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Don't Stay Put: Ride the (Credit) Wave

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Abstract

Information asymmetries and enforcement problems often limit commercial lenders' entry into low-income markets. Using detailed credit registry data with more than 32 million bank-borrower loan observations, we study the "failed" entry of commercial lenders into Bolivia's microfinance market in the mid-1990s, which led to an over-indebtedness crisis. Tracing borrowers' credit outcomes for nearly 10 years, we find that despite the commercial lenders' poorly adapted lending technologies, stronger adverse selection, and moral hazard problems, the increase in competition carried significant short-term and long-term credit benefits to borrowers by forcing microfinance institutions to improve their loan terms and reduce rents.

Keywords: banking, financial inclusion, microfinance, credit scoring, competition
JEL classification: G21, L2, O16, P34

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1. Introduction

The microfinance sector has been instrumental in improving financial inclusion in developing countries by harnessing "soft" information from client relationships and adapting lending technologies to overcome the heightened information frictions and enforcement problems in these markets (e.g., Besley and Coate, 1995; Armendáriz and Morduch, 2010; Kaboski and Townsend, 2012). Facilitated by continued advancements in information technology, markets traditionally served by microfinance institutions (MFIs) are increasingly exposed to a greater variety of financial institutions, offering a wider choice of products and services at potentially better terms.[1] Consequently, pertinent questions have shifted from not only assessing the impact of first-time access to credit, but also to understanding the effects such 'entries' may have on the intensive margin from the increased competition between incumbent and new lenders for common borrowers. A common expectation is that microfinance borrowers should benefit from obtaining access to commercial lenders with more sophisticated lending technologies, wider product provision, and cheaper funding. Such entries, however, are not common and not always successful. Overborrowing and incompatible lending technologies often lead to boom-bust cycles with long-term adverse effects on borrowers.[2]

To understand the possible drivers and consequences of "failed" entries on borrowers, we study the entry of commercial lenders (CLs) into Bolivia's microfinance market in the mid-1990s, which led to an over-indebtedness crisis and ended with the withdrawal of CLs from the microfinance market. Using detailed loan-level data from the Bolivian credit registry between 1995 and 2004, we zero into this episode to: i) trace the role adverse selection problems and incompatible lending technologies may have played on CLs' unsuccessful entry, and ii) assess the short-term and long-term effects on MFI borrowers' with respect to access and terms of credit. The Bolivian credit registry covers the universe of regulated lenders and borrowers and allows us to trace borrowers' credit histories, loan characteristics, and repayment over a considerably long period of nearly ten years. The dataset includes more than 32.6 million bank-borrower-loan observations on a monthly frequency for 1.2 million individual borrowers of MFIs and CLs.

Bolivia offers an interesting setting for analysis. During the 1990s, Bolivia had one of the most advanced and thriving microfinance sectors in the world, operating largely on commercial principles (i.e., for profit).[3] Observing the success of microfinance institutions (MFIs), new domestic and foreign lenders

[1] These aggregate trends can be observed in the World Bank's Global Financial Development Database and studies relying on these data (e.g., Cihák et al., 2012; Barajas et al., 2013; Sahay et al., 2015).

[2] New lenders, for example, may not internalize the negative externalities their loans may have on existing lenders, leading to overborrowing and defaults (Bizer and DeMarzo, 1992; Parlour and Rajan, 2001). Aggressive lending practices may also induce naïve, impulsive borrowers to take on too much debt, often for consumption purposes (Benton et al. 2007; Heidhues and Koszegi 2010; Di Maggio and Yao, 2021). More automated and centralized lending process, often used by larger commercial lenders, may also not be suited for screening and monitoring low income and low documentation borrowers (Berger and Udell 2006; Mian 2006; Liberti and Mian 2009; Skrastins and Vig, 2019).

[3] Bolivia's largest microfinance institution at the time, BancoSol, consistently topped the list of financial institutions in the country in terms of profitability, asset quality, and capital adequacy (Rhyne, 2002).

thought they could do better and began to aggressively target MFI customers. New entrants included domestic commercial banks—who, faced with increased competition on their corporate clients from foreign banks, decided to go "downstream"— as well as new domestic and foreign lenders using a range of lending technologies. Some of these entrants adopted traditional MFI lending technologies (e.g., joint liability group lending) by recruiting experienced loan-officers from incumbent MFIs, while others relied on arms-length lending technologies and credit scoring models widely used in consumer lending, enabled by advancements in information technologies, which allowed the processing of large data more efficiently. Within a short period of time, many MFI borrowers saw large increases in their borrowing and began defaulting. This was made worse when Bolivia's economy was hit by an external shock following Brazil's financial crisis and exchange rate devaluation in January 1999. Suffering large losses, many CLs withdrew from the microfinance market (see, e.g., Rhyne, 2002 for a detailed chronicle of this episode).

This paper zooms into this episode to understand the role adverse selection and lending technologies may have played in CLs' unsuccessful entry and its effects on the MFI borrowers' access and terms of credit, both in the short run and in the long run. To evaluate the CLs' risk appetite and screening abilities vis-à-vis the incumbent MFIs, we closely examine the *ex-ante* risk profile of MFI borrowers who switched to CLs. Crucially, the institutional setting and data availability allows us to distinguish between ex-ante borrower risk that is observable or unobservable to new perspective lenders, and thus assess adverse selection and how it varies with the lending technologies employed by different lenders (e.g., credit scoring models, joint liability group lending). We further study the terms of the MFI borrowers' initial uptake at CLs. We compare the terms the switching MFI borrowers receive at CLs with: i) their borrowing terms at their initial MFIs, and ii) the terms similar switching borrowers obtain at other MFIs. Using cohorts of loans originated during the entry phase of this episode, we evaluate the role CLs' lending practices had on ex-post borrower delinquency rates before the economy was hit by an external shock and CLs withdrew from the market. Overall, the results indicate that despite the CLs' poorly adapted lending technologies and worse adverse selection problems, the CLs' entry into the microfinance market carried significant benefits for MFI borrowers, both in the short term and in the long term.

In what follows, we summarize our key results and explain how they relate and contribute to the extant literature. We begin by studying how switching to CLs varied over the sample period.[4] Consistent with reports that CLs were trying to penetrate the microfinance market by targeting MFI customers, we find

[4] As in Ioannidou and Ongena (2010), we define a loan as a "switch" or "switching loan" when a borrower obtains a new loan from a lender with whom it did not have any prior or recent lending relation. We refer to such lenders as "outside lenders". Conversely, we define any lender with whom the borrower had a recent prior lending relation as "inside lenders". We effectively assume that proprietary borrower information, gathered through prior lending relations, becomes stale over time. Importantly, our definition of "switching" does not differentiate between borrowers that are "moving" permanently to a new lender and those that are "adding" a lending relationship. This is because any such distinction would depend on future and possibly endogenous responses of inside lenders to the borrower's switch.

that in mid-1996, switching rates from MFIs to CLs began increasing rapidly from less than 5% to more than 20% by the end of 1996. Switching rates remained high until mid-1998, when they began decreasing rapidly as CLs began receding from the microfinance market after suffering significant losses from loan defaults.

Focusing on the entry phase of the cycle, we find that MFI borrowers who switch to CLs obtain more attractive terms, both with respect to their initial MFIs and to what similar switching borrowers obtain at another MFI. They obtain loans that are larger, cheaper, with longer maturities, and without joint liability or collateral. Differences are economically quite large. For example, relative to their borrowing terms at their initial MFIs, CL loans are on average 52 percent larger, 3.2 pp cheaper, have 12.7 months longer maturities, are 59 pp less likely to have joint liability, are 13 pp less likely to have collateral, and 15.3 pp more likely to have personal guarantees, indicating that CLs may be compensating for the lack of collateral with personal guarantees. We also find that MFI-to-CL loans are 51 pp more likely to be denominated in a foreign currency (USD), exposing MFI borrowers to foreign exchange rate risk.

Studying the ex-ante risk profile of switching borrowers, we find that both MFIs and CLs are less likely to lend to *observably* riskier switchers than their current lenders (i.e., switchers have a lower incidence of known past delinquencies or defaults than non-switching MFI borrowers).[5] We find that both types of lenders try to "cherry pick" switchers with observably "clean" credit histories to a similar degree. Nevertheless, both types of lenders end-up with switchers with more *unobservable* past delinquencies, consistent with asymmetric information and "winner's curse" problems between current (inside) and new (outside) lenders.[6] Importantly, we find that CLs face stronger adverse selection problems than MFIs: unobservable past delinquencies are twice as likely among borrowers who switch to CLs than MFIs. This is a novel result as indicators of unobservable borrower risk are typically not available to researchers. Exploiting heterogeneity in CLs' lending technologies, we find that CLs' worse adverse selection problems are more pronounced in CLs that do *not* adapt their lending technologies to the microfinance market but use instead arms-length transaction technologies and credit scoring models developed for consumer loans.

Studying ex-post loan repayment, we find that MFI borrowers who switch to CLs have about 42 to 49 pp higher incidence of ex-post delinquency rates on their switching loans than similar MFI borrowers who switch to other MFIs. Importantly, those who switch within MFIs have instead very similar ex-post delinquency rates to those who stay at their initial MFIs. Further analyses, suggest that the MFI-to-CL switchers' higher ex-post delinquency rates at CLs are unlikely to be due to differences in ex-ante borrower

[5] Prior analyses (e.g., Berger, Frame, and Ioannidou, 2011) and robustness checks in our paper confirm that such past repayment problems do not represent obsolete information but are predictive of repayment problems on future loans.
[6] See, e.g., Sharpe (1990), Rajan (1992), von Thadden (2004), and Ioannidou and Ongena (2010).

risk, observed or unobserved, but rather the terms they were offered. In particular, we find that differences in delinquency rates remain very stable as we progressively match on ex-ante borrower risk or use control groups with different ex-ante borrower risk (e.g., switchers vs. non-switchers). In addition, exploiting heterogeneity in borrower and lender characteristics, we find that ex-post repayment problems are disproportionally higher for switchers to non-adaptive CLs that offered more aggressive terms. In particular, ex-post delinquency rates and defaults are systematically higher for borrowers with larger increases in total outstanding debt, for borrowers with foreign (USD) currency loans, and loans without joint liability. Importantly, our estimates for these results also remain stable as we progressively control for ex-ante borrower risk, both observed and unobserved. This indicates that these borrowers' relatively worse ex-post repayment performance is unlikely to be driven by selection issues, but rather by over-indebtedness, foreign exchange rate risk, and weaker ex-post monitoring from their peers.

Our dynamic difference-in-difference (DiD) analysis on the switchers' long-term credit outcomes further shows that despite CLs' poorly adapted lending technologies, more aggressive lending practices, and ensuing borrower defaults, the average MFI borrower who switches to CLs sees significant long-term benefits relative to similar borrowers who switch within MFIs. They are able to borrow more, at cheaper rates, and with longer maturities even in the long run. Benefits in terms of collateral are only transitory. MFI borrowers with repayment problems on their switching CL loans saw more modest long-term benefits, but even this group did not appear to fare relatively worse than before switching. Importantly, we also find that CLs' entry led MFIs to significantly improve their subsequent loan terms to both switching and non-switching MFI borrowers, particularly in areas where they lost more borrowers to CLs. Overall, our findings indicate that despite the CLs' poorly adapted lending technologies and borrower defaults, the resulting increase in competition from CLs' entry carried significant benefits to MFI borrowers, both in the short term and in the long term. It is also important to note that the pre-trends depicted by the dynamic DiD analyses show that the matched MFI-to-CL and MFI-to-MFI switchers exhibit parallel trends with respect to several credit outcomes (e.g., total outstanding loans, interest rates, maturity, collateral).

Our paper contributes to the literature on borrower credit outcomes from access to commercial lenders in traditional microfinance markets and is most closely related to Agarwal, Kigabo, Minoiu, Presbitero, and Silva (2021). The authors provide rigorous evidence of the commonly theorized "graduation" hypothesis in microfinance, by leveraging credit registry data from Rwanda and assessing outcomes from increased overlap between local MFIs and commercial banks. In their setting, the lower-income credit market was relatively unpenetrated, and expansion was primarily driven by a large-scale microcredit expansion program. The program is found to foster local development not only by bringing in a previously underbanked population into the formal financial sector, but also by allowing them to "graduate" to commercial banks by building credit histories. Providing evidence that such "graduation"

takes place is important because while many archetypal microfinance lending practices (such as starting with small loan sizes, short maturity, having frequent and fixed repayment schedules, joint liability, etc.), may be useful for mitigating information asymmetries, they may also explain why these loans have not generated more impact for borrowers. Capacity constraints and the ensuing rigidity of the loan contracts may inadvertently constrain borrowers, discourage risk-taking, and prevent productive clients from obtaining sufficient funding to pursue growth opportunities (Banerjee, 2013; Field et al., 2013). In Agarwal et al. (2021), the "graduating" borrowers are found to increase their levels of borrowing and obtain better loan conditions, without significant increases in ex-post loan repayment problems.

By contrast, ours is a setting where low-income borrowers were already served by relatively developed MFIs and then rapidly gained access to a wider range of commercial lenders, actively trying to penetrate the market. Such a scenario is typically viewed with concern in the microfinance literature, as incompatible lending technologies[7] and too much competition[8] are seen as leading to overborrowing (see Rhyne, 2002). In our setting, we document similar evidence of "graduation" and improved loan terms as Agarwal et al. (2021) but do observe much stronger adverse borrower performance issues in the short run. However, we are able to provide a new perspective on the "incompatibility story" by showing that in the long run, credit outcomes for the average microfinance borrower switching to CLs are quite positive and that even the adversely affected switchers recover in the medium term. We are also able to demonstrate how competition, particularly from non-adaptive CLs (i.e., those using the most different lending technologies), ultimately has a positive effect on microfinance institutions by forcing them to improve their overall loan terms. As such, both our and Agrawal et al. (2021)'s results are in line with a long-standing literature emphasizing the role of banks and financial development for growth and economic convergence (King and Levine, 1993; Jayaratne and Strahan, 1996; Beck et al. 2000, 2007), as well as studies documenting the wide range of economic benefits from financial inclusion programs in developing countries such as India (Burgess and Pande, 2005; Agarwal, Alok, Ghosh, Ghosh, Piskorski and Seru, 2017), Kenya (Allen, Carletti, Cull, Qian, Senbet and Valenzuela, 2021) and Mexico (Bruhn and Love, 2014), among many others.

Our results may also be relevant to recent trends in FinTech lending, where advances in information

[7] There are many studies that scrutinize the role of archetypal microfinance lending technologies at dealing, for example, with information asymmetries, adverse selection, and moral hazard issues. They typically analyze the role of joint liability lending (e.g., Giné and Karlan, 2014; Attanasio et. al., 2015), dynamic incentives (e.g., Giné et al., 2010), contract rigidity (e.g., Field et al., 2013) and focus predominantly on evaluating borrowers' loan performance with their original lender and within the short term (e.g., typically, their initial loan).

