Banking on Competition: The Spillover Effects of Bank Entry into Microfinance

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Abstract

This paper examines how the entry of commercial lenders transforms microfinance markets, focusing on borrower outcomes and market-wide spillovers. Using detailed credit registry data, we show that increased competition improves loan terms for both graduating and staying borrowers, generating sustained benefits. Our setting also allows us to document what happens when entry fails and entrants retreat following a crisis. Despite increasing defaults, borrowers who graduate to banks experience long-term gains, particularly through lower borrowing costs. Our findings highlight the broader benefits and risks of fostering competition in microfinance, providing valuable insights for policymakers and financial inclusion initiatives.

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I. Introduction

Access to credit is seen as a key driver of economic development (see, e.g., King and Levine, 1993; Jith and Strahan, 1996; Beck, Levine, and Loayza, 2000). However, despite the promise of microfinance as a tool for financial inclusion, evidence from randomized controlled trials (RCTs) shows that its impacts on borrowers are often modest and short-lived (e.g., Banerjee, Karlan, and Zinman, 2015). This has led to a growing recognition that RCTs may overlook the broader benefits of microfinance by not capturing general equilibrium and spillover effects (Banerjee et al., 2015).

Recent studies have begun to explore these broader impacts. For example, Breza and Kinnan (2021) highlight how microfinance stimulates local economies by increasing local consumption, while Agarwal, Kigabo, Minoiu, Presbitero, and Silva (2023) emphasize its role as a pathway to banks. By building credit histories with microfinance institutions (MFIs), borrowers can, in time, "graduate" to commercial banks, accessing more diverse and affordable financial products. While MFIs are often viewed as the most sustainable credit providers for low-income borrowers—given their specialized lending technologies designed for clients without collateral or formal documentation—graduation can help borrowers overcome the inherent capacity constraints of MFIs. Recognizing this potential, many governments in developing countries have launched financial inclusion programs and established credit registries to reduce information asymmetries (Pagano and Jappelli, 1993) and encourage competition between lenders.[1]

[1]Examples include financial inclusion initiatives in Africa (Allen, Carletti, Cull, Qian, Senbet, and Valenzuela, 2021; Agarwal et al., 2023), Eastern Europe (Brown, Guin, and Kirschenmann, 2016), India (Agarwal, Alok, Ghosh, Ghosh, Piskorski, and Seru, 2017; Burgess and Pande, 2005), and Mexico (Bruhn and Love, 2014). Furthermore, evidence from Bosnia and Herzegovina shows that the introduction of credit registries that require information

In this paper, we show that the benefits of graduation are much broader than previously documented. Beyond the direct benefits for graduating borrowers, such transitions can generate significant positive spillovers for "staying" borrowers by fostering competition. Due to asymmetric information and adverse selection, MFIs often charge high interest rates, extracting hold-up rents (Sharpe, 1990; Rajan, 1992), limiting borrowers' growth. By making borrowers' credit histories accessible through public credit bureaus, governments can facilitate entry into these markets, increasing competition. This not only enables graduating borrowers to secure better loan terms, but also pressures MFIs to offer improved terms to staying borrowers to prevent further client losses. These spillover effects can transform credit markets, amplifying the long-term economic impact of microfinance. However, competition also carries significant risks: high levels of rivalry in credit markets can destabilize the sector, leading to over-indebtedness as entrants aggressively compete for market share without internalizing externalities on other lenders (Bizer and DeMarzo, 1992; Parlour and Rajan, 2001).[2]

To examine these effects, we analyze how the entry of commercial lenders (CLs)—consisting primarily of commercial banks—into Bolivia's microfinance sector during the 1990s influenced the credit outcomes of both graduating and staying borrowers, both in the short term

sharing between MFIs and banks can improve loan quality by enabling lenders to better screen borrowers (de Haas, Millone, and Bos, 2021). Beck (2015) provides a critical survey of the microfinance literature and key challenges facing regulators.

[2]These dynamics are not unique to traditional banking. The rise of FinTech lenders has similarly introduced new competitive forces in credit markets, often leveraging alternative data sources and automated underwriting models to expand access to underserved borrowers (e.g., Fuster, Berg, and Puri, 2021; Di Maggio and Yao, 2021). However, as we discuss later, adverse selection and credit risk remain persistent challenges in large-scale unsecured lending, even with advances in technology.

and long term. Attracted by the high profitability of Bolivian MFIs and pressured by intensifying competition from foreign banks in their core markets, Bolivian banks, along with a few private financial funds, began actively targeting MFI clients. Within a year, the graduation rate from MFIs to CLs surged from 2.5% to over 25% (Figure 1). Although the entry of CLs increased competition in the microfinance market, it also contributed to rising debt levels and an increase in defaults among MFI borrowers (De Janvry, Sadoulet, McIntosh, Wydick, and Luoto, 2003). The situation deteriorated further with Brazil's financial crisis in 1999, which triggered widespread borrower defaults and ultimately led CLs to withdraw from the microfinance sector.

This episode provides a rare opportunity to study both phases of market dynamics: the expansion phase, marked by increased competition and borrower graduation to CLs, and the contraction phase, characterized by high borrower defaults and CLs' withdrawal. Our empirical analysis benefits from exceptionally detailed loan-level data from Bolivia's credit registry, which tracks nearly 2 million loans to 1.2 million borrowers across both MFIs and CLs. This granular dataset allows us to precisely follow individual borrowers over time, enabling a comprehensive assessment of how CLs' entry and subsequent exit affected credit terms for both graduating and staying MFI borrowers.

To examine how graduation to CLs relates to borrowers' financial outcomes, we compare the loan terms they receive from CLs with those they had from MFIs just before graduation, using a within-borrower analysis. On average, CL loans are 52% larger, 3.2 percentage points cheaper, and have maturities that are about a year longer than MFI loans. CL loans are also less likely to require collateral or joint liability, with the likelihood of joint liability dropping by nearly 60 percentage points, indicating that CLs rely far less on traditional microfinance lending methods such as group lending. Instead, CL loans more frequently require personal guarantees, which are

15 percentage points more common than in MFI loans. Additionally, over half of CL loans are denominated in USD, reflecting banks' funding sources. These results suggest that borrowers graduating to CLs gain access to larger, more flexible, and more affordable loans.

However, these results may be biased, as the decision to graduate is endogenous—graduating borrowers may be better-performing firms with growing credit needs. To address this concern, we conduct a second set of tests, comparing their loan terms to those of similar borrowers who switched within MFIs. Both groups demonstrate positive credit demand, successfully accessed new lenders, and may benefit from more attractive terms aimed to attract them (Ioannidou and Ongena, 2010). Using Coarsened Exact Matching and Random Forest, we match borrowers on time, region, initial lender, loan type, and borrower characteristics. Specifically, we compare loans issued in the same month and region with borrowers from the same incumbent MFI with similar *ex ante* risk characteristics, matching in total outstanding loans, credit rating, and repayment history, which are observable to new prospective lenders through the credit registry.

