and larger sample.

2 Three stylized facts

This section documents three simple stylized facts. 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.[7]

[7] 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-profits 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 decrease. 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 MFI entries, and are more likely to be from NGO to other forms that are more likely to be for-profit, see 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

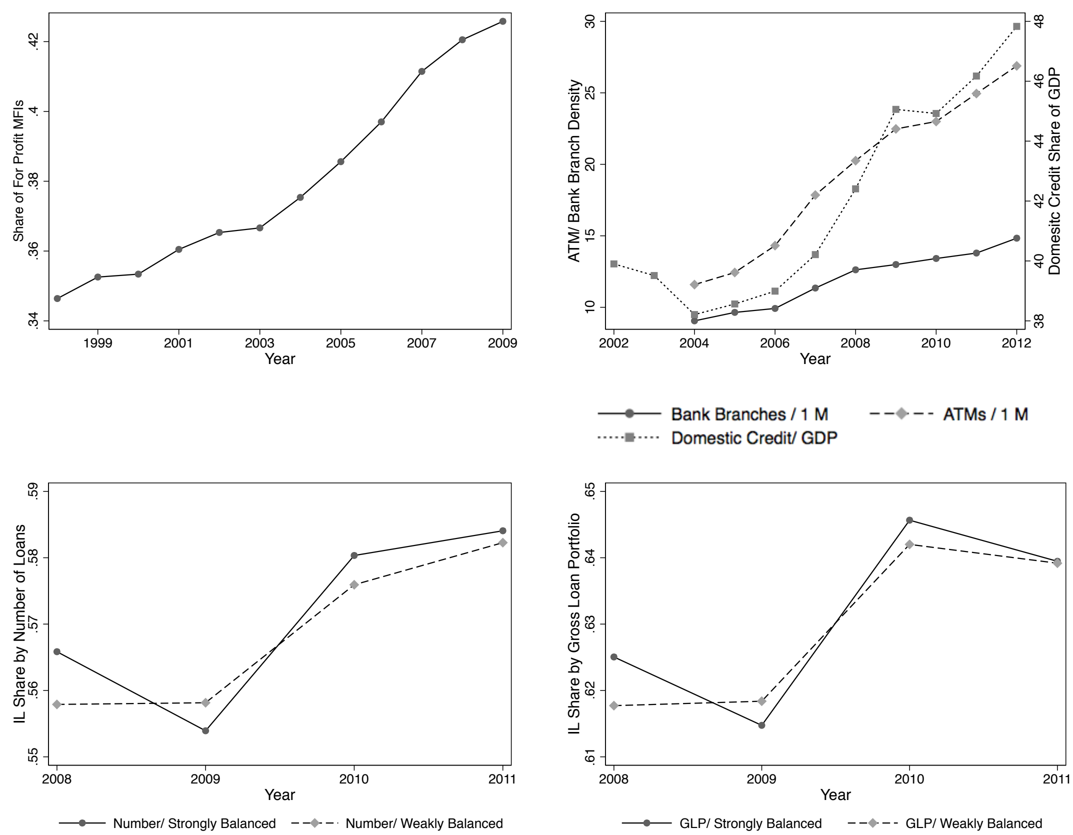

Figure 1: Three Stylized Facts. Top Left: Growing share of for-profit MFIs. Top Right: Increases in proxies for competitiveness. Bottom: Increase in individual liability lending measured by number of loans (left), or measured by gross loan portfolio (right).

Second, we document growth in three country-level variables that arguably proxy for credit market competition and are commonly referred to as proxies of financial access or financial depth (see e.g. Levine, 2005; Čihák et al., 2013).[8] The top right panel plots 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.[9] 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 identifying 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. Since reliable direct measures of the competitiveness for the microfinance sector do not exist, this suggests that the three proxy variables we explore may be reasonable.