[8] A few studies examine the effects of multiple lending relationships in microfinance markets and demonstrate how multiple lending relations can weaken borrower incentives to repay and drive default (McIntosh and Wydick, 2005; McIntosh, de Janvry, and Sadoulet, 2005; Guha and Chowdhury, 2013). The closest to ours is McIntosh, de Janvry, and Sadoulet (2005), who study the effects of competition between MFI lenders differing in their use of individual vs. joint liability lending on borrower outcomes. However, all of these past studies have exclusively looked at competition from within MFIs and also have been unable to examine the long-term outcomes for borrowers.

technology are facilitating the entry of new technology-driven lenders in low-income and low-documentation markets, traditionally unserved or underserved by incumbent lenders. Thus far, much of the existing evidence suggests that these FinTech entrants seek out differentiated market segments and traditionally disadvantaged groups (e.g., Hau et al., 2019; Frost et al. 2019; Di Maggio et al. 2021; Jagtiani and Lemieux 2019; Erel and Liebersohn, 2021). There are clear examples where such entries are facilitated by the ability of FinTech lenders to expand the information set with new data (e.g., Berg et al., 2020; Agarwal et al., 2020) or to improve the informational content of existing data (e.g., Fuster et al., 2021). However, to date, it is not at all clear that the growth of FinTech lending is driven by significant competitive advantages in screening and monitoring, but rather by the attractiveness of faster and streamlined processes (see a recent review of related literature by Fuster, Berg, and Puri, 2021). Concerns that easy and fast credit induce over-indebtedness and destabilize competition for common customers loom high.[9] Our results suggests that even in the absence of better screening and monitoring abilities and in the presence of aggressive lending policies and defaults as we show, the ensuing increase in competition from disruptive entrants is likely to have first-order positive effects for most borrowers, both in the short term and in the long term.

The remainder of the paper is organized as follows. In section 2 we describe our dataset, the information sharing environment, and the lending technologies of different lenders in our setting. In section 3 we study the frequency of switching across different groups of lenders and over time. In sections 4 and 5 we report on our main results and various robustness checks. In Section 6 we conclude.

2. Data and institutional setting

Our analysis utilizes data from the Central de Información de Riesgos Crediticios (CIRC), the public credit registry of Bolivia, managed by the Bolivian Superintendent of Banks and Financial Entities (SBEF). Since CIRC's creation in 1989, the SBEF requires all licensed financial institutions operating in Bolivia to record information on all loans (i.e., there is no minimum reporting threshold).

We have access to the entire credit registry for the period between January 1995 and June 2004. For each loan, we observe the identity of the bank originating each loan, the region and date of loan origination, the type of loan, the maturity date, and detailed contract information such as loan amount, interest rate, value of collateral securing the loan, and ex-post repayment (e.g., repayment, overdue payments, default). Borrower information includes a unique identification number that allows us to track borrowers across

[9] For example, in 2017, Chinese regulators introduced a series of regulations aiming to curb "reckless" expansion of FinTech lenders after a series of defaults and marketplace platform failures (Cornelli et al., 2020).

banks and time, the borrower's legal entity type (e.g., natural person, legally-recognized firm, non-profit organization), current and past lending relationships, the borrower's internal credit rating with each bank, and current and past credit history (i.e., overdue payments or default with any lender in the registry).

To help alleviate the otherwise pervasive information asymmetries in Bolivia's credit market, the SBEF requires that some of the information in the registry is shared among the participating institutions. After written authorization from a prospective customer, a lender can access the registry and obtain a credit report, which contains information on all outstanding loans of the prospective customer for the previous two months. The credit report includes the amount of any outstanding loans in the previous two months, the identity of the originating bank, the type of loan, the borrower's internal credit rating from the originating bank, the value of any overdue payments on these loans, and any prior defaults.

As in Berger, Frame, and Ioannidou (2011), we exploit this two-month information sharing window to create measures of ex-ante borrower risk that are either observable or unobservable to outside lenders (i.e., new perspective lenders) and use them to test hypotheses related to lenders' screening and levels of adverse selection in switching and non-switching borrower pools. In particular, defaults (i.e., loans with persistent overdue payments that are downgraded to the default status) are never erased from the registry and are part of the credit report that lenders obtain from the registry. Any prior defaults, no matter how old, are thus always observable through the registry to any lender, both inside and outside. Any overdue payments in the previous two months on outstanding loans are also part of the credit report and thus are observable to both inside and outside lenders. In contrast, overdue payments repaid more than two months ago are not part of the credit report. While this information is known to the borrower's inside lenders (through their relationship with the borrower), they are not observed by new prospective lenders, allowing us to construct an indicator of ex-ante borrower risk that is unobservable to new outside lenders. As shown in Berger, Frame, and Ioannidou (2011), and confirmed here for our sample, these unobservable past delinquencies do not reflect stale information, but contain valuable information predictive of future repayment problems on switching loans over and above of what is observable to outside lenders.

As in Berger, Frame, and Ioannidou (2011) the key assumption we maintain throughout the paper is that past delinquencies outside the information sharing window do not become known to outside lenders through other sources. This is likely in our setting for several reasons. First, besides the information shared through the registry, lenders have very limited reliable and verifiable information about potential borrowers. During the sample period, there is no other comprehensive private credit bureau operating in the country (de Janvry et al., 2003) and the vast majority of firms in Bolivia—let alone the micro-enterprises in our sample— do not have audited financial statements. Second, the strategic use of the information sharing window found in Ioannidou and Ongena (2010) as well as results in section 4.2 also

suggest that outside lenders do not become aware of these prior delinquencies through other sources.[10]

Our analysis focuses on the overlapping segment of the credit market between microfinance and consumer lenders. Like in many developing economies with large informal sectors and self-employment, there are blurred lines between productive and consumer lending. During the study period, consumer and micro-enterprise credit in Bolivia overlapped considerably, as micro-enterprises are typically informal household-run businesses. Credit from either source often ends up being used for a mixture of household and enterprise functions (Rhyne, 2002).[11] Hence, to better capture the overlapping segment of the credit market, we focus our analysis on loans to natural persons from the types of financial institutions that provide the majority of lending to households and microenterprises. Prior work using the CIRC thus far only studies loans of commercial banks to their corporate clients (e.g., Ioannidou and Ongena, 2011; Berger, Frame, and Ioannidou, 2011; Beck, Ioannidou, and Schaefer, 2018).

Drawing from Rhyne (2002) and de Janvry et al. (2003) we focus on and categorize financial institutions operating for profit into MFIs and CLs. MFIs include both microfinance banks and private financial funds (*Fondos Financieros Privados,* FFPs) and CLs include all commercial banks with consumer credit divisions and consumer credit FFPs. This categorization yields 6 MFIs (Banco Sol, Caja Los Andes, FIE, Eco Futuro, Prodem, and Fortaleza) and 13 CLs (Acceso, Fassil, Banco Santa Cruz, Banco Union, Banco De Credito De Bolivia, Banco Boliviano Americano, Banco Mercantil, Banco Economico, Banco Industrial, Banco Nacional De Bolivia, Banco Ganadero, Banco De La Paz, Financiero De La Comunidad), actively lending to both households and micro-enterprises during the study period.[12]

As discussed in Rhyne (2002), these financial institutions employed systematically different lending technologies. Most MFIs used relationship lending and traditional MFI lending technologies to mitigate both ex-ante adverse selection and ex-post moral hazard problems (e.g., solidarity-group loans for peer-screening and peer-enforcement, "zero tolerance" policies on delinquencies, routine loan officer-borrower visits, and "dynamic incentives" to motivate repayment through continued and progressively larger access to credit). As discussed in Rhyne (2002), a subset of CLs (e.g., Fassil, Banco Santa Cruz, and Financiero De La Comunidad) adopted these traditional MFI technologies and know-how by recruiting experienced

[10] Ioannidou and Ongena (2011) find that borrowers trying to switch to new lenders clear their past due payments on outstanding loans for those two months, manage to switch, but tend to return to nonperformance soon thereafter. This strategic use of the two-month information-sharing window supports the thesis that these prior delinquencies are not observable to new lenders. Our findings also show that while lenders are less likely to extend loans to switching borrowers with observable past delinquencies, they end up with borrowers with more unobservable past delinquencies, consistent with the idea that the latter are not observable to new perspective lenders.

[11] Rhyne (2002) describes how microfinance lenders ostensibly focused on lending for micro-entrepreneurial purposes, but loans were often diverted for consumption or other household functions. Conversely, while the consumer lenders in theory sought salaried borrowers, in practice, they ended up overlapping considerably with the micro-enterprise borrowers of microfinance lenders.

[12] Institutions are ordered in terms of size (largest to smallest) with respect to their number of unique borrowers.

loan officers from BancoSol. Other CLs (e.g., Acceso and most commercial banks) began instead targeting MFI borrowers using arms-length transaction technologies and credit scoring models, used widely in consumer lending, and separated loan origination from ex-post enforcement and collection.[13]

For example, referring to Acceso, Rhyne (2002, p.8) writes: "… *large, stable employers provided trustworthy information about a loan applicants' employment and salary and were willing to arrange loan repayment through payroll deduction. For customers with less-than-prime employers, Acceso relied on its own sophisticated credit scoring model… The internal management of loans also differs drastically from microcredit, which is based on loan officer responsibility for the whole client relationship… Acceso, for example, broke loan approval and collection into at least eight separate steps, each performed by a different person… The process begins with credit officers, really salespeople who earn most of their money on commissions... In contrast to microcredit, credit officers have no role in the important steps of verification, evaluation, or collection… Acceso was not alone. Nearly all the Bolivian banks also started consumer credit operations using virtually identical techniques to Acceso.*" Given their more arms-length and transactional approach, the CLs ultimately had lighter monitoring and enforcement mechanisms. For example, they tolerated much higher levels of delinquency to extract late repayment fines and mostly relied on automated processes to follow up on delinquent customers, primarily via mail (Rhyne 2002, p. 9). Using the information in Rhyne (2002) and de Janvry et al. (2003) about the lending technologies of each lender and the characteristics of their loan portfolios from the credit registry, in our empirical analysis we distinguish CLs into those using "adaptive" and "non-adaptive" lending technologies.

We exclude from our analysis loans from credit cooperatives, whose lending decisions are based on membership in the cooperative and where loan size is determined as a multiple of the client's deposits (Rhyne, 2002). During the sample period, there were also many small microfinance lenders operating outside the formal sector (e.g., NGOs) that do not report to the registry. These institutions have a more poverty-oriented and rural focus than their commercially operated counterparts in our sample and were not allowed to offer the full spectrum of lending and savings services as the regulated lenders we study in our analysis. To keep the analysis tractable, we also restrict our sample to types of loans that individually constitute at least 1% of the total loan originations of MFIs and CLs. This includes the following five loan categories: installment loans, fixed-term loans, credit cards, mortgages, and advances on checking accounts. Together, these categories constitute about 95% of the MFIs and CLs loan originations.

(Insert Table 1 about here)

[13] These lending technologies were the byproduct of advancements in information technologies that allowed processing of masses of information efficiently. See Berger and Udell (2006) for an in-depth discussion of transaction technologies.

Table 1 provides summary statistics of loans originated during the sample period by MFIs and CLs to existing customers (i.e., non-switching loans).[14] (Detailed definitions of all variables, along with any other variables used in the paper, are provided in Table A1.) In terms of borrower characteristics, CL borrowers tend to be larger than MFI borrowers: they have larger volumes of outstanding bank loans (USD 17,104 vs. USD 1,479), a larger fraction of them have multiple lending relationships (52% vs. 23%), and they have somewhat longer relationships with their lenders (19 vs. 17 months). CL borrowers are also riskier: at the time of loan origination, a larger fraction of CL borrowers has prior repayment problems (i.e., overdue payments or defaults on past loans), both observable and unobservable (12% vs. 7% and 7% vs. 2%, respectively), indicating CLs' higher tolerance of credit risk. In terms of average loan characteristics, CL loans are much larger (USD 5,984 vs. USD 2,371), cheaper (26% APR vs. 38% APR), and with longer maturities (20 months vs. 12 months). They are also more likely to have collateral (20% vs. 13%) or personal guarantees (44% vs. 35%) and are much less likely to have joint liability (13% vs. 73%). CL loans are also much more likely to be denominated in USD (86% vs. 43%) and to cover a broader spectrum of products such as credit cards and advances in the current account, whereas these product types do not exist for MFIs. CL loans are also less likely to require periodic repayments (only 58% of the have installment compared to 90% for MFIs). In terms of ex-post performance, a larger fraction of CL loans has repayment problems (e.g., overdue payments or defaults). Differences are stronger for overdue payments rather than eventual defaults or write-offs, consistent with commentaries that late payments were not only tolerated but welcomed by CLs who charged late payment fines and had the borrowers' salary to fall back on (Rhyne, 2002).

3. Switching definitions, frequencies, and characteristics

In this section, we study the frequency with which MFI borrowers "switch" to CLs (i.e., obtain a loan from a CL for the first time), how this frequency varies over the sample period, and how it compares to switching rates within MFIs over the same period as well as switching rates observed in other studies/countries.

As in Ioannidou and Ongena (2010), we define a loan as a *switch* or *switching loan* when a borrower obtains a new loan from a lender with whom it did not have any lending relationship during the prior 12 months. We call such lenders *outside lenders*. We allow that the borrower may have had prior loans from the outside lender in the past, but not in the past 12 months. Hence, in effect, we assume that borrower information, gathered through a prior lending relationship, can get stale as quickly as within one year.[15]

[14] The stars, ***, **, and *, next to mean values for CLs indicate whether these are statistically different from the mean values for MFIs at the 1%, 5%, and 10% levels, respectively.

[15] The choice of the 12-month threshold is motivated by empirical findings suggesting that a substantial portion of the lender's inside information is collected during the first year (Cole, 1998). Its use is further supported by Ioannidou and Ongena (2010) who show that similar results are obtained using longer windows of 24 or 36 months.

Conversely, we define any banks with whom the borrower had a lending relationship in the past 12 months as *inside lenders* and refer to loans from these lenders as *inside loans*. The switcher may have one or multiple inside lenders and may continue to borrow from these lenders in the future, even after switching to a new lender. Our definition of switching does not differentiate between borrowers that are "moving" permanently to a new lender and those that are "adding" a lending relationship. This is because any such distinction would depend on future and possibly endogenous responses of inside lenders to the borrower's switch. For example, "movers" may decide to reverse their initial decision depending on future offers from both the inside and outside lenders. Investigating what type of borrowers switch and what terms they obtain a loan from an outside CL is the pertinent question from the standpoint of our analysis.

Figure 1 offers a visual illustration of our definitions. The solid horizontal lines indicate the spell of a loan from a particular lender to a borrower i. At time $t=0$, borrower i obtains an outside loan (loan 2) from an outside lender (lender 2) i.e., a lender from whom the borrower did not have a loan in the past 12 months. The dashed horizontal line for lender 2 prior to the past 12 months, indicates that the borrower *may* have had a prior loan from this lender that expired more than 12 months prior to $t=0$. (The use of a dashed line instead of a solid line indicates that a particular feature, a prior loan in this case, is a possible but not a necessary condition.) At the time of the switch, the borrower i had outstanding inside loans from at least one inside lender (loan 1 from lender 1 and possibly loan 3 from lender 3). Loans 4 and 5 indicate possible future loans from the borrower's initial inside lender(s).

(Insert Figure 1 about here)

Table 2 offers descriptive statistics on the frequency of switching across the different types of lenders. During the 9.5-year sample period, MFIs (CLs) issued 860,715 (1,007,818) new loans to 709,196 (506,143) unique borrowers. Applying our definition of switching, we find 47,888 switching loans from MFIs to CLs to 47,151 unique borrowers. This implies that MFI-to-CL switching loans are about 5.56% (4.75%) of all loans originated by MFIs (CLs) over the same period. Similarly, MFI-to-CL switchers are about 6.65% and 9.32% of all MFI and CL customers. These switching rates are somewhat lower than in Agarwal et al. (2021) who apply the same definition of switching and find that about 11% of MFI borrowers switch to CLs for the first time at some point during an 8-year period. Importantly, the switching rates from MFI-to-CLs that we and Agarwal et al. (2021) document are considerably lower than the rates of switching *within* lender types found in prior studies (see, e.g., Farinha and Santos, 2002 and Ioannidou and Ongena, 2010).[16] Switching rates within lender type are also higher in our sample. As can be observed in

[16] Farinha and Santos (2002) document that 64% of the 1,577 Portuguese newly-created firms in their sample switch banks during the 16-year sample period they study. Ioannidou and Ongena (2010) also find that 22% of Bolivian firms switch amongst commercial banks over a 5-year period.