The results of these matching tests are consistent with those from the within-borrower analysis, indicating that graduation to CLs helps access more favorable loan terms. Robustness tests confirm that these benefits apply to graduates of both banks and private financial funds, though they are significantly larger for those graduating to banks.

Yet MFI borrowers who graduate to CLs may still differ systematically from those who switch within MFIs in ways that are not directly observable (e.g., they may be unobservably better firms). To address this concern, we examine the *ex ante* risk profiles of graduating, switching, and staying borrowers. Unlike previous studies, we can distinguish between ex ante risk characteristics that are *observable* and *unobservable* to new prospective lenders. This distinction is possible because not all aspects of a borrower's credit history recorded in the registry are shared with new lenders. Specifically, the credit registry's information-sharing window is limited to two months, meaning lenders only see a borrower's repayment behavior within this period. This short window allows us to construct a proxy for unobservable borrower risk by identifying recent delinquencies that occurred 3 to 12 months before graduation or switching. As we show, these earlier delinquencies, though not visible to new lenders, are highly predictive of future borrower defaults. Thus, this feature of our data enables a direct comparison of the unobservable risk profiles of graduating, switching, and staying borrowers.

We find that both CLs and MFIs are less likely to lend to graduating or switching borrowers with observable past repayment problems, suggesting that credit registries help lenders screen and select new clients. However, information asymmetries and adverse selection persist—particularly for CLs. Specifically, we find that unobservable past delinquencies among borrowers who graduate to CLs are twice as high as those among borrowers who switch within MFIs. This novel result indicates that CLs face stronger adverse selection problems than MFIs, challenging the notion that borrowers who graduate to CLs are unobservably less risky than those who switch within MFIs.

Furthermore, we find that adverse selection problems are less pronounced for CLs that adopt lending technologies pioneered by MFIs, such as joint liability group lending, which is better suited to borrowers lacking collateral. This result, made possible by the richness of our data and information-sharing framework, provides empirical evidence on the role of lending technologies in mitigating adverse selection. At the same time, it underscores the limitations of CLs' traditional lending practices in these markets.

When relying on unsecured individual lending and credit scoring models, CLs struggle to screen borrowers effectively, leading to more severe adverse selection problems. This challenge persists even today, both in developed and developing countries. Despite advances in data analytics and sophisticated credit scoring models, large-scale unsecured lending remains difficult. Even FinTech lenders engage in cream-skimming, targeting safer borrowers while avoiding the riskiest segments.[3] As a result, financial institutions serving the bottom of the pyramid continue to rely on some form of collateral or group-based mechanisms to counter adverse selection and credit risk.

To examine the long-term credit outcomes of graduating borrowers, we employ a dynamic difference-in-differences (DiD) framework, comparing changes in borrowing terms over time between borrowers who graduated to CLs and those who switched within MFIs. This dynamic approach allows us to assess how their borrowing terms evolved before and after transitioning to their new lenders. Importantly, our estimates show no significant differences in pre-trends in key credit outcomes—such as total outstanding loans, interest rates, maturity, and collateral—supporting the parallel trends assumption and strengthening the internal validity of our analysis. Despite CLs' poorly adapted lending technologies and the subsequent borrower defaults, we find that those who graduated to CLs experienced significant long-term improvements in borrowing terms.

While gains in total outstanding loans, loan maturity, and collateral requirements proved temporary, reductions in borrowing costs and joint liability requirements persisted over the long term, even as CLs withdrew from the microfinance market. For graduating borrowers who experienced repayment problems on their CL loans, the long-term benefits were more modest, but

[3] See, for example, Figure 3 and Table 3 in Di Maggio and Yao (2021).

their borrowing terms remained no worse than before graduating to CLs. To assess broader market effects, we estimate a full spillover model (Berg, Reisinger, and Streitz, 2021). Our findings indicate that competition from CLs forced MFIs to improve future loan terms not only to graduating borrowers, but also to those who remained with MFIs.

Our paper contributes to the microfinance literature by providing new insights into how microfinance fosters financial inclusion. Prior research emphasizes its role as a pathway to formal banking, showing that microcredit programs and credit registries help unbanked borrowers build credit histories and transition to CLs for better loan terms (e.g., Agarwal et al., 2023; de Haas et al., 2021). We extend this literature in three key ways. First, we show that the benefits of CLs' entry extend beyond direct lending. In addition to improving credit outcomes for graduating borrowers, competition generates positive spillovers for borrowers that remain with MFIs.

Second, our setting allows us to study both phases of market dynamics. Unlike prior studies that focus on the expansion phase, we document how borrowers' credit outcomes evolve when CLs retreat, providing a more comprehensive view of the risks and rewards of fostering competition in microfinance markets. Our findings suggest that competitive pressures, even from temporary entrants, can deliver lasting benefits. These results are novel and are supported by theories of industrial organization, which suggest that sustained market presence is not necessary for long-lasting benefits (Baumol, 1982). The evidence further suggests that incumbent MFIs may have adopted limit pricing strategies to deter CLs' re-entry (Gaskins, 1971) into the microfinance market.

Third, our analysis advances the literature on lending technologies and borrower selection by providing empirical evidence on the role of joint liability group lending in mitigating adverse selection. We find that CLs adopting joint liability practices outperform traditional individual lending models in screening risky borrowers. While the systematic use of collateral also reduces adverse selection, such cases are rare, as many low-income, low-documentation borrowers lack pledgeable assets. These findings highlight the limitations of CLs' reliance on individual liability and collateral-based models. Advances in data availability and processing capabilities may offer a path to more flexible and effective lending approaches.

II. Background

A. Bolivia's Microfinance Sector and CLs' Entry

During the 1990s, Bolivia had one of the most advanced and thriving microfinance sectors globally, operating predominantly on commercial principles (for-profit). For example, Bolivia's largest microfinance lender, BancoSol, consistently ranked among the country's top financial institutions in terms of profitability and asset quality (Rhyne, 2002).

MFIs used traditional microfinance lending practices to effectively screen and monitor borrowers. These included group loans with joint liability that leveraged peer screening and enforcement, strict "zero tolerance" policies on delinquencies, regular loan officer visits to borrowers, and dynamic incentives, where continued access to credit—and progressively larger loan amounts—was contingent on timely repayment.