The bottom left figure plots trends in MFIs' lending methodologies. For each MFI we compute, for each year it is available, the fraction of IL loans by number (weighting by size gives a very similar picture). Only around a quarter of MFIs report this variable in every year of 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: 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

change. In general, we expect each of these concerns to primarily affect the *level* of the for-profit share, rather than the qualitative trend.

[8] 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).

[9] The picture is very similar if we weight by the size or number of MFIs in each country.

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. Beyond the anecdotes, we are not aware of any systematic analysis of this trend.[10]

3 Model

We work with the same basic model as de Quidt, Fetzer and Ghatak (2013, forthcoming) and Allen (forthcoming). 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.[11] Borrowers' liability is limited to their cash on hand, so they cannot repay if unsuccessful. They discount exponentially with discount factor δ.[12]

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

[10]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.

[11]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 (2013a,b).

[12]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.

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 balance, otherwise her contract is terminated. The borrower 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.[13] 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 not be offered. In the former, both loans are repaid whenever at least one borrower succeeds, with probability $\pi^{JL} = p(2-p)$.[14] We define

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

[13]A possibility that we do not consider in this paper but analyze extensively in de Quidt, Fetzer and Ghatak (forthcoming) is that IL borrowers might also assist one another with repayment. There are many reasons why this is likely to be more difficult under IL.

[14]For simplicity, we will assume throughout the symmetric equilibrium such that subject to incentive compatibility, 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 alternative (time-invariant) repayment configurations.

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 $U - S$.[15] Thus the condition is $\delta V - 2r \geq \delta(U - S)$, or:

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

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 (for extensive discussion, see de Quidt, Fetzer and

[15] 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.

Ghatak (2013, forthcoming)). 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 $F(S)$.

Naturally, for IC1 to hold it must be that $V > U$. Credit cannot be so freely available that the borrower is always better off defaulting on her current loan and taking her outside option. We assume that there is always 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.

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 $2r < R$.[16] 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. In equilibrium, IC1 ensures that r can never exceed δpR, so we assume $\delta pR < \frac{R}{2}$ or:

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:

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

[16] 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).

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 assume a value for ρ and a maximum value for U, $\bar{U}$ such that IC1 is satisfied at $\hat{r}^{IL}$ (and therefore also at $\hat{r}^{JL}$ since $\hat{r}^{JL} < \hat{r}^{IL}$). Formally,

Assumption 2 $\rho \leq p r_{IC1}(\bar{U})$

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.[17] Given Assumption 2, a sufficient condition for $\hat{S} < 0$ 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

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

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 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 $\tilde{r}^{JL}(U,S) = \min\{r_{IC1}(U), r_{IC2}(U,S)\}$.[18]

When does the lender offer JL? He does if $q\tilde{r}^{JL}(U,S) > pr^{IL}(U)$, 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: $\tilde{S}(U) \geq \hat{S}(U)$.*

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 that under IL. Under IL the relevant incentive constraint (IC1) determines the maximum single payment the borrower is willing to make, $\delta(V-U) =$

[18] 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.

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.[19] 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 states 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 explore comparative statics on 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 assume that lenders are atomistic, each serving either two IL borrowers or one JL group. At the end of each period, lenders terminate all defaulting IL borrowers or JL groups. Then, for simplicity we assume that surviving

[19]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 $\frac{\frac{dr_{IC1}(U)}{dU}}{\frac{dr_{IC2}(U,S)}{dU}} = \frac{1}{2-\delta q} \in (0.5, 1)$.

IL borrowers are reshuffled to fill vacancies in other equivalent IL branches. This ensures that, with the exception of a trivial measure of "remainder" borrowers in the case of an odd number of defaults, branches either have two or zero vacancies at the beginning of the next period. We make the simplifying assumption that 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. 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 $F(\tilde{S}(U))$. Since the lender will always offer a contract such that $V > U$, borrowers always accept.