Table 2, MFI-to-MFI switching loans account for 11.43% (14.53%) of all loans originated by MFIs (all MFI customers) during the sample period. Similarly, the corresponding figures for CL-to-CL switches are 17.17% and 22.22%, respectively. The lower switching rates from MFIs to CLs are consistent with the idea that MFI borrowers, who are smaller and more informationally opaque, find it relatively more difficult to migrate to CLs rather than to another MFI.

(Insert Table 2 about here)

Figure 2 studies how the intensity of switching from MFIs to CLs varied over time. The number of MFI-to-CL loans in each month is expressed as a fraction of all MFI loan originations in the same month. At the beginning of the sample period, switching from MFI to CLs was infrequent, accounting for only 2-3% of all MFI loan originations. Starting from mid-1996, the intensity of switching began increasing rapidly, surpassing 20% of all MFI loan originations by the beginning of 1997. This is consistent with reports that CLs were actively trying to penetrate traditional MFI markets. After 1998, switching rates began decreasing again to about 5-6%, again consistent with reports that CLs receded from the microfinance market.

(Insert Figure 2 about here)

Appendix Table A2 provides additional information about the characteristics of MFI-to-CL switches in relation to Figure 1 and switches within lender type. Several patterns emerge. First, we observe that, in practice, only a very small fraction (less than 1%) of MFI borrowers who switch to CLs had a loan from that lender or another CL before $t=-12$. Those switching within lender types are much more likely to have had a loan from the outside lender in the past. Second, 26.74% of the MFI-to-CL switchers had multiple inside lenders prior to $t=0$, significantly higher than the 8.52% of MFI-to-MFI switchers. This suggests that MFI borrowers who are able to switch to CLs are relatively larger and more established entrepreneurs who were more likely to already have had past relationships with multiple lenders. This, however, may also simply reflect the CLs' higher tolerance for risk.[17] Third, the MFI-to-CL switchers are more likely at $t=0$ to have prior overlapping loans with their initial lenders and are more likely after $t=0$ to obtain additional new loans from their initial inside lenders than borrowers who switch within lender type. This suggests that relative to other switchers, MFI-to-CL switchers are more likely to be adding rather than substituting a lending relationship (e.g., to access products not offered by their existing microfinance lenders) or to be subsequently reversing their initial decision (e.g., when their CL failed or retracted from microfinance).

[17] Multiple lending relations can create coordination problems between lenders (Bolton and Scharfstein, 1996 and Bris and Welch, 2005) and increase borrowers' total indebtedness (Bizer and DeMarzo, 1992 and Parlour and Rajan, 2001), leading to a higher probability of default.

4. Short-term credit outcomes and borrower risk

In this section, we study the loan conditions the MFI-to-CL borrowers received at their new lenders, the *ex-ante* observable and unobservable risk of these borrowers, and their *ex-post* repayment on their switching loans. This short-run analysis focuses on switches and switching loans originated during the first phase of CLs' entry into the microfinance market from January 1996 to December 1998. To distinguish the role the CLs' lending practices may have played in the subsequent microfinance crisis and separate them from the economic shock that swept Bolivia's economy following Brazil's devaluation in January 1999, we focus our ex-post repayment analysis on switching loans that were either repaid or began experiencing repayment problems prior to January 1999 (i.e., before the economic shock from Brazil began influencing repayment).

To evaluate the credit outcomes of the MFI-to-CL switchers, we use coarsened exact matching (CEM). In particular, using CEM we compare the credit outcomes of the MFI-to-CL switchers against different comparison groups after matching on several variables, discussed below, depending on the outcome variable and objective of each comparison. Matching is a nonparametric method for controlling for confounding influences on the outcome variable and as such it has a lower degree of model dependence than alternative parametric approaches.[18] The key objective of matching is to prune observations from the data so that the remaining data used for estimation have a better balance (i.e., the empirical distributions of the various confounding factors are more similar). CEM belongs to a class of matching methods with attractive statistical properties (e.g., it applies monotonic imbalance bounding so that reducing the maximum imbalance on one variable has no effect on others).[19] To determine the estimation sample, the CEM process coarsens any continuous matching variables into a meaningful stratum and identifies exact matches based on the coarsened data plus any additional discrete variables. It then assigns weights to each observation to normalize any variance in the distribution between the matched observations within a given stratum. Strata without a match are weighted at zero and are thus dropped from the sample. The matched data, with the original uncoarsened values, can then be used to estimate differences in means in the outcome variable(s) between the two groups without the need to control for the matching variables, using a simple regression model as follows:

$$\boldsymbol{Y_{i,t}} = \boldsymbol{\beta_1 D_{i,t}} + \boldsymbol{\varepsilon_{i,t}}, \qquad (1)$$

where $\boldsymbol{Y_{i,t}}$ indicates the credit outcome of borrower $\boldsymbol{i}$ at time $\boldsymbol{t}$ and $\boldsymbol{D_{i,t}}$ is a (0,1) dummy variable distinguishing the observations into the two groups. $\boldsymbol{\varepsilon_{i,t}}$ is the idiosyncratic error term, assumed to be independent and identically distributed. The coefficient of interest, $\boldsymbol{\beta_1}$, indicates the average difference in the outcome variable between the two groups and is estimated using ordinary least squares (OLS).

[18] For example, regression analyses, where the various confounding factors are added in the model as control variables, require assumptions about how each factor affects the outcome variables (e.g., linear or non-linear dependence, order of non-linear dependence, relationship between different explanatory variables and possible interactions).

[19] See Iacus, King, and Porro (2011) for a description of the CEM algorithm and Blackwell, Iacus, King, and Porro (2010) for further discussion on CEM's additional attractive statistical properties.

Most of our analysis below on short-term credit outcomes and borrower risk relies on specifications of Eqn. (1) where the MFI-to-CL switchers are contrasted against different comparison groups (e.g., similar switching borrowers within MFIs or even non-switching borrowers). However, for a subset of our analysis on loan terms, we also contrast the terms that the MFI-to-CL switchers received at their new lenders with their borrowing terms at their initial MFIs just prior to switching. For this, we use an augmented specification of Eqn. (1) with borrower-fixed effects. $\boldsymbol{\beta_1}$ in this case is identified using *within-borrower* variation. Table 1 and Appendix Table A3 report summary characteristics of the borrower and loan characteristics of the various groups (Inside MFI loans; MFI-to-CL loan; MFI-to-MFI loans) prior to any matching.

4.1 CLs' loan terms and lending technologies

We begin in Table 3 by comparing the loan terms the MFI-to-CL switchers received at CLs with: i) their loan terms at their initial MFIs just prior to switching, and ii) the terms similar borrowers received when they switched to another MFI. Such comparisons can be informative about the borrowers' motivations for switching to CLs as well as the CLs' strategies and lending technologies for attracting MFI borrowers.

In Panel A, we compare the terms of the MFI-to-CL switching loans to the borrower's terms on outstanding loans from their initial MFIs. We report the $\hat{\beta}_1$ of augmented specifications of Eqn. (1) with borrower-fixed effects, where $D_{i,t}$ equals one for MFI-to-CL loans and equals zero for outstanding loans from their initial MFIs. The heading of each column indicates the dependent variable for each specification. When a borrower has multiple outstanding loans from their initial MFIs, we use the average loan terms, weighted by the size of the loan. To obtain the estimation sample, we require that matched loans are originated in the same region and are of the same type (installment, single payment, credit card, current account overdrafts, and mortgage loans). The latter condition makes the comparison of loan terms more meaningful.

In Panel B, we instead compare the terms of MFI-to-CL loans to the terms similar MFI borrowers received when switching to another MFI. $D_{i,t}$ in this case equals one for MFI-to-CL loans and equals zero for MFI-to-MFI loans. Apart from matching on region and loan type as in Panel A, we additionally require that the matched loans are originated in the same month-year to ex-ante similar borrowers, based on characteristics observable to both inside and outside lenders. We require that matched borrowers have the same inside lender, similar number of inside lenders (single vs. multiple), and similar total outstanding loans just prior to switching at $t = -1$. To further control for ex-ante observable borrower risk, we further match on: i) the borrower's worst credit rating in the prior 2 months, and ii) whether the borrower had delinquencies in the previous 2 months or any prior defaults. This information is part of the credit report a prospective lender can obtain from the registry and are thus observable to inside and outside lenders at the time of a loan

application.

(Insert Table 3 about here)

The results in Table 3 show clearly that MFI borrowers who switch to CLs obtain more attractive terms, both with respect to their initial MFIs and to what similar switching borrowers obtain at other MFIs. We find, for example, that switching loans at the CLs are on average a lot larger, cheaper, and have longer maturities. Moreover, they have less collateral or joint liability requirements. The differences are economically quite large. For example, relative to the switchers' terms at their initial MFIs, the CL loans are on average 52 percent larger, 3.2 pp cheaper, and have longer maturities by a little over a year (12.7 months). Furthermore, they are 13 pp less likely to have collateral, have 36.9 pp lower value-to-loan ratios, and are nearly 59 pp less likely to use joint liability. We also find that they are, instead, about 15.3 pp more likely to use personal guarantees, indicating that CLs may be compensating for the lack of collateral with personal guarantees. We also observe that MFI-to-CL loans are 51 pp more likely to be denominated in USD. A large fraction of CLs' deposit funding is also denominated in USD. Offering USD denominated loans may help CLs reduce foreign exchange mismatches between their assets and liabilities, but exposes microentrepreneurs, who derive most of their income in the domestic currency, to higher default risk. Results in Panel B against similar switchers within MFIs paint a similar picture to Panel A.

Overall, our findings in Table 3 indicate that turning to CLs carries important benefits for MFI borrowers. They are able to borrow a lot more, at cheaper rates and longer maturities, with less collateral or joint liability, and in USD. These more lenient terms may have contributed to ensuing higher delinquencies rates, due to both ex-ante adverse selection and ex-post moral hazard. In what follows, we study the ex-ante risk profile of borrowers who switched to CLs as well as their ex-post repayment performance, evaluating the empirical relevance of these two channels and the role the CLs' lending technologies may have played.

4.2 Ex-ante borrower risk: "cherry picking" and adverse selection

In this section, we study how the MFI-to-CL switchers compare to other switching and non-switching borrowers in terms of both observable and unobservable borrower risk at $t=0$. Such comparisons can be informative about CLs' willingness to lend to observably riskier borrowers and the type of borrowers they attract in terms of adverse selection, given the more attractive and lenient terms they offer.

Exploiting the data availability and the two-month information sharing window in the registry, we construct measures of ex-ante borrower risk based on the borrowers' past delinquencies or defaults, distinguishing whether they are observable or not to outside lenders through the credit registry. As in Berger, Frame, and Ioannidou (2011), we classify as observably riskier any borrowers who at the time of the switch (i.e., at $t=0$) had observable repayment problems on their credit report. Specifically, *Observably*

riskier borrower is a dummy variable that equals to one if the borrower had overdue payments of more than 30 days with any lender in the previous two months or any prior defaults and equals zero otherwise. *Unobservably riskier borrower,* instead, equals one if at *t=0* the borrower had a "clean" credit report, but had overdue payments of more than 30 days in the most recent period just prior to the information sharing window (i.e., between *t=-3* and *t=-12*), and equals zero otherwise. In Appendix Table A4, we confirm that these past delinquencies and defaults do not represent obsolete information. As can be observed in Table A4, both indicators contain valuable information predictive of future repayment problems on switching loans. Importantly, the unobservable borrower risk variable has informational value over and above the observable borrower risk variable and other observable borrower risk characteristics shared through the registry (column 1). This also holds when we additionally control for the borrower's terms at their initial MFI just prior to switching (column 2). Controlling for the borrower's terms at their inside lenders can help control for borrower risk that might be unobservable to us (the econometrician), but potentially observable to insider and outside lenders. We expect that if borrowers are riskier in dimensions we do not observe, this will likely be reflected in their borrowing terms with their inside lenders. The fact that both indicators of ex-ante borrower risk remain statistically significant, and their coefficients do not change much as we add these controls suggests that such omitted factors are unlikely to play a key role.

Next, in Table 4 we study how the MFI-to-CL switchers compare to other switching and non-switching borrowers using specifications of Eqn. (1) with *Observably riskier borrower* or *Unobservably riskier borrower* as the dependent variable. In Panel A, we compare the MFI-to-CL switchers against non-switching borrowers at MFIs. $D_{i,t}$ in this case equals one for MFI-to-CL loans and equals zero for non-switching MFI loans. We report results for three specifications with gradually more restrictive matching criteria to inspect the stability of our estimates as we gradually control for additional factors. In the first specification, we only require that the matched inside MFI borrowers also received a loan in the same month-year as the switching borrower. In the second specification, we additionally require that the matched inside loans were originated in the same region by the switcher's inside MFI. This helps absorb possible differences in borrower pools across different regions and lenders. In the third specification, we also match on observable borrower characteristics: whether the borrowers had multiple or single lending relationships and on the amount of their total outstanding loans at *t=0* to further control for borrower size.

(Insert Table 4 about here)

The results in columns (1)-(3) indicate that relative to inside MFIs, CLs are less likely to lend to MFI borrowers with observable past delinquencies in the registry (by about 0.3 to 0.7 pp). Recognizing their informational disadvantage relative to inside MFI lenders, outside CLs seem to try to "cherry pick" switching MFI borrowers, steering away from borrowers with observable past delinquencies or defaults.

Columns (4)-(6), however, show that they nevertheless end up with borrowers with significantly higher incidence of unobservable past delinquencies (by 8.7 to 10.2 pp). This is also true in column (7) where we further control for indicators of observable credit risk from the credit registry (i.e., worst credit rating with inside lenders and observable past delinquencies or defaults). These results are consistent with the idea that outside lenders (CLs in this case) face stronger *adverse selection* problems than inside lenders (MFIs in this case), consistent with theoretical predictions (see, e.g., Sharpe, 1990; Rajan, 1992; and von Thadden, 2004).

Switchers vs. Non-switchers

It is unclear from the results in Panel A whether the CLs' higher incidence of unobservably riskier borrowers is simply reflecting well-known difference in adverse selection between switching and non-switching groups or whether it is driven by screening weaknesses that are specific to CLs' and their lending practices. To inform this question, we study the incidence of observable and unobservable past repayment problems of MFI borrowers who switch to other MFIs. In Panel B of Table 4 we contrast the switchers within MFIs to non-switching MFI borrowers. $D_{i,t}$ equals one for MFI-to-MFI loans and equals zero for non-switching MFI loans. In Panel C, we also directly contrast the MFI-to-CL switchers to similar switchers within MFIs. $D_{i,t}$ in this case equals one for MFI-to-CL loans and equals zero for MFI-to-MFI loans.