In the mid-1990s, drawn by the high profitability of Bolivia's MFIs and facing growing competition from foreign banks in their core markets (Beck, Ioannidou, and Schäfer, 2018), CLs—comprising most commercial banks and a few private financial funds—began aggressively targeting MFI borrowers. To do so, they adopted a range of lending technologies. Some recruited experienced loan officers from MFIs and implemented traditional microfinance practices, including group lending and close borrower monitoring. Others, particularly the larger institutions (Stein, 2002), relied on arm's-length transactional technologies, such as credit scoring models already used in their consumer lending operations.[4] These transactional approaches typically separated loan origination from monitoring and enforcement, relying on automated processes and payroll deductions where feasible.[5] While these standardized systems enabled rapid scaling, they provided weaker borrower oversight and contract enforcement. To manage overdue payments, CLs often relied on automated procedures, such as mail-based follow-ups. According to Rhyne (2002), they deliberately tolerated late payments to generate additional revenue through fines, undermining borrowers' repayment discipline.

The CLs' entry led to high graduation rates and increased borrowing among MFI clients. This influx of credit was argued to have contributed to over-indebtedness and to have undermined

[4]Transaction technologies based on credit scoring became popular in the mid-1990s due to advancements in computing, which enabled the efficient processing of large volumes of data. See Berger and Udell (2006) for an in-depth discussion of lending technologies.

[5]For example, (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 micro-credit, 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 micro-credit, 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."*

the repayment ethics of MFI borrowers, who were used to stricter enforcement and monitoring (De Janvry et al., 2003). Soon after, many borrowers began to default, and these problems were exacerbated by an external economic shock triggered by Brazil's financial crisis in January 1999. Facing substantial losses, many CLs eventually withdrew from the microfinance market.

This episode highlights the broader challenges that many large commercial banks face in adapting their lending technologies to serve low-income and low-documentation borrowers and the associated risks. In this paper, we zoom in on this period to assess the impact of CLs' entry on the credit outcomes of both graduating and non-graduating MFI borrowers during both the initial entry phase and the subsequent period as CLs exited this market. This analysis allows us to document the broader effects that graduating from MFIs to CLs can entail, shedding light on both the opportunities and risks associated with fostering competition and financial inclusion in these markets.

B. Information Sharing and Lending Technologies

During the sample period, Bolivia maintained a centralized public credit registry accessible to *all* formal financial institutions. The registry played a key role in reducing information frictions and facilitating CLs' entry into the microfinance market. During the period, the registry was the main source of reliable information for screening and monitoring existing or prospective borrowers. At the time, there were no private credit bureaus and most small firms, particularly micro-enterprises, did not have formal financial records. The credit registry was especially valuable for evaluating new customers. With borrower consent, lenders could obtain a credit report with information on outstanding loans over the previous two months, including loan amounts, the identity of the lender, the borrower's credit ratings, and any overdue payments or prior defaults.

Although such short information-sharing windows are common in many credit registers (Miller, 2003) and are essential for screening borrowers, they only offer a limited snapshot of a borrower's credit risk. In this case, the two-month window leaves slightly older delinquencies unobservable to new lenders, perpetuating information asymmetries between existing ("inside") lenders and new ("outside") lenders and worsening adverse selection for new lenders.[6] As shown in Ioannidou and Ongena (2010), some borrowers took advantage of this short window by clearing overdue payments before switching to a new lender to present a clean record, only to fall behind on payments again shortly after switching. We exploit this two-month reporting window to construct proxies of *ex ante* borrower risk based on recent repayment history and study adverse selection.

In particular, we distinguish between recent repayment problems that are *observable* or *unobservable* to outside lenders. Observable borrower risk includes overdue payments or defaults recorded within the two-month reporting window, while unobservable borrower risk captures fairly recent repayment problems occurring 3 to 12 months before graduating or switching, which are outside the reporting window.[7] As we demonstrate later, our proxies of ex ante borrower risk

[6] Starting with Sharpe (1990), the terms "inside" lenders and "outside" lenders are used to distinguish between lenders with a prior lending relationship with a borrower—who possess proprietary inside information—and new lenders, who are relatively less informed about the borrower's creditworthiness.

[7] Berger, Frame, and Ioannidou (2011) employ a similar approach to distinguished between the ex ante and ex post theories of collateral (i.e., to test whether collateral serves as a signaling device to screen unobservably riskier borrowers or whether it is primarily required from observably riskier borrowers to mitigate ex-post frictions, such as moral hazard and costly state verification).

are predictive of repayment problems on future loans, providing insights into the adverse selection problems faced by outside lenders.

We use observable and unobservable borrower risk proxies to examine whether the credit registry helps outside lenders—both CLs and MFIs—screen MFI borrowers more effectively and whether CLs face stronger adverse selection than MFIs. In addition, we assess whether the severity of adverse selection varies systematically with the lending methods that CLs adopt when serving graduating MFI borrowers. This analysis is novel and made possible by Bolivia's granular credit registry data and information-sharing framework, which enables us to construct a proxy for unobservable borrower risk. Moreover, the variation in lending technologies among entrants provides a natural setting to explore how different lending models shape borrower selection.

In our analysis, we classify CLs into two groups: those that adapted their lending technologies to traditional microfinance practices (adaptive CLs) and those that continued using the lending technologies applied to their non-MFI segments (non-adaptive CLs). This classification is based on data from the credit registry and narrative accounts (Rhyne, 2002; De Janvry et al., 2003). Because the registry includes all loans issued by CLs—both to their regular non-MFI customers and to graduating MFI borrowers—we analyze patterns across all loans to identify systematic behavior. This allows us to distinguish between CLs that consistently issued loans to graduating MFI borrowers with characteristics similar to their non-MFI portfolios and those that regularly employed microfinance-specific features, such as group loans with joint liability.

III. Data

Our empirical analysis is based on data from the Bolivian public credit registry, Central de Información de Riesgos Crediticios (CIRC), managed by the Bolivian Superintendent of Banks and Financial Entities (SBFE). Since CIRC's creation in 1989, the SBEF has required all licensed financial institutions operating in Bolivia to report detailed information on every loan. Unlike many credit registries around the world, which often impose a minimum reporting threshold (Miller, 2003), the CIRC records every loan, regardless of its size. This is rare and allows us to capture detailed lending activity across all types of licensed financial institutions, including banks and MFIs. 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 originating lender, 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., repayments, overdue payments, defaults). Borrower information includes a unique identification number that allows us to track borrowers across lenders and time, the borrower's legal entity type (e.g., natural person, legally recognized firm, non-profit organization), current and past lending relationships, the internal credit rating of the borrower with each lender, and current and past credit history (i.e., overdue payments or defaults with any lender in the registry). The definitions of all the variables used in the analysis are provided in Table A1 in the Appendix.

Our empirical analysis examines the segment of the credit market that overlaps between microfinance and consumer lenders. In Bolivia, as in many developing economies with large informal sectors, the distinction between productive and consumer lending is often blurred.