Denote by $\hat{\eta}(U)$ ($\tilde{\eta}(U)$) the steady-state fraction of non-profit (for-profit) lenders offering IL. At non-profit (for-profit) lenders, new borrowers receive IL contracts with probability $F(\hat{S}(U))$ ($F(\tilde{S}(U))$). 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. 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 corresponding steady state JL shares are $1-\hat{\eta}(U) = \frac{1-F(\hat{S}(U))}{1-F(\hat{S}(U))p}$ and $1-\tilde{\eta}(U) = \frac{1-F(\tilde{S}(U))}{1-F(\tilde{S}(U))p}$.

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:

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

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, the model would 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 so are a less attractive outside option). It is straightforward to do so in a model with homogeneous S (i.e. F is degenerate), and we do so in de Quidt, Fetzer and Ghatak (2013). When S is homogeneous, it becomes more difficult to think about comparative statics, since 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.

Unfortunately, when S is heterogeneous we can derive U only as a complex implicit function that does not yield easily interpreted comparative statics. For this reason, we use our "reduced form" analysis 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.

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 3,482 observations, for the period from 2008 to 2011.[20] 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. Using these data we construct MFI-level IL portfolio shares, "IL shares."

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

[20]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.

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 879 (832), who report lending methodology by number of loans (gross loan portfolio) at least twice.[21] 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 assume for identification purposes that (at least qualitatively) any trends 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 on the MIX market. 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 MFIs. Table 1 presents summary statistics for the full sample, the weakly balanced and the strongly balanced sample.[22] 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

[21]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.

[22]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).

dataset, in particular on our key IL share and profit status variables, though we do find significant differences in some variables. The data we work with are the best available that contain lending methodology information.

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.[23] 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, e.g. by Beck (2007) or Ahlin, Lin and Maio (2011), see also Levine (2005); 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 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.

[23] 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.

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 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 quite widely, from 17 to 100 percentage points per 1 s.d. change, the latter implausible point estimate following from the linearity imposed on the specification), while non-profits raise theirs (all but one coefficient positive, ranging from -5 to +40 percentage points per 1 s.d. 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. To check, 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.[24]

Results are presented in Appendix Tables 6 and 7. The signs, magnitudes and precision of our main coefficients are highly robust, and if anything our 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 (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, Operating expense/assets. 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.

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,

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

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. Albeit, some of the point estimates are implausibly large–by imposing linearity our specification permits estimates of changes in portfolio shares that exceed 100 percent.

Overall, the evidence presented using three different proxy variables is broadly consistent with the theoretical predictions.

5 Conclusion

While it often claimed that joint liability is in decline, this paper is the first rigorous attempt to examine the trend empirically and to analyze its cause. We first 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 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–so we are unable to make quantitative claims based on our results.

A number of authors make an informal taste-based argument for the decline of JL, arguing that JL is inconvenient and uncomfortable for borrowers, who dislike having their social capital leveraged in this way. That may indeed be the case for some, but to generate a trend there must have been 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 tests). We show that commercialization predicts the decline without needing to resort to changing tastes, as was noted anecdotally by Karlan and Zinman (2009). We hope that this paper brings clarity and rigor to the discussion about the changing face of microfinance.

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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	0.57	879	0.25	0.57	348	0.70
IL Share by Loan Value	0.64	1476	0.63	843	0.71	0.63	337	0.95
Non Profit	0.60	1408	0.60	879	0.91	0.66	348	0.21
Non-Regulated	0.33	1768	0.39	879	<0.01	0.47	348	0.01
NGO	0.32	1898	0.37	879	0.01	0.45	348	0.01
Portfolio at Risk 90 days	6.43	1732	5.75	877	0.30	4.92	348	0.01
Return on Assets	-0.25	1657	0.46	877	0.01	1.39	348	0.01
Profit Margin	-4.88	1741	-0.42	878	<0.01	3.97	348	<0.01
MFI Risk Rating (1-5)	2.65	1920	2.95	879	<0.01	3.59	348	<0.01
Capital to Asset Ratio	36.77	1813	32.21	878	0.10	30.29	348	0.85
Debt to Equity Ratio	8.47	1772	4.87	878	0.16	7.34	348	0.08
Average Loan Balance	6405.76	1906	1422.42	879	0.55	1230.42	348	0.16
Cost per Borrower	304.37	1514	241.71	870	0.09	195.03	348	<0.01
Write Offs/ Assets	2.36	1623	2.18	876	0.32	2.19	348	0.60