With respect *to observable risk*, we find that results in Panel B are very similar to Panel A not only qualitatively, but also economically. This is consistent with the idea that similar to CLs, MFIs are equally less likely to lend to switching borrowers with observable past repayment problems than their inside lenders (i.e., they "cherry pick" to a similar extent). When in Panel C we directly compare the MFI-to-CL switchers to the MFI-to-MFI switchers, we find no differences between the two groups, consistent with the idea that both lenders are equally less likely to lend to switching borrowers with observable past repayment problems.

The results for *unobservable risk* are instead quite different. The positive and statistically significant coefficients in Panel B indicate that adverse selection problems relative to non-switching groups are also present when the outside lenders are MFIs, not only CLs. However, the point estimates in Panel B are about half of those in Panel A, indicating that the CLs' adverse selection problems in Panel A may not be solely due to differences between switching and non-switching groups. In fact, when in Panel C we contrast the MFI-to-CL switchers against other switching borrowers within MFIs, we find that CLs face stronger adverse selection problems than MFIs when lending to switching borrowers from MFIs. This is also true in column (7), where we further control for indicators of borrower risk shared in the registry.

CLs' lending technologies: joint liability and collateral use

In Table 5 we examine whether CLs' stronger adverse selection problems vary systematically with their lending technologies and the more lenient terms they offer. In particular, we re-estimate the last specifications of Panel C of Table 4 distinguishing CLs into two groups: those that adapted their lending

technologies to those used by MFIs (i.e., using joint liability group lending) and those that did not, henceforth denoted as "adaptive CLs" vs. "non adaptive CLs". Based on information in Rhyne (2002), de Janvry et al. (2003) and our data, we classify Fassil, Banco Santa Cruz, and Financiero De La Comunidad as adaptive CLs. We classify all other CLs as non-adaptive.[20] Appendix Table A5 reports descriptive statistics for the two groups of CLs. About 66% of switching loans from adaptive CLs have joint liability with an average number of borrowers equal to 2.60. In sharp contrast, only 9% of non-adaptive CLs' loans have joint liability and the average number of borrowers per loan is 1.09. Non-adaptive CLs make instead more extensive use of personal guarantees (76% vs. 47%). To facilitate comparisons, under 'All' we report again our results from Table 4 (columns 3 and 7) before distinguishing the CLs into adaptive and non-adaptive by re-estimating the same specifications for the two sub-samples.

We find that CLs' higher incidence of *unobservably riskier* borrowers is more pronounced in CLs that did not adapt their lending technologies and relied instead on transactional lending technologies, developed for corporate clients and consumer loans. In particular, estimates in column (6) indicate that relative to outside MFIs, non-adaptive CLs are 7.4 pp more likely to lend to MFI borrowers with unobservable past delinquencies or defaults. By comparison, this figure is considerably lower for adaptive CLs at 4.5 pp (column 5). In Panel B, we instead detect no significant differences between CLs and MFIs with respect to *observable borrower risk*, regardless of the lending technologies that CLs use (columns 2 and 3), indicating that adaptive and non-adaptive CLs cheery-pick switchers to a similar degree.

(Insert Table 5 about here)

In Table 6 we further distinguish the non-adaptive CLs into those that made extensive use of collateral vs. those that did not. Similar to joint liability group lending (e.g., Besley and Coate, 1995), collateral can also help mitigate both ex-ante asymmetric information and ex-post enforcement problems (see, e.g., Bester 1985; Bensako and Thakor 1987; Boot and Thakor, 1994; Gale and Hellwig, 1985; Albuquerque and Hapenhayn, 2004). Consistent with this prediction, we find that the incidence of *unobservably riskier* borrowers relative to MFIs is more than double for non-adaptive CLs that do not make use of collateral than for non-adaptive CLs that use collateral (7.8 vs. 3.6 pp). We also observe that the vast majority of MFI-to-CL loans are issued by non-adaptive CLs that do not use collateral (91.5%). The results with respect to *observable risk* further indicate that the non-adaptive CLs that do not use collateral may have a higher appetite for risk as they are also more likely to originate loans to observably riskier switchers

[20] We calculate the percentage of the lenders' new loans during the pre-crisis period that use joint liability lending. We consider lenders that had more than one-quarter of their new loan originations using joint liability as being adaptive, and those below that threshold as non-adaptive. In practice, most adaptive CLs use joint liability in more than 50% of their new loans, while many non-adaptive CLs either never use joint liability or use it for less than 20% of their loans.

(column (3). This result, however, appears to be economically quite small (0.3 pp).

(Insert Table 6 about here)

Overall, the results in this section indicate that outside lenders, both MFIs and CLs, are less likely to lend to observably riskier switchers than inside lenders, trying to "cherry pick" switchers based on their observable risk characteristics. Nevertheless, they both end up with more unobservably riskier borrowers than inside lenders, consistent with asymmetric information and "winner's curse" problems between inside and outside lenders (Sharpe, 1990; Rajan, 1992; von Thadden, 2004). CLs, however, face worse adverse selection problems than outside MFIs. We find that adverse problems are more pronounced for CLs that do not adapt their lending technologies to the microfinance market and use generally more lax terms (e.g., CLs that do not use either joint liability group lending or collateral).

4.3. Ex-post repayment problems

In this section, we compare the incidence of ex-post repayment problems of MFI-to-CL loans relative to the other two groups (i.e., inside MFI loans and MFI-to-MFI loans). Differences in ex-post repayment could arise because of both differences in *ex-ante* borrower risk, due to selection on observable and unobservable borrower risk, as well as *ex-post* frictions, due to differences in moral hazard and enforcement. Hence, to study how the MFI-to-CL loans fare ex-post, we estimate specifications of Eqn. (1), where the dependent variable equals one if a loan had any repayment problems (i.e., overdue payments, default, or written-off) any time after origination, and equals zero otherwise. For each comparison group, we estimate a number of specifications after matching on a gradually increasing set of lender, borrower, and loan characteristics to inspect the stability of our estimates as we control for different factors.

In Panel A of Table 7, we contrast the incidence of ex-post delinquencies or defaults on MFI-to-CL loans relative to inside MFI loans.[21] We report results for seven specifications. The matching criteria in the first three specifications aim to absorb differences in ex-ante borrower risk that is *observable* to both inside and outside lenders. We begin in column (1) by matching only on the month-year of loan origination to gradually by column (3) matching on all information that is shared through the registry. The matching criteria in the next four specifications aim instead to absorb borrower risk that is observable to inside lenders, but *unobservable* to outside lenders and potentially us (the econometrician). We begin in column (4) by matching on unobservable past NPLs to gradually by column (7) matching on the borrowers' loan terms at their inside MFIs just prior to switching. We match on the borrowers' average interest rate,

[21] In unreported robustness tests, we also estimate corresponding specifications using a narrower definition of ex-post nonperformance that includes only loans with persistent overdue payments that have been downgraded to the default status and/or written-off. The results are very similar and available on request.

maturity, collateral, personal guarantees, and joint liability on outstanding loans at *t=-1*.[22] Matching on firms' borrowing terms just prior to switching can help us absorb for ex-ante borrower characteristics that are observable to inside lenders, reflected in their loan terms, but potentially unobservable to outside lenders and us. The (in)stability of our estimates as we additionally match on these characteristics may thus offer an indication of how likely it is that such factors drive differences in ex-post repayment.

(Insert Table 7 about here)

We find that MFI-to-CL loans have a significantly higher incidence of ex-post repayment problems than inside MFI loans to ex-ante similar borrowers. The differences between the two groups are quite large: the MFI-to-CL switchers have between a 41 to 44 pp higher incidence of ex-post repayment problems on their switching loans than similar borrowers on inside MFI loans. Importantly, the size of the estimated coefficients remains fairly stable across the seven specifications, indicating that the MFI-to-CL loans' worse ex-post performance is unlikely to be due to differences in ex-ante borrower risk, either observable or unobservable, and more likely to be due to differences in ex-post frictions.

Additional results in Panels B and C further support this conclusion. In particular, contrasting MFI-to-MFI loans against inside MFI loans in Panel B yields minimal differences in ex-post performance. Once we match on basic lender and borrower characteristics, the two groups have the same incidence of ex-post repayment problems, despite the arguably large differences in adverse selection between the two groups, found in Table 4 (i.e., the incidence of unobservable past delinquencies is 9-10 pp higher among the MFI-to-CL switcher than non-switching borrowers from the same MFIs). Furthermore, in Panel C, we find that the MFI-to-CL loans have between a 42 to 49 pp higher incidence of ex-post repayment problems than MFI-to-MFI loans. The estimated coefficients are also generally stable as we progressively match on ex-ante unobservable risk and are slightly larger than in Panel A. If adverse selection was driving the higher incidence of delinquencies and defaults on MFI-to-CL loans, we would expect a decrease in the estimated coefficients as we move from Panels A to C where differences in adverse selection between the groups are reduced to about (from about 9-10 pp down to 4.6-6.8 pp; see Table 4, Panels A and C).

Overall, the results in Table 7 show that MFI borrowers who switch to CLs have a higher incidence of ex-post repayment problems than similar MFI borrowers who either stay at their initial MFIs or switch to another MFI instead of a CL. Several findings—the stability of the estimates across the seven specifications, the lack of differences in Panel B, and the slightly larger estimates in Panels C relative to

[22] Interest rate at *t=-1* from inside lender is calculated as the weighted average interest rate on all outstanding loans at *t=-1*. We use the contractual loan amount for the weights. Maturity at *t=-1* from inside lenders is defined similarly to the interest rate variable to equal the weighted average contractual maturity of all outstanding loans at *t=-1*. Collateral at *t=-1* is a (0,1) dummy variable flagging whether at least one of the borrowers' inside loans has collateral.

A— suggest that the MFI-to-CL switchers' higher delinquencies rates are unlikely to be driven by *ex-ante* borrower risk, observable or unobservable, and more likely to be due to *ex-post* frictions.

Cross-sectional heterogeneity

Next, in Table 8, we study the cross-sectional heterogeneity in ex-post repayment problems of borrowers who switch to CLs. In particular, we compare the incidence of ex-post repayment problems between MFI-to-CL and MFI-to-MFI switching loans (as in Table 7, Panel C) allowing for interaction terms between $D_{i,t}$ and the switchers' borrowing terms. Specifically, we allow for interactions with: i) the ratio between the switchers' total bank debt at *t=1* and *t=-1*, reflecting the percentage change in the switcher's total bank debt around the time of switching, ii) a dummy variable indicating whether the switching loan was denominated in a foreign currency (i.e., USD), and iii) whether the switching loan uses joint liability. These analyses aim to understand whether over-indebtedness, exchange rate risk, and peer screening and monitoring are potential channels driving the MFI-to-CL switchers' higher delinquency rates. For each model, we report results of two specifications. The first matches on indicators of observable borrower risk, corresponding to Table 7, column (3). The second additionally matches on indicators of unobserved borrower risk, corresponding to the most saturated specification of Table 7 in column (7).

(Insert Table 8 about here)

We find that ex-post repayment problems are systematically higher for borrowers who saw larger relative increases in their total bank loans when they switched to a CL, as well as for borrowers who received foreign currency loans or loans without joint liability. The estimated coefficients point to fairly large differences. In Panel A, for example, the interaction coefficients indicate that each standard deviation increase in the ratio between MFI-to-CL switchers' total bank debt at *t=-1* and *t=1* (which is around 13.19 in practice) is associated with 4.5 pp higher delinquency rates. In Panels B and C, the interaction coefficients are nearly as large as the coefficients of $D_{i,t}$, indicating that delinquency rates are nearly twice as large for borrowers that received foreign currency-denominated loans or loans without joint liability. Borrowers that received foreign currency loans from their outside lenders have higher delinquency rates by 22.7 pp, while those that received joint liability loans have lower delinquency rates by 41.4 pp. These differences may be driven by both higher adverse selection (i.e., unobservably riskier borrowers are more likely to be attracted or accept larger, foreign currency loans or loans without joint liability) and higher ex-post frictions (i.e., these terms increase a borrower's probability of default through higher indebtedness, foreign exchange rate risk, and lower peer monitoring). The remarkable stability of our estimates as we move from column (1) to column (2), matching on several indicators that arguably correlate with unobserved borrower risk, suggest that higher ex-post frictions is again a more likely explanation, consistent with our results from Table 7.

5. Long-term credit outcomes

Next, we study how the long-term credit outcomes of MFI-to-CL switchers compare relative to similar MFI borrowers who switched to another MFI instead of a CL. Contrasting the evolution of these groups over a longer period, before and after switching, can help us understand not only how the MFI-to-CL switchers' credit outcomes fare in the long run, but to also observe any differences in pre-trends between the matched groups. For this analysis, we estimate a dynamic difference-in-difference (DiD) specification at the borrower level. In particular, using the matched sample of borrowers from Panel B of Table 3, we collect all their outstanding loans from up to 12 months prior to switching and up to 36 months after (i.e., $t \in [-12, 36]$) and compute each borrower's total outstanding loans from all lenders in each period t, their average interest rate, maturity length, and collateral requirements.[23] We then collapse the data at the borrower-month level and estimate the following dynamic DiD model:

$$Y_{i,t} = \alpha_0 + \sum_{t \neq -1}^{n} \beta_{1,t} * D_{i,t} * I(t) + \mu_i + \eta_t + \varepsilon_{i,t}, \qquad (2)$$

where $Y_{i,t}$ indicates the credit outcome of borrower i in month t. For total outstanding debt, we use a log transformation of the dependent variable so that the coefficients can be interpreted as percentage differences relative to the match group. $D_{i,t}$ in this case is equal to one for MFI-to-CL switchers, and equal to zero for MFI-to-MFI switchers. $I(t)$ are (0,1) dummy variables for every month, except for $t = -1$, which we use as the base period for comparison. An advantage of this model is that we can include borrower-fixed effects, μ_i, to absorb any unobservable time-invariant borrower characteristics that may not be fully absorbed by our matching variables, as well as time-fixed effects, η_t, to further control for any aggregate time-series trends. The inclusion of borrower fixed effects, however, also implies that we rely on variation from borrowers who switched to both MFIs and CLs.[24] The estimated coefficients, $\beta_{1,t}$, measure the differences in the credit outcomes between the matched groups over time, relative to the omitted base period.

In Figure 3 we report the estimated coefficients and their 95% confidence intervals. The results show that switching to CLs is beneficial to borrowers. Although some of the initial benefits fade over time to a degree, significant long-term benefits remain: those switching to CLs are able to borrow more, cheaper,

[23] In the computation of a borrowers' total outstanding loans and loan terms, we do not include non-performing loans that have passed their contractual maturity date (i.e., "non-active" loans) or written-off loans. To account for differences in the use of joint liability across different lenders, we compute a borrower's total outstanding loans using amounts on individual loans that are scaled by the number of borrowers on each loan.

[24] One potential concern from the inclusion of borrower fixed effects is that results for these borrowers may not be generalizable to all switchers. We thus also estimated comparable models without the borrower fixed effects. The main results are very similar and are available on request.

and at longer maturities than similar borrowers who switch within MFIs even in the long run. The benefits of switching to CLs with respect to collateral are instead only transitory.[25] After an initial dip, the MFI-to-CL group converges to a new steady-state with a similar incidence of collateral as before switching. In terms of pre-trends, the results show that the groups of switchers are likely to satisfy the "parallel trends" assumption, as prior to switching the difference between the two groups with respect to most variables was fairly stable over time, until it changed sharply when the borrowers switched to outside lenders.[26]

(Insert Figure 3 about here)

In Figure 4 we study how the switching borrowers' long-term credit outcomes vary depending on whether they experienced repayment problems on their switching loans from CLs. About 30% of MFI-to-CL switchers experience some form of repayment problem on their switching loan (overdue payment or default). We again use the MFI-to-MFI switchers as a control group. We find that borrowers who go past due or default on their switching loans see smaller long-term benefits from switching to CLs, especially with respect to their total loan amounts and loan interest rates. Importantly, while this group seems to benefit less from switching to CLs, it does not appear to be significantly worse-off than before switching.