Micro-enterprises, typically informal and household-run, frequently use credit from both sources to finance business and household needs.[8] To capture this intersection, we focus on loans to natural persons from the financial intermediaries that provide the majority of lending to households and micro-enterprises.

Drawing from Rhyne (2002) and De Janvry et al. (2003), we classify for-profit lenders into two groups—MFIs and CLs—based on their traditional market orientation. The MFI group includes institutions that specialize in microfinance and includes both private financial funds (Fondos Financieros Privados, FFPs) and one bank that maintained an exclusive focus on microfinance throughout the sample period. In contrast, the CL group includes lenders that do not specialize in microfinance. This group consists of a mix of FFPs and full-service commercial banks offering a broad spectrum of financial products.

In particular, our MFI group includes in total six financial institutions—Caja Los Andes, FIE, Eco Futuro, Prodem, Fortaleza, and BancoSol. All are legally registered as FFPs, except for BancoSol, which is a commercial bank. The CL group includes ten commercial banks (e.g., Banco Santa Cruz, Banco de Crédito de Bolivia, Banco Mercantil) and three FFPs (Acceso, Fassil, and Financiero de la Comunidad).

Although both commercial banks and FFPs are deposit-taking institutions regulated by the SBFE, they are subject to distinct prudential requirements. During the sample period, FFPs faced a higher minimum capital adequacy ratio (12.6% vs. 8% for banks) and more stringent liquidity

[8]For example, Rhyne (2002) highlights how microfinance lenders, while ostensibly targeting micro-entrepreneurs, often saw loans diverted for household consumption or other purposes. Similarly, consumer lenders, who aimed primarily to serve salaried borrowers, frequently overlapped with micro-enterprise clients served by microfinance institutions.

reserve requirements (MicroCredit Innovations Department, 2001). In our robustness tests, we leverage the fact that both the MFI and CL groups include a mix of banks and FFPs to examine whether differences in the ex ante risk profiles of borrowers graduating to CLs are driven by greater risk-bearing capacity.

Cooperatives are excluded from the sample because their lending decisions are based on cooperative membership and their loan sizes depend on the size of their deposits. Furthermore, our sample does not include small microfinance lenders operating outside the formal sector, such as NGOs, which do not report to the registry. These institutions have a stronger rural and poverty-focused orientation than the commercially operated lenders in our study and were not permitted to offer the full range of lending and savings services available to the regulated lenders in our sample.

To keep the analysis tractable, we restrict our sample to loan types that each represent at least 1% of total loan originations by MFIs and CLs. This includes five types of loans: installment loans, fixed-term loans, credit cards, mortgages, and advances on checking accounts. Together, these categories account for approximately 95% of all new loans issued by MFIs and CLs during the study period.

A. Defining Borrower Transitions and Descriptive Statistics

To analyze borrower movements across lenders, we categorize borrower transitions into three types: switching, graduation, and staying. Switching refers to movements between lenders of the same type, either from one MFI to another (MFI-to-MFI) or from one CL to another (CL-to-CL). Instead, graduation occurs when a borrower transitions from an MFI to a CL for the first time i.e., gains access to a CL. Staying describes cases where a borrower continues borrowing from the same institution (inside lender), whether an MFI or a CL, without transitioning to a new lender (outside lender). These definitions provide a structured framework for analyzing borrower behavior over time.

To identify these movements across lenders, we adopt the methodology of Ioannidou and Ongena (2010). A *switching loan* is defined as a new loan issued by a lender with whom the borrower did not have a loan in the previous 12 months—referred to as an outside lender. We apply this definition to borrowers who move between lenders of the same type, either MFI-to-MFI or CL-to-CL. For consistency, we apply the same definition to *graduation loans*, with the only difference being that the borrower transitions across lender types, moving from MFI to CL rather than within the same category.

While this approach ensures consistency in identifying lender transitions, it does not strictly guarantee that an MFI-to-CL graduation loan represents the borrower's first time accessing credit from a CL. However, in practice, this is overwhelmingly the case. For example, in 1996, when these transitions began occurring at scale, fewer than 8% of borrowers making an MFI-to-CL transition had previously held a loan with any CL before $t = -12$. This suggests that nearly all MFI-to-CL transitions indeed represent first-time access to commercial credit (i.e., a "graduation").

Finally, *staying loans* are loans issued by a lender with whom the borrower had a loan in the previous 12 months, and the issuing lenders are referred to as inside lenders. The 12-month threshold reflects the gradual erosion of an inside lender's informational advantage in the absence of continued engagement.[9]

[9]Figure A.1 in the Online Appendix illustrates these definitions. At $t = 0$, an MFI borrower i obtains a new loan

Table 1 presents summary statistics on borrower transitions to new lenders (MFIs or CLs). Over the 9.5-year sample period, MFIs issued 860,715 loans to 709,196 borrowers, while CLs issued 1,007,818 loans to 506,143 borrowers. We identified 47,888 MFI-to-CL loans involving 47,151 borrowers, accounting for 5.56% of all MFI loans and 4.75% of all CL loans. Borrowers moving from MFIs to CLs represent 6.65% of all MFI borrowers and 9.32% of all CL borrowers. These figures are somewhat lower than those reported by Agarwal et al. (2023), who, using a similar definition, found that 11% of MFI borrowers took out CL loans for the first time over an eight-year period. By contrast, switching within lender types is significantly more common: MFI-to-MFI loans account for 11.43% of all MFI loans, involving 14.53% of MFI borrowers. Similarly, CL-to-CL loans represent 17.17% of all CL loans, involving 22.22% of CL borrowers. The relatively low frequency of MFI-to-CL transitions compared to within-type switching suggests that many micro-entrepreneurs face challenges in accessing credit from commercial lenders.

[Insert Table 1 approximately here]

Figure 1 depicts the evolution of borrower graduation from MFIs to CLs over the sample period. The vertical axis measures the number of MFI-to-CL loans as a share of total MFI loans issued each month. Early in the sample period, such transitions were rare, accounting for just 2%–3% of all MFI loans. However, beginning in mid-1996, the share rose sharply, exceeding 25%

(loan 2) from an outside lender (lender 2), which can be either an MFI or a CL. If lender 2 is an MFI, this represents an MFI-to-MFI switching loan. If lender 2 is a CL, this represents an MFI-to-CL graduation loan. Dashed lines represent optional features, such as an older loan from the outside lender or future loans from the borrower's inside lenders (lenders 1 and 3).

by early 1997, consistent with reports of CLs aggressively targeting MFI borrowers. After 1998, the graduation rate declined to 5%–6%, reflecting CLs' retreat from the microfinance sector.