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	0.48	112	0.47	100	0.52	0.51	64	0.03
Mobile Phones/100 people	74.66	111	73.13	99	0.20	82.19	63	0.01
Agriculture share in GDP	18.18	103	18.52	92	0.63	15.64	61	0.02
Industrial sector share in GDP	29.07	103	28.28	92	0.27	28.96	61	0.96
Service sector share in GDP	53.20	104	53.70	93	0.25	56.13	62	$<$0.01
Development Aid as share of GDP	6.70	106	6.19	95	0.49	5.30	61	0.16
GDP Growth Rate	3.89	110	4	98	0.20	3.82	64	0.96
GDP per capita	3.70	110	3.33	98	0.04	3.78	64	0.74
Domestic Credit / GDP	4.52	105	4.34	93	0.49	4.70	61	0.41
Commercial bank density	1.31	111	1.29	100	0.83	1.65	64	$<$0.01
ATM Density	2.28	109	2.16	98	0.10	2.61	63	0.08

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	-0.583	-0.875*	-0.225	-0.567	-0.447	-0.213
	(0.646)	(0.510)	(0.169)	(0.359)	(0.288)	(0.138)
Non Profit	-0.137**	-0.175**		-0.094*	-0.164***	
	(0.058)	(0.075)		(0.050)	(0.045)	
Non-Profit x Bank Branch Density	0.658	1.115*	0.308	0.674**	0.640*	0.241*
	(0.511)	(0.598)	(0.194)	(0.286)	(0.323)	(0.143)
Joint test:						
Comp + Non-Profit x Comp = 0?	.075	.24*	.082	.107	.193**	.027
	(.41)	(.131)	(.115)	(.25)	(.0855)	(.06)
MFIs	348	348	348	879	879	879
Countries	64	64	64	93	93	93
Observations	1392	1392	1392	2758	2758	2758

Panel B: IL Share by Gross Loan Portfolio

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.893	-0.986**	-0.167	-0.739**	-0.652**	-0.179
	(0.629)	(0.421)	(0.116)	(0.325)	(0.256)	(0.110)
Non Profit	-0.148***	-0.176***		-0.116***	-0.167***	
	(0.050)	(0.060)		(0.042)	(0.041)	
Non-Profit x Bank Branch Density	0.847*	1.381**	0.315	0.790***	0.908***	0.284
	(0.485)	(0.534)	(0.223)	(0.274)	(0.316)	(0.176)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.045	.395**	.147	.051	.256**	.105
	(.396)	(.154)	(.168)	(.238)	(.12)	(.113)
MFIs	340	340	340	832	832	832
Countries	60	60	60	93	93	93
Observations	1360	1360	1360	2607	2607	2607
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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 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 as reported 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 report 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.

We village banks the lending method is less clear as for pure individual liability lenders, the main analysis treats them as JL lenders, and we also exclude all MFIs that, at some point, reported strictly positive village lending in regression Table 11.

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.