(Insert Figure 4 about here)

(Spillover) effects of competition

In Table 9, we further study how the CLs' entry into the microfinance market affected the subsequent loan terms that switching and non-switching borrowers received from MFIs. Such analyses can be informative of whether the increased competition from CLs forced MFIs to improve the terms they offered to switching borrowers and whether they carried positive spillover effects to non-switching MFI borrowers.

We begin by flagging MFIs that experienced a high degree of competition from the CLs' entry. To do so, we compute the fraction of borrowers that each MFI lost to CLs in each region between 1995:1 and 1996:12 (i.e., during the initial entry period when competition from CLs increased rapidly; see Figure 2) and construct a new variable, $HC_{j,k}$, that equals 1 if the lender's j fraction in region k is higher than the sample median, and equals 0 otherwise.

Using $HC_{j,k}$, we examine how competition from CLs may have forced MFIs to improve the terms of their subsequent loans to *switchers*. For this analysis, we take MFI borrowers who switched for the first time to a CL any time between 1997:1 and 2001:12 (i.e., right after the initial entry period) and trace all

[25] In unreported robustness tests, we find that results for value-to-loan ratios are similar.
[26] This is not the case if we do not match or if we compare switching vs. non-switching borrowers. As expected, the groups in these cases do not exhibit stable pre-trends.

loans these borrowers received from their inside MFIs, both before and after switching. We then estimate:

$$Y_{i,j,t} = a + \beta * HC_{j,k} * Post_{i,t} + \mu_i + \eta_t + \theta_{j,k} + \varepsilon_{i,j,t} \qquad (3)$$

where $Y_{i,j,t}$ indicates the terms of new loans (log of loan amount, interest rate, maturity, and collateral) from MFI j to borrower i originated in period t. $Post_{i,t}$ equals 1 after borrower i obtains a switching loan from a CL and equals zero otherwise. As before, μ_i and η_t indicate borrower- and time-fixed effects, respectively, while $\theta_{j,k}$ denotes lender-region fixed effects. The DiD coefficient, β, measures how the terms on new loans from MFIs change differentially where competition from CLs was high.

The results are reported in Panel A of Table 9 and indicate that in areas where MFIs face high competition from CLs, the switchers saw significant subsequent improvements in their borrowing terms from their MFIs. In particular, we find that new loans to switchers from inside MFIs are 7.3 percent larger after the borrower switched to a CL. In areas where MFIs experienced a larger increase in competition from CLs, these loans are also cheaper and have longer maturities than before. While collateral requirements generally increase for switchers, we similarly find that they exhibit significant decreases in areas where inside MFI lenders have lost a larger fraction of their borrowers to CLs.

(Insert Table 9 about here)

Using $HC_{j,k}$, we also examine whether CLs' entry had spillover effects on *non-switching* MFI borrowers. For this analysis, we trace all MFI borrowers that never switched to a CL and study how their loan terms at their inside MFIs changed after their MFIs lost a large fraction of borrowers to CLs by estimating:

$$Y_{i,j,t} = a + \beta * HC_{j,k} * Post_t + \mu_i + \theta_{j,k} + \varepsilon_{i,j,t}, \qquad (4)$$

where now $Post_t$ equals 1 if the loan is originated after 1997 (i.e., t >1997:1), and equals 0 otherwise. All other variables are defined as in Eqn. (3). Results are reported in Panel B of Table 9. We observe that the benefits from competition carry over to non-switching borrowers as well, who also receive larger amounts, cheaper loans, longer maturities, and lower collateral requirements. The benefits to non-switching borrowers appear to be even stronger in terms of size. Negative externalities from outside loans are not present for this group and inside MFIs may have competed more aggressively to retain these customers.

Overall, our findings indicate that despite CLs' poorly adapted lending technologies, high risk-taking, and borrower defaults associated with their entry into the microfinance market, the ensuing increase in competition carried significant long-term benefits on most MFI borrowers' access and terms of credit. The minority of MFI borrowers who experienced repayment problems benefit less from switching to CLs, but even this group does not fare relatively worse than prior to switching. Importantly, we also observe that competition from CLs led MFIs to subsequently improve their loan terms to both switchers and non-

switchers. This was particularly pronounced in areas where competition from CLs was high.

6. Conclusions

Using detailed credit registry data with more than 32 million bank-borrower-loan observations, we study the "failed" entry of commercial lenders into Bolivia's thriving microfinance market in the mid-1990s, which ended with an over-indebtedness crisis. Observing the success of the microfinance lenders, many commercial lenders seeking new profitable market segments expanded into the low-income market by targeting the customers of microfinance institution using arms-length lending technologies and credit models from consumer lending. Using the Bolivian credit registry, we zero into this episode to trace the factors that may have contributed to this "failed" entry and their short- and long-term effects on low-income borrowers' access and terms of credit. Tracing borrowers' credit outcomes for nearly 10 years, we find that despite the commercial lenders' poorly adapted lending technologies, stronger adverse selection problems and borrower defaults, the ensuing increase in competition carried significant short-term and long-term benefits to borrowers. Borrowers who switched to commercial lenders are able to borrow more, cheaper, at longer maturities, and without joint liability or collateral. The increased competition, particularly from non-adaptive CLs (i.e., those using arms' lengths technologies and credit scoring), had a significant knock-on effect on microfinance institutions, forcing them to improve their overall loan terms. Overall, our results indicate that even when new entrants do not necessarily possess better screening and monitoring abilities and when such entries induce over-indebtedness and widespread defaults, the increase in competition can carry significant positive effects on borrowers' access and terms of credit.

References

Agarwal, Sumit, Thomas Kigabo, Camelia Minoiu, Andrea F. Presbitero, and André F. Silva. 2021. Serving the underserved: microcredit as a pathway to commercial banks. *The Review of Economics and Statistics*, 1-45.

Agarwal, Sumit, Alok Shashwat, Ghosh Pulak, and Sudip Gupta. 2020. Financial Inclusion and alternate credit scoring for the millennials: Role of big data and machine learning in fintech. *Working Paper*.

Agarwal, Sumit, Alok Shashwat, Ghosh Pulak, Ghosh Soumya, Piskorski Tomasz, and Amit Seru. 2017. Banking the unbanked: What do 255 million new bank accounts reveal about financial access? *Columbia Business School Research Paper*, 17-12.

Albuquerque, Rui and Hugo A. Hopenhayan. 2004. Optimal lending contracts and firm dynamics. *Review of Economic Studies*, 71(2), pp. 285-315.

Armendáriz, Beatriz and Jonathan Morduch. 2010. *The Economics of Microfinance*. MIT press.

Allen, Franklin, Carletti Elena, Cull Robert, Qian Jun QJ, Senbet Lemma, and Patricio Valenzuela. 2021. Improving access to banking: Evidence from Kenya. *Review of Finance*, 25(2), pp. 403-447.

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

Banerjee, Abhijit. 2013. Microcredit under the microscope: what have we learned in the past two decades, and what do we need to know? *Annual Review of Economics*, 5(1), pp. 487-519.

Banerjee, Abhijit, Dean Karlan, and Jonathan Zinman. 2015. Six randomized evaluations of micro- credit: Introduction and further steps. *American Economic Journal: Applied Economics*, 7(1), pp. 1– 21.

Barajas, Adolfo, Thorsten Beck, Era Dabla-Norris, and Reza Yousefi. 2013. Too cold, too hot, or just right? Assessing financial sector development across the globe. *IMF Working Paper* No. 13/81.

Beck, Thorsten, Asli Demirguc-Kunt, and Maria Soledad Martinez Peria. 2007. Reaching out: Access to and use of banking services across countries. *Journal of Financial Economics*, 85(1), pp. 234–266.

Beck, Thorsten, Ross Levine, and Norman Loayza. 2000. Finance and the sources of growth. *Journal of Financial Economics*, 58(1), pp. 261–300.

Beck, Thorsten, Vasso Ioannidou, and Larissa Schäfer. 2018. Foreigners vs. natives: Bank lending technologies and loan pricing. *Management Science*, 64(8), pp. 3792–3820.

Benton, Marques, Meier Stephan, and Charles Sprenger. 2007. Overborrowing and undersaving: Lessons and policy implications from research in behavioral economics, *Federal Reserve Bank of Boston Discussion Paper 07-4*.

Bensanko David and Anjan V. Thakor. 1987. Collateral and Rationing: Sorting Equilibria in Monopolistic and Competitive Credit Markets. *International Economic Review*, 28(3), pp. 671-689.

Berg, Tobias, Valentin Burg, Ana Gombović and Manju Puri. 2020. On the rise of fintechs: Credit scoring using digital footprints. *Review of Financial Studies*, 33(7), pp. 2845-2897.

Berger, Allen N, W Scott Frame, and Vasso Ioannidou. 2011. Tests of ex ante versus ex post theories of

collateral using private and public information. *Journal of Financial Economics,* 100(1), pp. 85–97.

Berger, Allen N. and Gregory F. Udell. 2006. A more complete conceptual framework for SME finance. *Journal of Banking and Finance*, 30(11), pp. 2945-2966.

Besley, Timothy and Stephen Coate. 1995. Group lending, repayment incentives and social collateral. *Journal of Development Economics*, 46, pp. 1-18.

Bester, Helmut. 1985. Screening vs. rationing in credit markets with imperfect information. *American Economic Review*, 75(4), pp. 850-855.

Bizer, David S., and Peter M. DeMarzo. 1992. Sequential banking. *Journal of Political Economy*, 100(1), pp. 41-61.

Bolton, Patrick, and David S. Scharfstein. 1996. Optimal debt structure and the number of creditors. *Journal of Political Economy*, 104(1), pp.1-25.

Boot, Arnoud and Anjan V. Thakor. 1994. Moral hazard and secured lending in an infinitely repeated credit market game, *International Economic Review*, 35(4). Pp. 899-920.

Boot, Arnoud and Anjan V. Thakor. 2000. Can relationship banking survive competition? *The Journal of Finance,* 55(2), pp. 679–713.

Bris, Arturo., and Ivo Welch. 2005. The optimal concentration of creditors. *The Journal of Finance*, 60(5), 2193-2212.

Bruhn, Miriam and Inessa Love. 2014. The real impact of improved access to finance: Evidence from Mexico. *The Journal of Finance,* 69(3), pp. 1347–1376.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, 130(3), pp. 453–483.

Burgess, Robin and Rohini Pande. 2005. Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review,* 95(3), pp. 780–795.

Carpena, Fenella, Shawn Cole, Jeremy Shapiro, and Bilal Zia. 2012. Liability structure in small-scale finance: evidence from a natural experiment. *The World Bank Economic Review,* 27(3), pp. 437–469.

Cihák, Martin, Asli Demirgüç-Kunt, Erik Feyen, and Ross Levine. 2012. Benchmarking financial systems around the world. *World Bank Policy Research Working Paper* 6175.

Cole, Rebel A. 1998. The importance of relationships to the availability of credit. *Journal of Banking and Finance,* 22(6), pp. 959–977.

Cornelli, Giulio, Jon Frost, Leonardo Gambacorta, Raghavendra Rau, Robert Wardrop, and Tania Ziegler. 2020. Fintech and big tech credit: a new database. *BIS Working Papers*, No 887.

De Janvry, Alain, Elisabeth Sadoulet, Craig McIntosh, Bruce Wydick, and Kill Luoto. 2003. Credit bureaus and the rural microfinance sector: Peru, Guatemala, and Bolivia. Collaborative Research Support Program. The University of California and The FAO Office for Latin America.

De Janvry, Alain, Craig McIntosh, and Elisabeth Sadoulet. 2010. The supply-and demand-side impacts of credit market information. *Journal of Development Economics,* 93(2), pp. 173–188.

Di Maggio, Marco and Vincent Yao. 2021. Fintech Borrowers: Lax-Screening or Cream-Skimming? *Review*

of Financial Studies, 34(10), pp. 4546-4618.

Di Maggio, Marco, Ratnadiwakara, Dimuthu, and Don Carmichael. 2021. Invisible Primes: Fintech Lending with Alternative Data. *Working Paper*.

Farinha, Luısa and Joao Santos. 2002. Switching from single to multiple bank lending relation- ships: Determinants and implications. *Journal of Financial Intermediation*, 11(2), pp. 124–151.

Field, Erica, Rohini Pande, John Papp, and Natalia Rigol. 2013. Does the classic microfinance model discourage entrepreneurship among the poor? Experimental evidence from India. *American Economic Review*, 103(6), pp. 2196–2226.

Frost, Jon, Leonardo Gambacorta, Yi Huang, Hyun Shin, and Pablo Zbinden. 2019. BigTech and the changing structure of financial intermediation. *Economic Policy*, 34(100), pp. 761-799.

Gale, Douglas and Martin Hellwig. 1985. Incentive-compatible debt contracts: the one-period problem. *Review of Economic Studies*, 52(4), ppp. 647-663.

Giné, Xavier, Pamela Jakiela, Dean Karlan, and Jonathan Morduch. 2010. Microfinance games. *American Economic Journal: Applied Economics*, 2(3), pp. 60-95.

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

Guha, Brishti and Prabal Roy Chowdhury. 2013 .Micro-finance competition: Motivated micro-lenders, double-dipping and default. *Journal of Development Economics*, 105, pp. 86–102.

Hau, Harald, Yi Huang, Hongzhe Shan, and Zixia Sheng. 2019. How FinTech enters China's credit market. *AEA Papers and Proceedings*, 109, pp. 60–64.

Heidhues, Paul and Botond Kőszegi. 2010. Exploiting Naïvete about Self-Control in the Credit Market. *American Economic Review*, 100(5), pp. 2279-2303.

Erel, Isil and Jack Liebersohn. 2020. Does fintech substitute for banks? Evidence from the Paycheck Protection Program. *NBER Working Paper No. 27659*.

Fuster, Andreas, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther. 2021. Predictably Unequal? The Effects of Machine Learning on Credit Markets. *Journal of Finance*, forthcoming.

Fuster, Andreas, Tobias Berg, and Manju Puri. 2021. FinTech Lending. *Annual Review of Financial Economics*, 14.

Iacus, Stefano, Gary King, and Giuseppe Porro. 2012. Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, 20(1), pp. 1–24.

Ioannidou, Vasso, Nicola Pavanini, and Yushi Peng. 2021. Collateral requirements and adverse selection in lending markets. *Journal of Financial Economics*, forthcoming.

Ioannidou, Vasso and Steven Ongena. 2010. Time for a change: Loan conditions and bank behavior when firms switch banks. *The Journal of Finance*, 65(5), pp. 1847–1877.

Jayarantne, Jith and Philip E. Strahan. 1996. The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, 111(3), pp. 639-670.

Jagtiani Julapa and Catharine Lemieux. 2019. The roles of alternative data and machine learning in fintech

lending: Evidence from the LendingClub consumer platform. *Financial Management*, 48, pp. 1009–1029.

Liberti, Jose and Atif Mian. 2009. Estimating the effect of hierarchies on information use. *The Review of Financial Studies*, 22(10), pp. 4057-4090.

Kaboski, Joseph P., and Robert M Townsend. 2012. The Impact of credit on village economies. *American Economic Journal: Applied Economics*, 4(2), pp. 98–133.