[Insert Figure 1 approximately here]

B. Loan Characteristics and Lending Models: MFIs vs. CLs

Table 2 provides summary statistics on the characteristics of staying loans issued by MFIs and CLs in our sample. Staying loans represent credit extended by an inside lender to an existing borrower, capturing the core lending technologies each lender employs with its established clients. These loans offer a baseline for understanding differences in MFI and CL lending models. We observe that MFI loans are, on average, smaller, carry higher interest rates, and have shorter maturities compared to CL loans. Although both MFIs and CLs make some use of collateral and personal guarantees, these features are less prevalent in MFI loans, reflecting the challenges of serving low-income borrowers who typically have limited assets to pledge (Beck, 2015; Besley, 1995).

What stands out is MFIs' extensive reliance on joint liability group lending, a defining feature of their lending models. Specifically, 65% of staying loans from MFIs involve joint liability, with an average of 2.25 borrowers per loan. In contrast, only 11% of CLs' staying loans involve joint liability, and these loans have an average of just 1.19 borrowers per loan. This high reliance on joint liability group lending highlights one of the foundational innovations of MFIs, designed to address the challenges of lending in this segment by mitigating ex ante frictions like adverse selection (Ghatak, 1999) and ex-post challenges such as monitoring and enforcement (Besley and Coate, 1995).

In addition, CL loans are more likely to be denominated in USD, reflecting the highly dollarized funding structure of CLs (Ioannidou and Penas, 2010). CLs also offer a broader range of financial products, including credit cards and advances on checking accounts, many of which lack the periodic repayment schedules typical of MFI loans. These loan characteristics highlight the divergence in the lending models of MFIs and CLs, with MFIs catering to low-income borrowers through group lending, and CLs offering products more suited to higher-income customers.

[Insert Table 2 approximately here]

IV. Results

A. Graduating Borrowers' Short-term Credit Outcomes

In this section, we analyze the loan terms that graduating MFI borrowers receive from CLs. This analysis builds on the important insights of Agarwal et al. (2023), who show that transitioning to CLs allows unbanked borrowers to access larger, cheaper loans with longer maturities. Complementing their findings, our study provides a more comprehensive analysis by examining additional loan features—including collateral requirements, joint liability structures, personal guarantees, and currency denomination— captured in our dataset. In addition, while their study focuses on a subsidized credit expansion program, our setting examines borrower transitions driven entirely by market forces, allowing us to verify whether the benefits of transitioning to CLs persist when graduation is purely market-driven and not influenced by policy interventions.

First, we compare these terms with the borrowers' last loans from their initial MFIs before graduation. This within-borrower analysis helps assess how loan terms change when the borrower graduates from an MFI to a CL. We estimate:

$$Y_{i,t} = \beta_1 D_{i,t} + \gamma_i + \varepsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ represents the loan terms of borrower i at the time of the graduation in period t. $D_{i,t}$ is a dummy variable equal to 1 if the loan to borrower i is a graduation loan from a CL and 0 if it is a loan from borrower's i inside MFI. The sample includes only graduating borrowers before and after graduation. γ_i represents borrower fixed effects, which control for time-invariant characteristics of the borrower. The error term $\varepsilon_{i,t}$ is assumed to be independent and identically distributed. To ensure meaningful comparisons, we match on REGION and LOAN_TYPE using coarsened exact matching (CEM) before estimation. Although one could control for REGION and LOAN_TYPE directly in an OLS regression by adding them as covariates, matching provides a less restrictive approach by not imposing a specific functional form on how these factors influence loan terms.[10]

The results of this analysis, presented in Panel A of Table 3, indicate that borrowers who graduate from MFIs to CLs receive significantly more favorable loan terms. Specifically, graduation loans from CLs are on average, larger, cheaper, and have longer maturities compared

[10] Matching methods like CEM are nonparametric, meaning they do not assume a linear or specific non-linear relationship between the control variables and the outcome. This is particularly useful when dealing with multiple variables, as is the case in our later analyses, where it becomes difficult to specify the appropriate functional form. For consistency, we apply matching from the outset.

to their last loans from MFIs. For example, graduation loans are approximately 52% larger, 3.2 percentage points cheaper, and have maturities that are 12.7 months longer. In addition, graduation loans are 13 percentage points less likely to require collateral, have value-to-loan ratios that are 36.9 percentage points lower, and are nearly 59 percentage points less likely to require joint liability. Instead, CLs rely more frequently on personal guarantees, which are 15.3 percentage points more common in CL loans. Furthermore, graduation loans are 51 percentage points more likely to be denominated in USD, reflecting CLs' reliance on USD-denominated funding and the associated risk this poses for borrowers earning income in local currency.

[Insert Table 3 approximately here]

Endogeneity Concerns Our findings thus far suggest that graduating to CLs allows MFI borrowers to improve their borrowing terms. However, this interpretation is tenuous and assumes that if the borrowers had not graduated to CLs, they would have continued to receive similar loan terms from their inside MFIs. Because graduation is an endogenous decision, our estimates may be biased by unobserved heterogeneity. For example, it is possible that the better loan terms observed for these borrowers reflect the fact that only better firms are able to graduate to CLs. In other words, borrowers who graduate to CLs may be systematically different from those who continue borrowing from their initial MFIs in ways that influence their loan terms.

Hence, in a second set of tests, we compare the loan terms MFI borrowers receive upon graduating to CLs with those obtained by similar MFI borrowers who switch within MFIs. This comparison helps mitigate concerns about omitted variable bias by ensuring that both groups consist of borrowers with positive credit demand that transition to new lenders during the same month. For this analysis, we estimate specifications similar to equation (1) without borrower-fixed effects, where $D_{i,t}$ is equal to 1 if the loan is a graduation loan from a CL, and 0 if it is a switching loan from an MFI. To ensure comparability between the two groups, we match loans based on several factors, including REGION, LOAN_TYPE, the identity of the borrower's inside lender, whether they had multiple inside lenders, and other borrower characteristics observable to both lenders at the time of loan application, such as TOTAL_OUTSTANDING_LOANS, WORST_CREDIT_RATING, and recent delinquencies (NPL) or prior defaults (DEFAULT).

The results, presented in Panel B of Table 3, show that even when compared to similar borrowers switching within MFIs, MFI-to-CL graduates continue to receive significantly more favorable loan terms. Similarly to Panel A, we find that MFI-to-CL graduates obtain larger loans, lower interest rates, longer maturities, and face less stringent collateral and joint liability requirements. These findings further support the idea that graduating to CLs provides MFI borrowers with improved access to credit.

To further validate these results, we apply a Random Forest (RF) classification model, which allows us to account for potential complexities in how borrower characteristics affect graduation. Unlike CEM, which matches based on exact bins of the matching variables, RF creates a predictive model that combines multiple features and can capture subtler, non-linear patterns in the data. This flexibility allows RF to better account for complex interactions among borrower characteristics and the likelihood of graduating to a CL, offering an advantage in reducing unobserved heterogeneity.