B 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	0.57	830	0.40	0.56	340	0.63
IL Share by Loan Value	0.64	1476	0.63	832	0.95	0.62	340	0.89
Non Profit	0.60	1408	0.61	832	0.40	0.63	340	0.47
Non-Regulated	0.33	1768	0.38	832	0.25	0.46	340	0.02
NGO	0.32	1898	0.38	832	$<$0.01	0.44	340	0.01
Portfolio at Risk 90 days	6.43	1732	5.67	830	0.20	4.82	340	$<$0.01
Return on Assets	-0.25	1657	0.37	830	0.06	1.55	340	0.01
Profit Margin	-4.88	1741	-0.80	831	0.01	4.29	340	$<$0.01
MFI Risk Rating (1-5)	2.65	1920	2.98	832	$<$0.01	3.60	340	$<$0.01
Capital to Asset Ratio	36.77	1813	32.25	831	0.11	30.06	340	0.75
Debt to Equity Ratio	8.47	1772	4.98	831	0.12	7.40	340	0.07
Average Loan Balance	6405.76	1906	1384.06	832	0.26	1278.33	340	0.27
Cost per Borrower	304.37	1514	237.14	823	0.05	200	340	$<$0.01
Write Offs/ Assets	2.36	1623	2.17	829	0.30	2.16	340	0.54

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	-1.091	-1.492***	-0.321	-0.715*	-0.604*	-0.260
	(0.741)	(0.527)	(0.199)	(0.386)	(0.337)	(0.170)
Non Profit	-0.160***	-0.193***		-0.119***	-0.178***	
	(0.050)	(0.052)		(0.038)	(0.040)	
Non-Profit x Bank Branch Density	1.330**	1.949***	0.478**	1.010**	0.989**	0.383**
	(0.643)	(0.653)	(0.197)	(0.407)	(0.386)	(0.160)
Further Interactions:						
Urban population share	-0.026	-0.056	-0.990	-0.250	1.544	-0.443
	(0.452)	(1.283)	(1.383)	(0.265)	(1.410)	(0.905)
Non Profit x Urban population share	0.129	-0.085	-0.207	0.095	-0.219	-0.340
	(0.487)	(0.526)	(1.844)	(0.358)	(0.387)	(1.826)
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	0.006	-0.008
	(0.026)	(0.028)	(0.009)	(0.022)	(0.023)	(0.011)
Joint test:						
Comp + Non-Profit x Comp = 0?	.239	.456**	.157	.295	.385***	.123*
	(.519)	(.177)	(.11)	(.375)	(.146)	(.0691)
MFIs	334	334	334	794	794	794
Countries	58	58	58	82	82	82
Observations	1335	1335	1335	2521	2521	2521
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	-1.212	-1.339**	-0.221*	-0.843**	-0.807*	-0.273**
	(0.782)	(0.579)	(0.123)	(0.374)	(0.411)	(0.109)
Non Profit	-0.173***	-0.189***		-0.136***	-0.173***	
	(0.050)	(0.053)		(0.039)	(0.041)	
Non-Profit x Bank Branch Density	1.492**	1.987**	0.514**	1.216***	1.294**	0.520***
	(0.720)	(0.763)	(0.221)	(0.431)	(0.506)	(0.173)
Further Interactions:						
Urban population share	0.096	0.607	0.218	-0.174	1.332	-0.340
	(0.425)	(1.238)	(1.210)	(0.263)	(1.729)	(0.832)
Non Profit x Urban population share	0.341	0.220	0.381	0.202	-0.043	0.240
	(0.379)	(0.452)	(2.028)	(0.324)	(0.345)	(2.107)
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	-0.014***
	(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?	.281	.648***	.294*	.372	.487**	.247**
	(.517)	(.209)	(.146)	(.325)	(.191)	(.107)
MFIs	327	327	327	754	754	754
Countries	54	54	54	82	82	82
Observations	1307	1307	1307	2394	2394	2394
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	-0.178**		-0.103		-0.167***		-0.130***	
	(0.083)		(0.073)		(0.049)		(0.042)	
Non-Profit x Bank Branch Density	1.127*	0.165	1.178*	0.203*	0.644*	0.175**	0.740**	0.152*
	(0.666)	(0.100)	(0.702)	(0.102)	(0.345)	(0.086)	(0.324)	(0.085)
MFIs	348	348	348	348	879	879	875	875
Countries	64	64	64	64	93	93	93	93
Observations	1392	1392	1347	1347	2758	2758	2613	2613