King, Robert and Ross Levine. 1993. Finance and growth: Schumpeter might be right. *The Quarterly Journal of Economics*, 108(3), pp. 717–737.

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

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

Mian, Atif. 2006. Distance constraints: The limits of foreign lending in poor economies. *The Journal of Finance*, 61(3), pp. 1465-1505.

Parlour, Christine A., and Uday Rajan. 2001. Competition in loan contracts. *American Economic Review*, 91(5), pp. 1311-1328.

Petersen, Mitchell A., and Raghuram G. Rajan. 1995. The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics*, 110(2), pp. 407–443.

— . 2002. Does distance still matter? The information revolution in small business lending. *The Journal of Finance*, 57(6), pp. 2533–2570.

Raghuram. G. Rajan. 1992. Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance*, 47(4), pp. 1367-1400.

Rhyne, Elisabeth. 2002. Commercialization and crisis in Bolivian microfinance. Development Alternatives. Inc., Bethesda, MA.

Sahay, Ratna, Martin Cihák, Papa N'Diaye, Adolfo Barajas, Ran Bi, Diana Ayala, Yuan Gao, Annette Kyobe, Lam Nguyen, Christian Saborowski. 2015. Rethinking financial deepening: stability and growth in emerging markets. *IMF Staff Discussion Note*, No. 15/08.

Sharpe, Steven. 1990. Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The Journal of Finance*, 45(4), pp. 1069–1087.

Skrastins, Janis and Vikrant Vig. 2019. How organizational hierarchy affects information productions. *Review of Financial Studies*, 32(2), pp. 564-604.

Von Thadden, Ernst-Ludwig. 1995. Long-term contracts, short-term investment and monitoring. *The Review of Economic Studies*, 62(4), pp. 557–575.

Figure 1: Definitions of switching, inside loans/lenders, and outside loans/lenders

This figure depicts our definitions of switching, inside and outside loans, and inside and outside lenders. Consider a borrower that at time *t=0*, obtains a loan (loan 2) from a lender (lender 2) from which he did not have any outstanding loans in the past 12 months. We refer to loan 2 as an "outside loan" or "switching loan" and lender 2 as the "outside lender". The horizontal solid line for lender 2 indicates the loan spell of loan 2. The horizontal dashed line for lender 2 prior to *t=-12*, indicates that the borrower may have had a prior loan from this lender that expired more than 12 months before *t=0*. (The use of a dashed line instead of a solid line indicates that this is possible, but not necessary.) At *t=0*, the borrower had an outstanding inside loan from at least one inside lender (loan 1 from lender 1 and possibly loan 3 from lender 3). We refer to loans 1 and 3 as "inside loans" and lenders 1 and 3 as the switcher's "inside lenders". Loans 4 and 5 indicate that it is possible that the borrower receives new loans from his initial inside lender(s) after *t=0*.

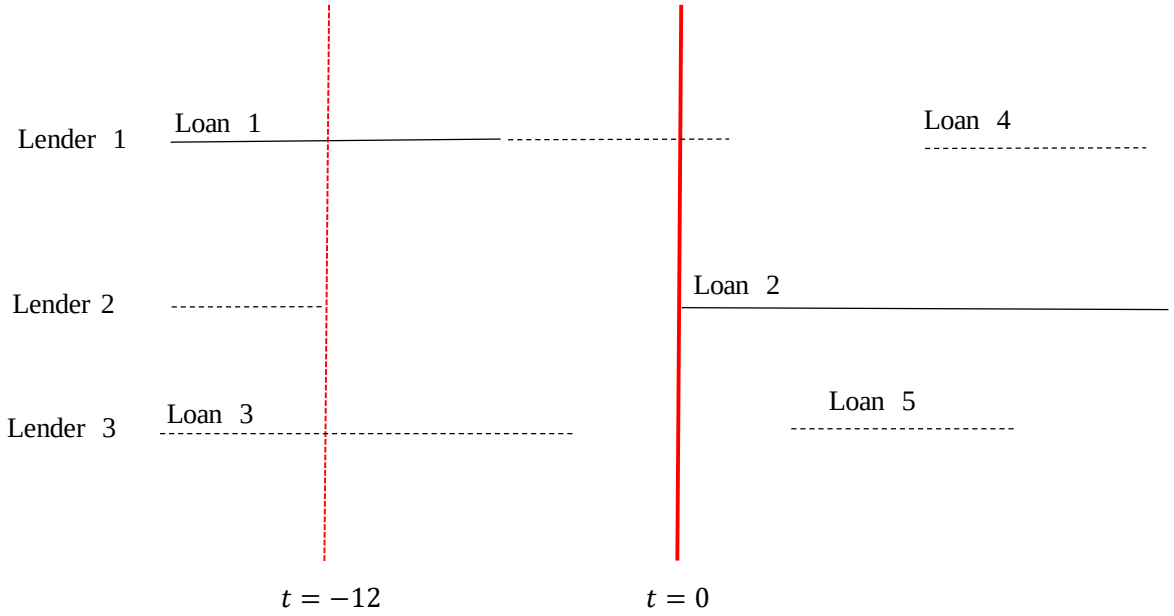

Figure 2: Switching rates from MFIs to CLs over time

The figure depicts the intensity of MFI-to-CL switching from January 1995 to June 2004, measured as the ratio of all MFI-to-CL loans in a given month over the total number of new MFI loans in that month.

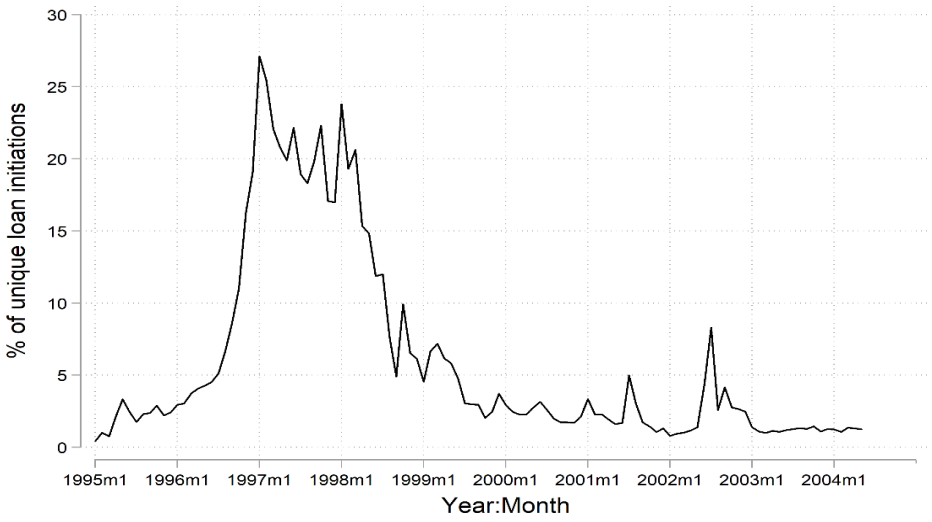

Figure 3: Long-term credit outcomes: MFI-to-CLs vs. MFI-to-MFI

This figure compares the credit outcomes of MFI-to-CL switchers to the credit outcomes of matched MFI-to-MFI borrowers before and after the switching. Each graph reports the estimated DiD coefficients of specifications of Eqn. (2) and their 95% confidence intervals using the matched sample of borrowers in Panel B of Table 3. We report results for total outstanding loans, interest rates, maturity and collateral (% of loans that are secured) from up to 12 months before switching and up to 36 months after switching.

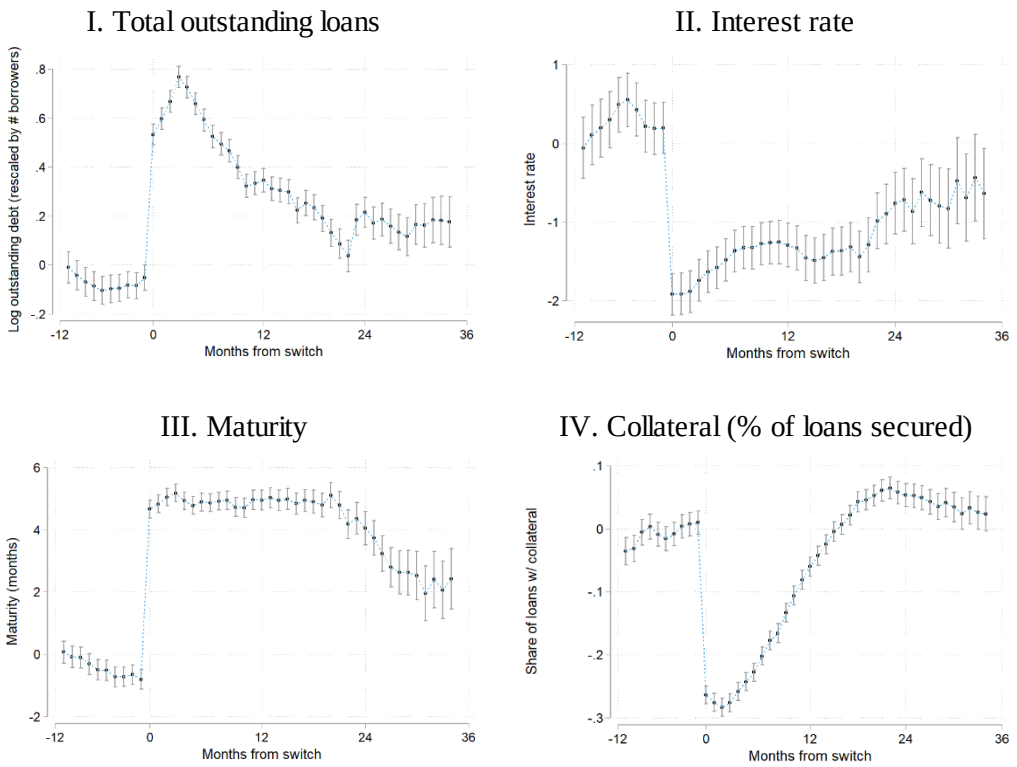

Figure 4: Long-term credit outcomes: repayment problems vs. no repayment problems

This figure reports the estimated coefficients of specifications of Eqn. (2) and their 95% confidence intervals. We report results for total outstanding debt, interest rates, maturity and collateral (% of loans that are secured). In Panel A, we compare outcomes for MFI-to-CL switchers who had any repayment problems (NPL, default, or write-offs) on the switching loan. In Panel B, we compare outcomes for MFI-to-CL switchers who did not have any repayment problems on the switching loan. The comparison group in both cases is MFI-to-MFI switching loans to similar (matched) borrowers. The sample period covers switching loans from January 1996 and December 1998 and any associated loans for the borrowers between January 1995 to December 2001.

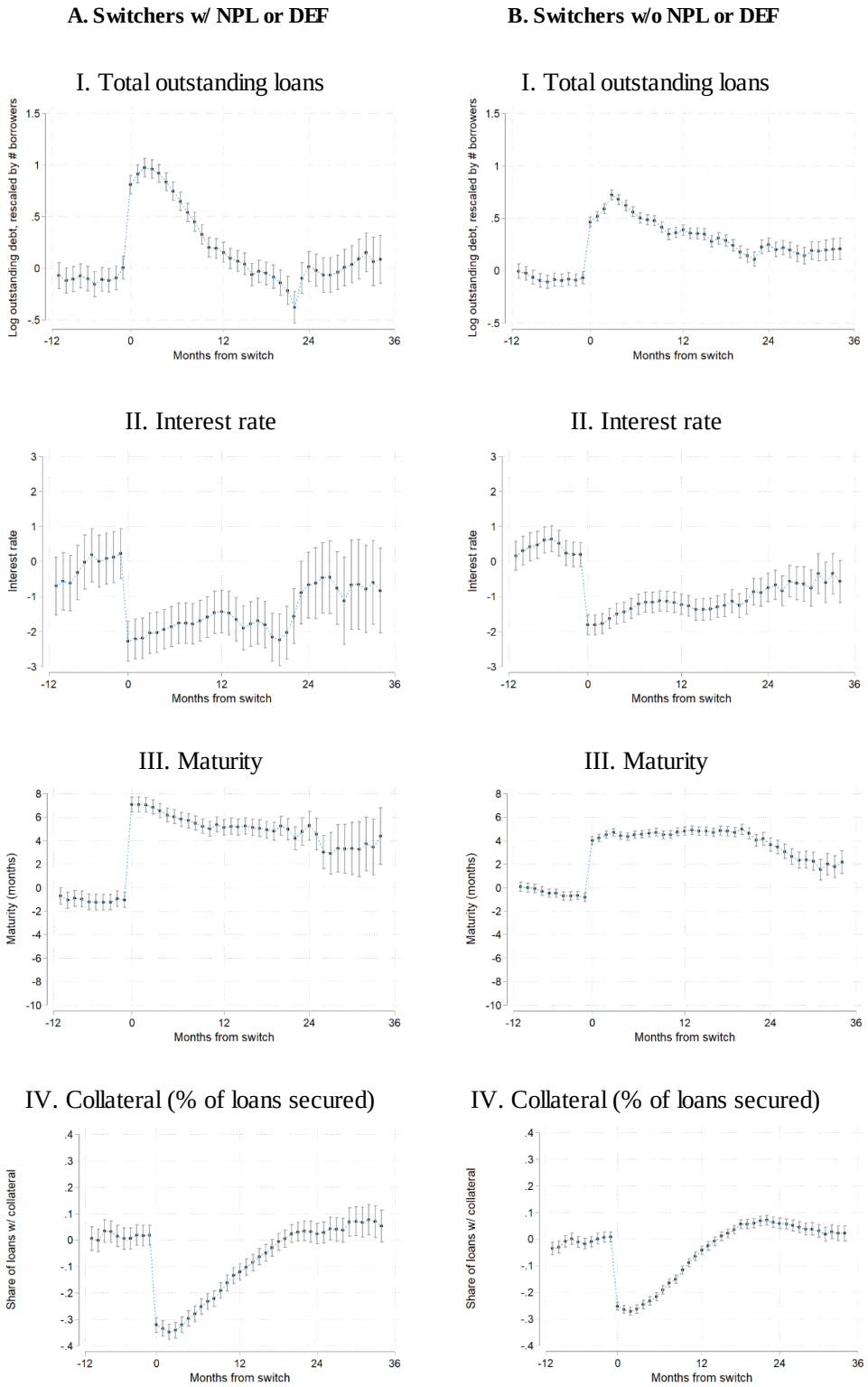

Table 1: Borrower and loan characteristics of MFIs and CLs to existing customers

This table presents summary statistics for borrower, loan, and loan repayment characteristics of MFI and CL inside loans between January 1995 and 2004. The summary statistics are calculated at the loan origination level. Loan amounts are expressed in USD. ***, **, * indicate whether differences in the mean of the two groups are statistically significant at the 1%, 5%, and 10% levels, respectively.