Specifically, we first divide the sample of borrowers (MFI-to-CL graduates and MFI-to-MFI switchers) into a 50:50 training and test dataset. We train the RF model using the training data set to predict whether a given borrower is likely to graduate to a CL, based on the same set of matching variables used in Panel B. The RF model identifies patterns in these variables to classify borrowers as MFI-to-CL graduates or MFI-to-MFI switchers. Once trained, we use the RF model to classify the observations in the test data set. Specifically, we focus on actual MFI-to-MFI switchers that are predicted by the RF model to be likely MFI-to-CL graduates. This revised comparison group allows us to conduct a more rigorous test by contrasting MFI-to-CL graduates with MFI-to-MFI switchers that the model predicts would have been equally likely to graduate to CLs.[11]

We then estimate weighted OLS regressions similar to equation (1), where the RF propensity scores serve as weights. The results using RF, shown in Panel C of Table 3, remain consistent with those obtained using CEM. Borrowers who graduate to CLs continue to receive larger loans with more attractive terms than similar borrowers who switch within MFIs. This consistency across methods reinforces the notion that transitioning to CLs offers tangible benefits for MFI borrowers. However, since RF, while helpful, cannot fully eliminate concerns about unobserved heterogeneity, we next examine the ex ante observable and unobservable risk profiles of graduates to assess whether systematic differences in borrower characteristics explain these differences in loan terms.

Robustness Check: Banks vs. FFPs Our results in Table 3 indicate that graduating from an MFI to a CL allows borrowers to access more attractive loan terms. All else equal, we would expect these graduation benefits to be stronger when the CL is a commercial bank rather than an

[11] In Online Appendix Figure A.2, we report the curve of the "receiver operating characteristic" (ROC) and the metric of the "area under the curve" (AUC). They help illustrate that the RF model exhibits high accuracy in classification (i.e., in terms of maximizing true positives while minimizing false positives), but also avoids over-fitting. For a detailed discussion of RF classification models and applications, see Breiman (2001).

FFP, given banks' greater scale, broader scope of operations, and lower cost of capital. To test this hypothesis, we re-estimate the baseline model (Panel B of Table 3), including an interaction term that identifies whether borrowers graduated to a commercial bank versus an FFP (with graduates to FFPs as the reference group). Results are reported in Table 4.

Consistent with expectations, we find that MFI borrowers graduating to banks experienced significantly larger improvements in their borrowing terms than those graduating to FFPs. While MFI graduates to FFPs also secured larger loans, longer maturities, and reduced collateral and joint liability requirements (relative to borrowers who switched within MFIs), they faced slightly higher interest rates on their graduating loans. These results indicate that the large pricing gains we observe for MFI-to-CL graduates in our baseline are primarily driven by the MFI borrowers graduating to banks.

[Insert Table 4 approximately here]

B. Ex Ante Risk Profile of Graduating Borrowers

In this section, we study the ex ante risk profiles of MFI borrowers who graduate to CLs or switch to other MFIs. In particular, we compare the ex ante risk profiles of MFI-to-CL graduates and MFI-to-MFI switchers with those of staying borrowers to assess differences in observable and unobservable borrower risk. For these analyses, we estimate equation (1), where the dependent variable is either OBSERVABLE_BORROWER_RISK or UNOBSERVABLE_BORROWER_RISK. For the MFI-to-CL tests, the key explanatory variable, $D_{i,t}$, equals 1 for graduation loans and equals 0 for staying loans. For the MFI-to-MFI tests, $D_{i,t}$ equals 1 for switching loans and equals 0 for staying loans.

Using CEM, we progressively refine our matching criteria to assess the stability of our estimates. First, we match graduating or switching borrowers with stayers who also received a loan in the same month-year, ensuring both had positive credit demand. Next, we further require that the matched staying loans were originated in the same region and inside MFI, controlling for variation in borrower pools. In the third specification, we also match on MULTIPLE_INSIDE_LENDERS and TOTAL_OUTSTANDING_LOANS at $t = 0$, which are visible to outside lenders through the credit registry. Finally, for UNOBSERVABLE_BORROWER_RISK, we add a fourth specification that matches on prior recent NPLs and DEFAULT, ensuring comparability in observable borrower risk.

Table 5 presents the results. Panel A examines MFI-to-CL graduates, while Panel B focuses on MFI-to-MFI switchers. The borrowers in both groups are less likely to have observable past repayment problems than staying borrowers, with similar coefficients. This indicates that CLs and MFIs are similarly less likely to extend loans to new borrowers with observable repayment problems. This result suggests that the credit registry helps both types of lenders identify new borrowers with clean credit histories.

However, since the credit registry provides only partial information (covering a two-month window), information asymmetries persist. Both CLs and MFIs end up lending to borrowers with unobservable past delinquencies—those with repayment problems just outside the observable window (i.e., from $t = -3$ to $t = -12$). While both MFIs and CLs attract borrowers with unobservable past delinquencies, the incidence of such risk is significantly higher for CLs. In Panel A, the coefficient of UNOBSERVABLE_BORROWER_RISK for MFI-to-CL graduates is roughly double that for MFI-to-MFI switchers in Panel B.

This becomes clearer in Panel C when we directly compare graduates with switchers.

Here, $D_{i,t}$ equals 1 for graduating MFI-to-CL loans, and 0 for switching MFI-to-MFI loans. Although there is virtually no difference in observable borrower risk between the two groups—i.e., both MFIs and CLs appear equally likely to lend to borrowers with observably clean credit histories—the incidence of unobservable risk is substantially higher among MFI-to-CL graduates. The economic magnitude of the difference is quite substantial. The point estimate in the last column is 0.068, meaning that unobservable borrower risk is 6.8 percentage points higher among MFI-to-CL loans. Given that the average UNOBSERVABLE_BORROWER_RISK for MFI-to-CL loans is 0.10, this represents an increase of nearly 67%.

This finding is important for two key reasons. First, since graduates to CLs are unobservably riskier borrowers (not safer), the better terms offered by CLs are more likely to reflect a genuine positive effect of graduating to CLs. Second, it indicates that CLs face stronger adverse selection and screening challenges than MFIs i.e., while both lender types avoid borrowers with observable repayment problems, CLs end up lending to a higher proportion of borrowers with unobservable risk. This is a new result made possible by the two-month information-sharing window and the richness of our data, which allow us to construct a proxy for ex ante unobservable borrower risk.