Panel B: IL Share by Gross Loan Portfolio

	Strongly Balanced				Weakly Balanced			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non Profit	-0.180***		-0.100		-0.173***		-0.138***	
	(0.066)		(0.070)		(0.044)		(0.040)	
Non-Profit x Bank Branch Density	1.398**	0.156	1.318**	0.142	0.932***	0.186	0.918***	0.147
	(0.592)	(0.149)	(0.584)	(0.169)	(0.338)	(0.130)	(0.313)	(0.132)
MFIs	340	340	340	340	832	832	828	828
Countries	60	60	60	60	93	93	93	93
Observations	1360	1360	1318	1318	2607	2607	2469	2469
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	-0.583	-0.875*	-0.225	-0.567	-0.447	-0.213
	(0.646)	(0.510)	(0.169)	(0.359)	(0.288)	(0.138)
Non Profit	-0.137**	-0.175**		-0.094*	-0.164***	
	(0.058)	(0.075)		(0.050)	(0.045)	
Non-Profit x Bank Branch Density	0.658	1.115*	0.308	0.674**	0.640*	0.241*
	(0.511)	(0.598)	(0.194)	(0.286)	(0.323)	(0.143)
Joint test:						
Comp + Non-Profit x Comp = 0?	.075	.24*	.082	.107	.193**	.027
	(.41)	(.131)	(.115)	(.25)	(.0855)	(.06)
MFIs	348	348	348	879	879	879
Countries	64	64	64	93	93	93
Observations	1392	1392	1392	2758	2758	2758
Panel B:	(1)	(2)	(3)	(4)	(5)	(6)
ATM Density	-0.559	-0.484	-0.135	-0.529	-0.216	-0.123
	(0.534)	(0.457)	(0.305)	(0.432)	(0.358)	(0.197)
Non Profit	-0.158**	-0.210***		-0.108**	-0.184***	
	(0.059)	(0.076)		(0.050)	(0.047)	
Non-Profit x ATM Density	0.412	0.558	0.056	0.265	0.231	0.146
	(0.442)	(0.539)	(0.354)	(0.407)	(0.369)	(0.194)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.147	.074	-.079	-.264	.015	.023
	(.302)	(.278)	(.281)	(.217)	(.114)	(.0826)
MFIs	346	346	346	866	866	866
Countries	63	63	63	91	91	91
Observations	1348	1348	1348	2671	2671	2671
Panel C:	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Credit Share	-1.290**	-1.874***	-1.107***	-0.948**	-0.820*	-1.102***
	(0.535)	(0.580)	(0.372)	(0.372)	(0.487)	(0.379)
Non Profit	-0.158***	-0.235***		-0.115**	-0.193***	
	(0.051)	(0.062)		(0.049)	(0.044)	
Non-Profit x Domestic Credit Share	1.077*	1.725**	0.660	0.757*	0.816	0.962***
	(0.565)	(0.743)	(0.404)	(0.401)	(0.538)	(0.360)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.212	-.149	-.447	-.191	-.003	-.14
	(.291)	(.341)	(.307)	(.215)	(.363)	(.205)
MFIs	338	338	338	835	835	835
Countries	61	61	61	88	88	88
Observations	1352	1352	1352	2644	2644	2644
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	-0.893	-0.986**	-0.167	-0.739**	-0.652**	-0.179
	(0.629)	(0.421)	(0.116)	(0.325)	(0.256)	(0.110)
Non Profit	-0.148***	-0.176***		-0.116***	-0.167***	
	(0.050)	(0.060)		(0.042)	(0.041)	
Non-Profit x Bank Branch Density	0.847*	1.381**	0.315	0.790***	0.908***	0.284
	(0.485)	(0.534)	(0.223)	(0.274)	(0.316)	(0.176)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.045	.395**	.147	.051	.256**	.105