	MFIs			CLs	
Variables	Mean		Sd	Mean	Sd
Borrower characteristics					
Total outstanding loans	1,479	***	3,222	17,104	36,238
Multiple relationships	0.23	***	0.42	0.52	0.50
Relationship length (in months)	17.23	***	13.87	19.17	16.98
Observable past NPLs/Defaults	0.07	***	0.26	0.12	0.33
Unobervable past NPLs	0.02	***	0.14	0.07	0.25
Loan characteristics					
Loan amount	2,371	***	3,238	5,984	7,332
Loan amount per borrower	953	***	1,471	5,473	7,040
Interest rate	37.68	***	9.01	25.94	11.57
Maturity (in months)	11.87	***	10.90	19.89	23.30
Collateral	0.13	***	0.34	0.20	0.40
Value-to-loan ratio	2.05		2.41	2.16	110.14
Personal guarantees	0.35	***	0.48	0.44	0.50
Foreign currency (US$)	0.43	***	0.50	0.86	0.35
Num. borrowers	2.50	***	1.30	1.23	0.70
Joint liability	0.73	***	0.44	0.13	0.34
Loan type					
Installment loan	0.90	***	0.31	0.58	0.49
Fixed-term loan	0.10	***	0.30	0.18	0.39
Credit card	0.00	***	0.00	0.11	0.32
Advances in checking a/cs	0.00	***	0.00	0.10	0.30
Mortgages	0.01	***	0.07	0.02	0.16
Ex-post loan performance					
NPL	0.10	***	0.31	0.17	0.38
Default	0.05	***	0.22	0.08	0.27
Write-off	0.02	***	0.14	0.03	0.16
Observations	798,548			420,128	

Table 2: Switching rates within and across lender types

This table presents the number of unique loan originations and borrowers in the Bolivian CIRC for natural persons from January 1995 to June 2004. It then provides the percentage of these loan originations and borrowers that were outside loan switches within or across microfinance institutions (MFIs) and consumer lenders (CLs).

	Num. Loans	Num. Borrowers
All loan originations		
From MFIs	860,715	709,196
From CLs	1,007,818	506,143
MFI-to-CL	47,888	47,151
As a % of all MFI	5.56%	6.65%
As a % of all CL	4.75%	9.32%
MFI-to-MFI	98,347	103,080
As a % of all MFI	11.43%	14.53%
As a % of all CL	9.76%	20.37%
CL-to-CL	173,050	112,452
As a % of all MFI	20.11%	15.86%
As a % of all CL	17.17%	22.22%

Table 3: Loan terms and lending technologies

This table compares the terms of MFI-to-CL loans with the borrower's terms on outstanding loans from their initial MFIs (Panel A) and the terms that similar switching borrowers obtained at other MFIs (Panel B), using different specifications of Eqn. (1). The heading of each column indicates the dependent variable in each specification. In Panel A, Eqn. (1) is augmented with borrower fixed effects and $D_{i,t}$ equals one for MFI-to-CL loans and equals zero for outstanding loans from the switching borrower's initial MFI. The estimation sample is obtained after matching on the region of loan origination and type of loan using coarsened exact matching (CEM). In Panel B, $D_{i,t}$ equals one for MFI-to-CL loans and equals zero for MFI-to-MFI loans. The estimation sample is obtained using CEM after matching on the month-year of loan origination, region, type of loan, identity of inside lender(s), and several borrower characteristics observable to both inside and outside banks at *t=0*. In all cases, Eqn. (1) is estimated with OLS. Standard errors, reported in parentheses, are clustered at the provider-month level. *** p<0.01, ** p<0.05, * p<0.1.

	Log(Amount per borrower)	Interest Rate	Maturity	Collateral	Value-to-Loan	Joint Liability	Personal Guarantee	Foreign Currency
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. MFI-to-CL vs. Inside MFI loans								
$D_{i,t}$	0.520***	-3.205***	12.672***	-0.130***	-36.925***	-0.588***	0.153***	0.508***
	(0.054)	(0.425)	(0.653)	(0.031)	(7.721)	(0.029)	(0.032)	(0.014)
Total Obs	56,274	56,274	56,274	56,274	56,274	56,274	56,274	56,274
MFI-to-CL	15,036	15,036	15,036	15,036	15,036	15,036	15,036	15,036
Inside MFI	41,238	41,238	41,238	41,238	41,238	41,238	41,238	41,238
Controls								
Borrower fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Matching variables								
Region	Y	Y	Y	Y	Y	Y	Y	Y
Loan type	Y	Y	Y	Y	Y	Y	Y	Y
B. MFI-to-CL vs. MFI-to-MFI								
$D_{i,t}$	1.127***	-2.379***	15.692***	-0.375***	-99.026***	-0.441***	0.423***	0.672***
	(0.105)	(0.915)	(0.878)	(0.075)	(19.57)	(0.067)	(0.074)	(0.024)
Total Obs	24,548	24,548	24,548	24,548	24,548	24,548	24,548	24,548
MFI-to-CL	10,134	10,134	10,134	10,134	10,134	10,134	10,134	10,134
MFI-to-MFI	14,414	14,414	14,414	14,414	14,414	14,414	14,414	14,414
Matching variables								
Month-Year of loan origination	Y	Y	Y	Y	Y	Y	Y	Y
Region	Y	Y	Y	Y	Y	Y	Y	Y
Loan type	Y	Y	Y	Y	Y	Y	Y	Y
Inside lender(s)	Y	Y	Y	Y	Y	Y	Y	Y
Multiple inside lenders	Y	Y	Y	Y	Y	Y	Y	Y
Total oustanding debt at t=-1	Y	Y	Y	Y	Y	Y	Y	Y
Worst credit rating (prior 2 months)	Y	Y	Y	Y	Y	Y	Y	Y
Observable past NPLs/Defaults	Y	Y	Y	Y	Y	Y	Y	Y

Table 4: Ex-ante borrower risk: Observable and unobservable past delinquencies and defaults

This table compares the MFI-to-CL switchers to other switching and non-switching borrowers in terms of ex-ante observable and unobservable risk using different specifications of Eqn. (1). The heading of each column indicates the dependent variable of each specification. "Observably riskier borrower" is a dummy set to one if the borrower had overdue payments within the previous two months from the switching loan or any prior loan defaults. "Unobservably riskier borrower" is set to one if at *t=0* the borrower had overdue payments repaid more than two months prior to the switching loan. In Panels A and B, we compare the MFI-to-CL (MFI-to-MFI) switchers against non-switching borrowers at other MFIs. $D_{i,t}$ in this case equals one for MFI-to-CL (MFI-to-MFI) loans and equals zero for non-switching MFI. In Panel C we contrast the MFI-to-CL switchers against MFI-to-MFI switchers. $D_{i,t}$ equals one for MFI-to-CL loans and equals zero for MFI-to-MFI loans. For each panel, we report results with gradually more restrictive criteria using coarsened exact matching (CEM). At a minimum, we require that the matched borrowers have loans originated in the same month-year. In more restrictive specifications, we further require that loans are originated in the same region, the matched borrowers have the same inside lender(s), and they are similar with respect to other borrower characteristics observable to both inside and outside lenders. In the most restrictive specifications for unobservable risk, we compare the incidence of unobservable risk for borrowers with similar observable risk through the registry. In all cases, Eqn. (1) is estimated with OLS. Standard errors, reported in parentheses, are clustered at the provider-month level. *** p<0.01, ** p<0.05, * p<0.1.

	Observably riskier borrower			Unobservably riskier borrower			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. MFI-to-CL vs. Inside MFI loans							
$D_{i,t}$	-0.003**	-0.003**	-0.009***	0.102***	0.100***	0.087***	0.089***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Total Obs	110,108	109,370	108,164	110,108	109,370	108,164	101,629
MFI-to-CL	14821	14774	14565	14821	14774	14565	14255
Inside MFI	95287	94596	93599	95287	94596	93599	87374
B. MFI-to-MFI vs. Inside MFI loans							
$D_{i,t}$	-0.003*	-0.007***	-0.007***	0.052***	0.052***	0.048***	0.046***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Total Obs	111,182	105,470	98,005	111,182	105,470	98,005	81,883
MFI-to-MFI	15814	15753	15481	15814	15753	15481	15047
Inside MFI	95368	89717	82524	95368	89717	82524	66836
C. MFI-to-CL vs. MFI-to-MFI loans							
$D_{i,t}$	0.000	-0.007	0.001	0.046***	0.044***	0.046***	0.068***
	(0.001)	(0.007)	(0.002)	(0.006)	(0.008)	(0.009)	(0.008)
Total Obs	30,602	30,051	28,483	30,602	30,051	28,483	25,284
MFI-to-CL	14,821	14,637	13,317	14,821	14,637	13,317	10752
MFI-to-MFI	15,781	15,414	15,166	15,781	15,414	15,166	14532
Matching variables							
Month-Year of loan origination	Y	Y	Y	Y	Y	Y	Y
Region		Y	Y		Y	Y	Y
Inside lender(s)		Y	Y		Y	Y	Y
Multiple inside lenders at t=-1			Y			Y	Y
Total oustanding debt at t=-1			Y			Y	Y
Worst credit rating (prior 2 months)							Y
Observable past NPLs/Defaults							Y

Table 5: Ex-ante borrower risk: Adaptive CL vs. Non-Adaptive CLs

This table compares the MFI-to-CL switchers to other switching borrowers within MFIs in terms of ex-ante observable and unobservable risk using different specifications of Eqn. (1). The dependent variable in columns (1)-(3) is "Observably riskier borrower", a dummy variable that equals one if the borrower had overdue payments within the previous two months from the switching loans or any prior loan defaults. The dependent variable in columns (4)-(6) is "Unobservably riskier borrower", a dummy variable that equals one if the borrower had overdue payments repaid more than two months prior to the switching loan. In all specifications, $D_{i,t}$ equals one for MFI-to-CL loans and equals zero for MFI-to-MFI loans. For both dependent variables, we report results for 'All' CLs (columns 3 and 7 of Table 4 replicated here to facilitate comparison) and for sub-samples of 'Adaptive' and 'Non-Adaptive' CLs separately. In all cases, Eqn. (1) is estimated with OLS. Standard errors, reported in parentheses, are clustered at the provider-month level. *** p<0.01, ** p<0.05, * p<0.1.

	Observably riskier borrower			Unobservably riskier borrower		
	All CLs	Adaptive CLs	Non-Adaptive CLs	All CLs	Adaptive CLs	Non-Adaptive CLs
MFI-to-CL vs. MFI-to-MFI loans	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}$	0.001	-0.005	0.003	0.068***	0.045***	0.074***
	(0.002)	(0.004)	(0.002)	(0.008)	(0.012)	(0.008)
Total Obs	28,483	16,333	24,826	25,284	12368	22,925
MFI-to-CL	13,317	3,548	9,750	10,752	2187	8,547
MFI-to-MFI	15,166	12,785	15,076	14,532	10181	14,378
Matching Variables						
Month-year loan origination	Y	Y	Y	Y	Y	Y
Region	Y	Y	Y	Y	Y	Y
Inside Lender(s)	Y	Y	Y	Y	Y	Y
Multiple inside lenders at t=-1	Y	Y	Y	Y	Y	Y
Total outstanding debt at t=-1	Y	Y	Y	Y	Y	Y
Worst credit rating (prior 2 months)				Y	Y	Y
Observable past NPLs/Defaults				Y	Y	Y

Table 6: Ex-ante borrower risk: Non-adaptive CLs using vs. non-using collateral

This table compares the MFI-to-CL switchers to non-adaptive CLs to other switching borrowers within MFIs in terms of ex-ante observable and unobservable risk using different specifications of Eqn. (1). The dependent variable in columns (1)-(3) is "Observably riskier borrower", a dummy variable that equals one if the borrower had overdue payments within the previous two months from the switching loans or any prior loan defaults. The dependent variable in columns (4)-(6) is "Unobservably riskier borrower", a dummy variable that equals one if the borrower had overdue payments repaid more than two months prior to the switching loan. In all specifications, $D_{i,t}$ equals one for MFI-to-CL loans and equals zero for MFI-to-MFI loans. For both dependent variables, we report results of 'All' non-adaptive CLs (columns 1 and 4 of Table 5, replicated here to facilitate comparison) and for sub-samples of non-adaptive CLs that use of collateral ('Use Collateral') or do not use of collateral ('Do Not Use Collateral'). In all cases, Eqn. (1) is estimated with OLS. Standard errors, reported in parentheses, are clustered at the provider-month level. *** p<0.01, ** p<0.05, * p<0.1.

	Observably riskier borrower			Unobservably riskier borrower		
	All	Use Collateral	Do Not Use Collateral	All	Use Collateral	Do Not Use Collateral
MFI-to-CL vs. MFI-to-MFI loans	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}$	0.003	-0.002	0.003*	0.074***	0.036*	0.078***
	(0.002)	(0.004)	(0.002)	(0.008)	(0.019)	(0.008)
Total Obs	24,826	14,151	23,885	22,925	11,689	21,959
MFI-to-CL	9,750	820	8,930	8,547	727	7,820
MFI-to-MFI	15,076	13,331	14,955	14,378	10,962	14,139
Matching Variables						
Month-year loan origination	Y	Y	Y	Y	Y	Y
Region	Y	Y	Y	Y	Y	Y
Inside Lender(s)	Y	Y	Y	Y	Y	Y
Multiple inside lenders at t=-1	Y	Y	Y	Y	Y	Y
Total outstanding debt at t=-1	Y	Y	Y	Y	Y	Y
Worst credit rating (prior 2 months)				Y	Y	Y
Observable past NPLs/Defaults				Y	Y	Y

Table 7: Ex-post loan repayment problems

This table compares the MFI-to-CL switchers to other switching and non-switching borrowers in terms of ex-post loan repayment using different specifications of Eqn. (1). The dependent variable, "Ex-post repayment problems", equals one if a loan had any repayment problems (i.e., overdue payments, default, or written-off) any time after origination, and equals zero otherwise. In Panels A and B, we compare the MFI-to-CL (MFI-to-MFI) switchers against non-switching borrowers at other MFIs. $D_{i,t}$ in this case equals one for MFI-to-CL (MFI-to-MFI) loans and equals zero for non-switching MFI loans. In Panel C we contrast the MFI-to-CL switchers against MFI-to-MFI switchers. $D_{i,t}$ equals one for MFI-to-CL loans and equals zero for MFI-to-MFI loans. For each panel, we report results with gradually more restrictive criteria using coarsened exact matching (CEM). The matching criteria in columns (1)-(3) aim to absorb differences in ex-ante borrower risk that are observable to both inside and outside lenders. The matching criteria in columns (4)-(7) aim instead to absorb borrower risk that is observable to inside lenders, but unobservable to outside lenders and potentially us (the econometrician). The (in)stability of our estimates as we additionally match on these characteristics offer an indication of how likely it is that such factors drive any differences in ex-post repayment. In all cases, Eqn. (1) is estimated with OLS. Standard errors, reported in parentheses, are clustered at the provider-month level. *** p<0.01, ** p<0.05, * p<0.1.