[Insert Table 5 approximately here]

Robustness Tests: Banks vs. FFPs An alternative interpretation of our findings is that the higher unobservable risk among MFI-to-CL graduates reflects differences in risk appetite or risk-bearing capacity, rather than differences in screening ability. CLs—being typically larger, more diversified, and subject to fewer regulatory constraints than MFIs—may simply be more willing to lend to riskier borrowers.

Hence, to assess this possibility, we leverage the fact that MFIs and CLs sometimes share the same legal form and replicate our analysis within sub-samples defined by legal form. Since FFPs face stricter capital and liquidity requirements and generally have lower risk-bearing capacity than banks, re-estimating our baseline specifications within sub-samples of either only banks or only FFPs (i.e., where both the MFIs and CLs are either banks or FFPs) should help mitigate this channel. If higher incidence of unobservable borrower risk was primarily driven by differences in risk appetite or risk-bearing capacity, we would expect the effects to weaken or disappear in these sub-samples.

As shown in Online Appendix Table A.1, however, the differences in UNOBSERVABLE_BORROWER_RISK remain large and statistically significant in both the banks-only and FFPs-only sub-samples. This suggests that differences in risk appetite or risk-bearing capacity are unlikely to explain the higher incidence of unobservable risk associated with MFI-to-CL loans. In the next section, we examine the role of lending technologies. Before turning to this analysis, we first validate our two proxies for ex ante borrower risk.

Validation Test To ensure that OBSERVABLE_BORROWER_RISK and UNOBSERVABLE_BORROWER_RISK meaningfully capture ex ante borrower risk, we test whether they predict future repayment problems on switching loans. In Online Appendix Table A.2, we estimate a probit regression model where the dependent variable is EX_POST_REPAYMENT_PROBLEMS, a dummy variable that equals 1 if the borrower had overdue payments or defaulted on their graduation or switching loan, and 0 otherwise. The key explanatory variables are our two proxies of ex ante borrower risk.

We report results from two specifications. The first specification includes lender and region fixed effects along with borrower characteristics such as MULTIPLE_RELATIONSHIPS, TOTAL_OUTSTANDING_LOANS, and WORST_CREDIT_RATING. The second specification adds controls for outstanding loan terms—including INTEREST_RATE, COLLATERAL, PERSONAL_GUARANTEES, and JOINT_LIABILITY—which reflect the inside lender's risk assessment and capture borrower characteristics not directly observable in our data.

In both cases, the OBSERVABLE_BORROWER_RISK and UNOBSERVABLE_BORROWER_RISK indicators have positive and statistically significant coefficients, with consistent point estimates. These results confirm that our proxies predict future repayment problems and defaults, reinforcing their validity and confirming that they do not simply reflect outdated information.

C. Adverse Selection and CLs' Lending Technologies

Our previous analysis shows that CLs face greater adverse selection and screening challenges than MFIs, as the MFI-to-CL graduates they attract are more likely to have unobservable past repayment problems. These challenges stem from well-known credit market frictions in less developed countries (LDCs), where borrowers often lack collateral, and legal barriers hinder efficient contract enforcement. Under such conditions, credit markets tend to attract riskier borrowers whose types are unobservable to lenders, driving safer borrowers away as interest rates rise. These frictions are believed to be a key reason why CLs often struggle to lend to low-income borrowers in LDCs.

Despite these frictions, many MFIs around the world have been able to successfully lend to low-income borrowers, which raises the question: what makes unsubsidized lending by MFIs feasible in such challenging environments? Since the success of Grameen Bank, a large body of research has focused on group lending with joint liability, a key innovation of MFIs. In this lending model, borrowers are required to form small groups, where each member acts as a guarantor of the loans of others, creating joint liability. Group lending is believed to not only mitigate ex post frictions by facilitating peer monitoring and peer pressure (Stiglitz, 1990; Besley and Coate, 1995; Armendáriz de Aghion, 1999), but to also mitigate ex ante frictions such as adverse selection through assortative matching (Ghatak, 1999, 2000; Van Tassel, 1999) and risk pooling (Armendáriz de Aghion and Gollier, 2000). By attracting safer borrowers back to the market, group lending can improve welfare in terms of aggregate social surplus (Ghatak, 1999).

However, the effectiveness of group lending in mitigating adverse selection remains highly debated, both theoretically and empirically. For example, Laffont and N'Guessan (2000) shows that group lending does not necessarily help mitigate adverse selection if borrowers do not know each other well or if collusion among members is possible. Several other studies raise concerns related to dynamic incentives, limited liability, and effectiveness in marginal economic environments.[12] Empirical evidence is similarly mixed: some studies find that joint liability improves borrower selection (e.g., Carpena, Cole, Shapiro, and Zia, 2013; Khandker, Khalily, and Khan, 1995), while others raise concerns about its sustainability and effectiveness (e.g., (Morduch, 1999; Giné and Karlan, 2014)).[13]

[12]More recently, Guttman (2008) shows that the reduced adverse selection result does not hold if earlier models are extended to incorporate dynamic incentives (i.e., the threat of not being refinanced if the group defaults). Ahlin (2015) and Ahlin and Waters (2016) show that limited liability and marginal economic environments further constrain the ability of group lending to mitigate adverse selection.

[13]Empirical evidence on repayment rates is also similarly mixed (see, e.g., Giné, Jakiela, Karlan, and Morduch,

In this section, we examine whether CLs that adopted microfinance-specific practices, such as group lending, faced lower adverse selection than those that retained their individual lending technologies. A key challenge in such analyses is the lack of direct data on lenders' practices. However, with access to the full credit registry, we can systematically classify CLs based on their observed lending practices. To distinguish between adaptive and non-adaptive CLs, we define a CL as adaptive if joint liability loans account for more than 25% of their MFI-to-CL loans and non-adaptive otherwise. This cut-off provides a meaningful distinction between lenders that incorporated microfinance techniques at scale and those that maintained a more traditional, individual-based approach. Fassil, Banco Santa Cruz, and Financiero De La Comunidad fall into the adaptive category, and their lending patterns closely resemble those of MFIs. About 66% of MFI-to-CL loans from adaptive CLs use joint liability, with an average of 2.6 borrowers per loan (Table A.3 in the Online Appendix), which is similar to what we observed earlier for MFIs (Table 2). In contrast, non-adaptive CLs primarily rely on individual lending, consistent with their traditional approach to existing customers. Only 9% of their MFI-to-CL loans use joint liability, with an average of just 1.1 borrowers per loan, closely mirroring their standard lending practices.