	(.396)	(.154)	(.168)	(.238)	(.12)	(.113)
MFIs	340	340	340	832	832	832
Countries	60	60	60	93	93	93
Observations	1360	1360	1360	2607	2607	2607
Panel B:	(1)	(2)	(3)	(4)	(5)	(6)
ATM Density	-0.938**	-0.375	-0.045	-0.639*	-0.454	-0.192
	(0.361)	(0.381)	(0.311)	(0.343)	(0.304)	(0.217)
Non Profit	-0.168***	-0.201***		-0.133***	-0.189***	
	(0.049)	(0.056)		(0.044)	(0.043)	
Non-Profit x ATM Density	0.646**	0.863**	0.385	0.289	0.419	0.078
	(0.307)	(0.331)	(0.400)	(0.339)	(0.289)	(0.235)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.292	.488	.34	-.349*	-.036	-.113
	(.234)	(.323)	(.362)	(.179)	(.129)	(.0991)
MFIs	338	338	338	819	819	819
Countries	59	59	59	91	91	91
Observations	1318	1318	1318	2514	2514	2514
Panel C:	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Credit Share	-1.274***	-1.381**	-1.223***	-1.167***	-0.632	-1.035**
	(0.473)	(0.579)	(0.402)	(0.330)	(0.441)	(0.394)
Non Profit	-0.161***	-0.208***		-0.140***	-0.198***	
	(0.043)	(0.061)		(0.039)	(0.041)	
Non-Profit x Domestic Credit Share	0.745	1.221	1.004**	0.775**	0.772	0.937**
	(0.516)	(0.757)	(0.421)	(0.351)	(0.479)	(0.373)
Joint test:						
Comp + Non-Profit x Comp = 0?	-.529*	-.16	-.219	-.392*	.14	-.098
	(.303)	(.328)	(.249)	(.224)	(.368)	(.261)
MFIs	333	333	333	790	790	790
Countries	58	58	58	88	88	88
Observations	1329	1329	1329	2501	2501	2501
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	-0.494	-0.631*	-0.158	-0.686**	-0.376	-0.170
	(0.355)	(0.374)	(0.116)	(0.326)	(0.347)	(0.108)
Non Profit	-0.186***	-0.204***		-0.095*	-0.173***	
	(0.058)	(0.070)		(0.052)	(0.045)	
Non-Profit x Bank Branch Density	0.621	0.844*	0.219	0.672*	0.605	0.209*
	(0.446)	(0.483)	(0.141)	(0.343)	(0.388)	(0.117)
Joint test:						
Comp + Non-Profit x Comp = 0?	.127	.214	.06	-.014	.23**	.039
	(.316)	(.152)	(.0927)	(.216)	(.0958)	(.0502)
MFIs	257	257	257	689	689	689
Countries	59	59	59	91	91	91
Observations	1013	1013	1013	2087	2087	2087

Panel B: IL Share by Gross Loan Portfolio

	Strongly Balanced			Weakly Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial bank density	-0.453	-0.473	-0.059	-0.744**	-0.597*	-0.070
	(0.319)	(0.316)	(0.067)	(0.305)	(0.349)	(0.078)
Non Profit	-0.185***	-0.189***		-0.131***	-0.191***	
	(0.060)	(0.070)		(0.047)	(0.047)	
Non-Profit x Bank Branch Density	0.612	0.648	0.280	0.774**	0.821**	0.238*
	(0.458)	(0.450)	(0.175)	(0.356)	(0.397)	(0.128)
Joint test:						
Comp + Non-Profit x Comp = 0?	.158	.175	.221	.029	.224*	.169**
	(.333)	(.17)	(.133)	(.224)	(.122)	(.0812)
MFIs	249	249	249	647	647	647
Countries	54	54	54	92	92	92
Observations	948	948	948	1906	1906	1906
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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.