	Ex-post repayment problems						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. MFI-to-CL vs. Inside MFI							
$D_{i,t}$	0.436***	0.418***	0.422***	0.420***	0.419***	0.406***	0.407***
	(0.031)	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)
Total Obs	110,108	108,164	101,629	100,516	96,080	85,850	84,952
MFI-to-CL	14,821	14,565	14,255	13,729	13,426	12,417	12,315
Inside MFI	95,287	93,599	87,374	86,787	82,654	73,433	72,637
B. MFI-to-MFI vs. Inside MFI							
$D_{i,t}$	0.014*	-0.004	0.002	0.003	0.000	-0.001	-0.001
	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Total Obs	111,182	98,005	81,883	81,223	77,574	71,447	70,847
MFI-to-MFI	15,814	15,481	15,047	14,764	14,396	13,560	13,456
Inside MFI	95,368	82,524	66,836	66,459	63,178	57,887	57,391
C. MFI-to-CL vs. MFI-to-MFI							
$D_{i,t}$	0.415***	0.420***	0.471***	0.471***	0.485***	0.487***	0.487***
	(0.031)	(0.034)	(0.030)	(0.030)	(0.029)	(0.028)	(0.028)
Total Obs	30,602	28,483	25,284	24,719	23,242	21,603	21,326
MFI-to-CL	14,821	13,317	10,752	10,336	9,312	8,467	8,363
MFI-to-MFI	15,781	15,166	14,532	14,383	13,930	13,136	12,963
Matching variables							
Month-year of loan origination	Y	Y	Y	Y	Y	Y	Y
Region		Y	Y	Y	Y	Y	Y
Inside lender(s)		Y	Y	Y	Y	Y	Y
Multiple lenders at t=-1		Y	Y	Y	Y	Y	Y
Total bank debt at t=-1		Y	Y	Y	Y	Y	Y
Worst rating at t [-1,-2]			Y	Y	Y	Y	Y
Observable past NPLs/Defaults at t=-1			Y	Y	Y	Y	Y
Unobservable past NPLs at t=-1				Y	Y	Y	Y
Average interest rate at t=-1					Y	Y	Y
Average maturity at t=-1						Y	Y
Collateral at t=-1						Y	Y
Personal guarantee at t=-1						Y	Y
Joint Liability at t=-1							Y

Table 8: Ex-post loan repayment problems

This table compares MFI-to-CL and MFI-to-MFI switchers in terms of ex-post loan repayment using augmented specifications of Eqn. (1) that include interactions with the switchers' borrowing terms at their new lenders. In Panel A, we allow for interactions between $D_{i,t}$ and the ratio between the switcher's total outstanding bank debt at *t=1* and *t=-1*. In Panel B, we allow for an interaction term with a dummy variable indicating whether the borrower obtained a switching loan that was denominated in a foreign currency. In Panel C, we allow for an interaction term with a dummy variable indicating whether the borrower obtained a switching loan with joint liability. In all cases, the dependent variable is "Ex-post repayment problems", which equals one if a loan had any repayment problems (i.e., overdue payments, default, or written-off) any time after origination, and equals zero otherwise. The matching variables in column (1) absorb differences in observable borrower risk, corresponding to column (3) of Table 7. The matching variables in column (2) additionally match on indicators of unobservable borrower risk, corresponding to column (7) of Table 7. In all cases, Eqn. (1) is estimated with OLS. Standard errors, reported in parentheses, are clustered at the provider-month level. *** p<0.01, ** p<0.05, * p<0.1.

	Ex-post repayment problems	
	(1)	(2)
A. Indebtedness		
$D_{i,t}$	0.423***	0.435***
	(0.034)	(0.032)
$D_{i,t}$* (Total bank debt at *t+1* / Total bank debt at *t-1*)	0.003***	0.003***
	(0.001)	(0.001)
(Total bank debt at *t+1* / Total bank debt at *t-1*)	0.001	0.001
	(0.001)	(-0.001)
B. Exchange rate risk		
$D_{i,t}$	0.256***	0.278***
	(0.037)	(0.039)
$D_{i,t}$* Foreign currency switching loan	0.227***	0.205***
	(0.042)	-0.045
Foreign currency switching loan	0.008	0.026
	(0.025)	-0.025
C. Peer screening and monitoring		
$D_{i,t}$	0.491***	0.501***
	(0.028)	(0.030)
$D_{i,t}$* Joint liability switching loan	-0.411***	-0.418***
	(0.041)	-0.045
Joint liability switching loan	-0.099***	-0.086***
	(0.021)	-0.024
Total Obs	25,284	21,326
MFI-to-CL	10,752	8,363
Inside MFI	14,532	12,963
Matching variables		
Month-year of loan origination	Y	Y
Region	Y	Y
Inside lender(s)	Y	Y
Multiple lenders at t=-1	Y	Y
Total bank debt at t=-1	Y	Y
Worst rating at t [-1,-2]	Y	Y
Observable past NPLs/Defaults at t=-1	Y	Y
Unobservable past NPLs at t=-1		Y
Average interest rate at t=-1		Y
Average maturity at t=-1		Y
Collateral at t=-1		Y
Personal guarantee at t=-1		Y
Joint Liability at t=-1		Y

Table 9: Spillover effects on MFI loan terms for switchers and non-switchers

This table examines whether CLs' entry into the microfinance market affected the subsequent loan terms that switching and non-switching borrowers received from MFIs. Panel A reports results for switching MFI borrowers using Eqn. (3). The dependent variable for each specification is indicated by the heading of each column. The key explanatory variable, $HC_{j,k}$, equals 1 if during the initial period of CLs' entry into the microfinance market (i.e., from 1995:1 to 1996:12), the MFI lender j had an above median fraction of borrowers switching to CLs, and equals zero otherwise. $Post_{i,t}$ equals 1 after borrower i obtained their first switching loan from a CL and equals zero otherwise. Eqn. (3) is estimated using all inside MFI loan originations between 1995:1 and 2001:12 for MFI borrowers who switched for the first time to a CL any time after 1997. Panel B reports results for non-switching MFI borrowers using Eqn. (4). $Post_i$ equals 1 if the loan was originated after 1997 and equals zero otherwise. All other variables are defined as in Panel A. Eqn. (4) is estimated using all inside MFI loans to MFI borrowers that never switch to a CL. In all cases, the specifications are estimated with OLS. Standard errors, reported in parentheses, are clustered at the provider-month level. *** p<0.01, ** p<0.05, * p<0.1.

	Log(Amount per borrower)	Interest Rate	Maturity	Collateral
A. Switchers to CLs	(1)	(2)	(3)	(4)
$Post_{i,t}$	0.073***	-0.019	-0.05	0.185***
	(-0.017)	(-0.142)	(-0.109)	(0.027)
$HC_{j,k} * Post_{i,t}$	0.001	-0.681***	0.816***	-0.237***
	(-0.02)	(-0.19)	(-0.135)	(0.032)
Total Obs	108,592	108,594	100,037	89317
R-square	0.795	0.741	0.699	0.728
Controls				
Borrower FE	Y	Y	Y	Y
Lender-Region FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
B. Non-switchers to CLs				
$Post_t$	0.479***	-1.257***	2.025***	0.009
	(-0.04)	(-0.146)	(-0.199)	(0.015)
$HC_{j,k} * Post_t$	0.047	-0.867***	0.990***	-0.297***
	(-0.032)	(-0.248)	(-0.139)	(0.053)
Total Obs	576,404	576,404	501,577	576404
R-square	0.829	0.794	0.738	0.721
Controls				
Borrower FE	Y	Y	Y	Y
Lender-Region FE	Y	Y	Y	Y

Appendix

Table A1: Variable names and definitions

This tables reports the variable names and definitions of all variables in the analysis.

Variable Names	Definitions
Borrower characteristics	
Total outstanding loans	total amount of oustanding loans in US$
Multiple relationships	=1 if borrower has outstanding loans from two or more different lenders at time *t*
Relationship length (in months)	number of months between first loan origination with lender and time *t*
Observable past NPLs/Defaults	defaults
Unobervable past NPLs	=1 if overdue payments repaid more than two months prior to time *t*
Loan characteristics	
Loan amount	loan amount at loan origination in US$
Loan amount per borrower	loan amount in US$ divided by number of borrowers
Interest rate	annual contractual interest rate at loan origination
Maturity	number of months between loan origination and maturity
Collateral	=1 if collateral was pledged at loan origination, and =0 otherwise
Value-to-loan ratio	collateral value to loan amount
Personal guarantees	= 1 if loan is secured through personal guarantees, and =0 otherwise
Foreign currency (US$)	loans are in US$
Num. borrowers	number of borrowers associated with loan
Joint liability	=1 if a joint liability loan (i.e., multiple borrowers), and =0 otherwise
Loan type	
Installment loan	=1 if loan type is an installment loan
Fixed-term loan	=1 if loan type is a fixed-term loan
Credit card	=1 if loan type is credit card transaction
Advances in checking a/cs	=1 if loan type is an advance from a checking account or current account
Mortgages	=1 if loan type is a mortgage
Ex-post loan performance	
NPL	=1 if the a loan had 30+ overdue payments anytime after origination, and =0 otherwise
Default	=1 if the loan was downgraded to default status any time after origination, =0 otherwise
Write-off	=1 if the loan was written off any time after origination, =0 otherwise
Ex-post repayment problems	=1 if the loan had any repayment problems (i.e., overdue payments, default, or written-off) any time after origination, and equals one otherwise.

Table A2. Switching characteristics

This table compares the characteristics of switchers from MFI-to-CLs, MFI-to-MFIs, and CLs-to-CLs. It first provides the percentage of switching loans where the borrower had an outside lender prior to 12 months before the switching loan. Next, it provides the percentage of switching loans where the borrower had multiple inside lenders or outstanding inside loans at the time of the switch. Finally, it provides the percentage of switching loans where the borrower had a subsequent new loan from their original inside lender after the time of the switch. These results cover switching within and across these lender categories for all natural persons captured in the Bolivian CIRC during the time period from January 1995 to June 2004.

MFI-to-CL	
Loans from outside lender before *t=-12*	0.93%
Loans from multiple inside lenders before *t=0*	26.74%
Outstanding inside loans at *t=0*	69.73%
New loans from inside MFI lender(s) after *t=0*	36.00%
MFI-to-MFI	
Loans from outside lender before *t=-12*	11.21%
Loans from multiple inside lenders before *t=0*	8.52%
Outstanding inside loans at *t=0*	50.80%
New loans from inside MFI lender(s) after *t=0*	20.67%
CL-to-CL	
Loans from outside lender before *t=-12*	8.67%
Loans from multiple inside lenders before *t=0*	17.67%
Outstanding inside loans at *t=0*	36.92%
New loans from inside MFI lender(s) after *t=0*	16.77%

Table A3: Borrower and loan characteristics of MFI-to-CL and MFI-to-MFI loans

This table presents summary statistics for borrower, loan, and loan repayment characteristics of MFI-to-CL loans as well as MFI-to-MFI loans between January 1995 and June 2004. The summary statistics are calculated at the loan origination level. Loan amounts are expressed in USD.

	MFI-to-CL		MFI-to-MFI	
	Mean	Sd	Mean	Sd
Borrower characteristics				
Total outstanding loans	3,412	4,920	1,512	2,474
Multiple relationships	0.74	0.44	0.52	0.50
Relationship length (in months)	1.27	8.19	9.51	17.70
Observable past NPLs/Defaults	0.05	0.21	0.03	0.18
Unobervable past NPLs	0.10	0.30	0.05	0.23
Loan characteristics				
Loan amount	2,744	3,926	1,813	2,831
Loan amount per borrower	2,242	3,464	975	1,629
Interest rate	32.84	10.74	34.53	7.80
Maturity (in months)	24.16	18.46	15.31	12.53
Collateral	0.14	0.34	0.25	0.44
Value-to-loan ratio	1.71	3.44	1.77	1.97
Personal guarantees	0.61	0.49	0.11	0.31
Foreign currency (US$)	0.94	0.24	0.54	0.50
Num. borrowers	1.44	0.97	1.97	0.95
Joint liability	0.23	0.42	0.67	0.47
Loan type				
Installment loan	0.88	0.33	0.96	0.21
Fixed-term loan	0.05	0.22	0.04	0.19
Credit card loan	0.04	0.19	0.00	0.00
Advances in checking a/cs	0.02	0.15	0.00	0.00
Mortgages	0.01	0.11	0.01	0.09
Ex-post loan performance				
NPL	0.30	0.46	0.11	0.32
Default	0.16	0.37	0.07	0.26
Write-off	0.08	0.28	0.02	0.15
Observations	47,888		98,347	

Table A4: Ex-post repayment problems and ex-ante borrower risk

This table reports estimation results of Probit regressions testing whether the ex-ante observable and unobservable risk variables we constructed have informational value in predicting the repayment performance of switching loans over and above other observable borrower characteristics. The sample includes all switching loans from MFIs and CLs between 1996 and 2001. The dependent variable, *Ex-post repayment problems*, is a dummy variable set to one if the loan had any repayment problems (i.e., overdue payments, default, or written-off) any time after origination, and equals zero otherwise. The two key explanatory variables, *Observably riskier borrower* and *Unobservably riskier borrower*, are dummy variables indicating whether at the time of loan origination the borrower had prior repayment problems on past loans that were either observable or unobservable to outside lenders through the registry. Column (1) reports a baseline specification where we control for lender and region fixed effects as well as other firm characteristics shared through the registry (as in Table 7, column 2). The specification in column (2) further controls for other firm characteristics that correlate with borrower risk observable to inside lenders, but are potentially unobservable to outside lenders and us, the econometrician (as in Table 7, column 7). Standard errors clustered at the provider-month level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Ex-post repayment problems	
	(1)	(2)
Observably riskier borrower	0.645***	0.635***
	(0.067)	(0.067)
Unobservably riskier borrower	0.152***	0.148***
	(0.017)	(0.017)
R-square	0.078	0.083
Total Obs	97,416	97,416
Additional controls		
Lender FE	Y	Y
Region FE	Y	Y
Multiple lenders at t=-1	Y	Y
Total bank debt (rescaled by # borrowers) at t=-1	Y	Y
Worst rating at t [-1,-2]	Y	Y
Average interest rate at t=-1		Y
Average maturity at t=-1		Y
Collateral at t=-1		Y
Personal guarantee at t=-1		Y
Joint Liability at t=-1		Y

Table A5: Borrower and loan characteristics: Adaptive vs. Non-Adaptive CLs

This table presents summary statistics for borrower, loan, and loan repayment characteristics of MFI-to-CL switching loans originated between 1996 and 2001. We distinguish between CLs that adopted MFI lending technologies such as joint liability and those that did not, denoted as "Adaptive CLs" vs. "Non-Adaptive CLs". Based on information in Rhyne (2002), de Janvry et al. (2003) and our data, we classify Fassil, Banco Santa Cruz, and Financiero De La Comunidad as adaptive CLs. We classify all other CLs as non-adaptive. The summary statistics are calculated at the loan origination level. Loan amounts are expressed in USD.

	MFI-to-CL loans			
	Adaptive CLs		Non-Adaptive CLs	
	Mean	Sd	Mean	Sd
Borrower characteristics				
Total outstanding loans	2,382	3,571	3,670	4,777
Multiple relationships	0.73	0.44	0.76	0.43
Relationship length (in months)	0.53	4.18	0.65	5.44
Observable past NPLs/Defaults	0.03	0.17	0.06	0.23
Unobervable past NPLs	0.08	0.27	0.11	0.32
Loan characteristics				
Loan amount	2,863	3,688	2,630	3,584
Loan amount per borrower	1,361	2,127	2,477	3,446
Interest rate	32.5	9.47	34.34	10.4
Maturity (in months)	15.02	16.38	26.76	13.85
Collateral	0.17	0.37	0.10	0.30
Value-to-loan ratio	1.23	0.70	2.24	2.81
Personal guarantees	0.47	0.50	0.76	0.42
Foreign currency (US$)	0.92	0.27	0.95	0.22
Num. borrowers	2.60	1.43	1.09	0.29
Joint liability	0.66	0.47	0.09	0.29
Loan type				
Installment loan	0.86	0.35	0.92	0.27
Fixed-term loan	0.12	0.33	0.01	0.08
Credit card loan	0.01	0.12	0.04	0.19
Advances in checking a/cs	0.00	0.04	0.03	0.17
Mortgages	0.00	0.07	0.01	0.08
Ex-post loan performance				
NPL	0.18	0.38	0.38	0.49
Default	0.11	0.32	0.20	0.40
Write-off	0.03	0.18	0.11	0.32
Observations	11,762		33,008	