Using this classification and UNOBSERVABLE_BORROWER_RISK, we examine whether adaptive CLs are better able to screen borrowers than non-adaptive CLs. Specifically, we re-estimate the final specification from Panel C of Table 5, comparing the unobservable borrower risk of MFI-to-CL and MFI-to-MFI loans, distinguishing between adaptive and non-adaptive CLs. The results, reported in Table 6, show that CLs' higher incidence of unobservable borrower risk is lower for adaptive CLs. We find that adaptive CLs are 4.6 pps more likely than MFIs to

2010, Carpena et al., 2013; Feigenberg, Field, and Pande, 2013; Giné and Karlan, 2014; Attanasio, Augsburg, De Haas, Fitzsimons, and Harmgart, 2015).

lend to graduating MFI borrowers with unobservable past delinquencies or defaults (column 1). This figure is nearly twice as high for non-adaptive CLs, at 7.4 pps (column 2). Further in columns (3) and (4) of Table 6 we distinguish non-adaptive CLs into those that made extensive use of collateral vs. those that did not. Similar to joint liability group lending, collateral can also help mitigate adverse selection (Bester, 1985). Our findings confirm this: non-adaptive CLs that systematically employ collateral exhibit substantially lower adverse selection problems (3.6 vs. 7.8 pps). However, as indicated by the large disparity in the number of observations between columns (3) and (4), such cases remain in the minority.

[Insert Table 6 approximately here]

These findings highlight the challenges large commercial banks face in lending to low-income, low-documentation borrowers who often lack the records and assets needed for collateral-based credit. Traditional bank models—relying on individual liability, credit scoring, and collateral—are ill-suited for screening in this segment, while MFIs' joint liability models, though more effective, are often seen as too restrictive. Advances in data processing and technology may, in time, help bridge this gap by improving both risk assessment and collateral registries. D'Andrea, Hitayezu, Kpodar, Limodio, and Presbitero (2024), for example, show that mobile internet accelerates land titling, making it easier for MFI borrowers to use land as collateral and transition to banks.

D. Long-term Credit Outcomes of Graduating Borrowers

In this section, we study how the long-term credit outcomes of MFI-to-CL graduates compare relative to similar MFI borrowers who switched within MFIs. Contrasting these groups over a longer period, both before and after transitioning to new lenders, can help us understand not only how the MFI-to-CL graduates' 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 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 up to 12 months before transitioning and up to 36 months after (i.e., $t \in [-12, 36]$) and compute the TOTAL_OUTSTANDING_LOANS of each borrower from all lenders in each period t and their average INTEREST_RATE, MATURITY, and COLLATERAL on these loans. We then collapse the data at the borrower-month level and estimate:

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

where $Y_{i,t}$ indicates the credit outcome of borrower i in month t. For TOTAL_OUTSTANDING_LOANS, we use a logarithmic transformation of the dependent variable so that the coefficients can be interpreted as percentage differences relative to the control group. $D_{i,t}$ is equal to one for MFI-to-CL graduates and equal to zero for MFI-to-MFI switchers.

$I(t)$ represents (0,1) dummy variables for every month, except for $t = -1$, which we use as the base period for comparison. The estimated coefficients $\beta_{1,t}$ measure the differences in credit outcomes between the matched groups over time, relative to the omitted base period. Time-fixed effects η_t control for any aggregate time series trends.

In robustness tests, we also include borrower-fixed effects, μ_i, which absorb any unobservable time-invariant characteristics of the borrower that may not be fully captured by our matching variables. Identification of the parameters in this case relies on variation from borrowers who graduate to CLs and switched to another MFI.

Figure 2 presents the estimated coefficients from equation (2) along with their 95% confidence intervals. The results indicate that MFI-to-CL graduates experience persistent benefits. In particular, while some initial advantages fade over time, significant long-term gains remain. Borrowers who graduate to CLs continue to access credit at lower costs and with reduced joint liability requirements compared to similar borrowers who switch within MFIs. In contrast, the benefits related to total loan volume, maturity, and collateral appear to be temporary.[14] For instance, after an initial decline in collateral requirements, the MFI-to-CL group stabilizes at a steady state similar to pre-graduation levels. Regarding pre-trends, the results suggest that the matched groups likely satisfy the parallel trends assumption. Before $t = 0$, differences between the two groups remain fairly stable over time, with no evidence of diverging pre-trends.

[Insert Figure 2 approximately here]

In Figure A.4 in the Online Appendix, we analyze how the long-term credit outcomes of MFI-to-CL graduates vary depending on whether they experienced repayment problems on their graduation loans from CLs (EX_POST_REPAYMENT_PROBLEMS=1). About 30% of MFI-to-CL graduates experience some form of repayment problem (e.g., overdue payments 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 graduation or switching loans see similar long-term benefits in terms of INTEREST_RATE and JOINT_LIABILITY. With respect to all other variables, both

[14]Robustness tests, using augmented specifications of equation (2) with borrower-fixed effects paint a slightly more positive picture with long-run benefits also for maturity and total debt (Figure A.3 in the Online Appendix).

groups return to their initial steady state and do not appear to fare worse than before transitioning to new lenders.

Overall, these findings suggest that CLs' entry had lasting effects on microfinance borrowers, even after CLs exited. Competition from CLs may have pressured MFIs to improve their pricing and reduce joint liability requirements. In the next section, we explore these competitive dynamics, including spillover effects on staying borrowers.

E. Competition and Spillover Effects

In Table 7, we study how the entry of CLs into the microfinance market affected the subsequent loan terms that graduating and staying borrowers received from MFIs. This analysis can be informative of whether the increased competition from CLs forced MFIs to improve the terms they offered to graduating borrowers and whether they carried positive spillover effects on staying borrowers. In particular, using all MFI loan originations between 1996:01 and 2001:12 to graduating and staying borrowers, we estimate the following full spillover model as in Berg et al. (2021):

$$\begin{aligned} Y_{i,j,k,t} = \alpha + \beta_1 \text{POST}_{i,t} + \beta_2 \text{HC}_{j,k,t} \times \text{POST}_{i,t} \\ + \beta_3 \text{HC}_{j,k,t} \times (1 - \text{POST}_{i,t}) + \mu_i + \eta_t + \theta_{j,k} + \varepsilon_{i,j,k,t}, \end{aligned} \tag{3}$$

where $Y_{i,j,k,t}$ indicates the terms of new loans (AMOUNT, INTEREST_RATE, MATURITY, and COLLATERAL) to borrower i, from MFI j, in region k, originated in period t. $\text{POST}_{i,t}$ equals 1 after borrower i obtains a graduation loan for the first time and equals zero otherwise. The variable $\text{HC}_{j,k,t}$ indicates whether MFI j faces a high degree of competition from CLs in region k.

The variable is predetermined and calculated at the lender-region-month level using the fraction of MFI j borrowers in region k who graduated to CLs in the previous 6 months (i.e., $t-1$ to $t-6$). To facilitate the interpretation of the estimated coefficients, $\text{HC}_{j,k,t}$ is set equal to 1 if this fraction is greater than the sample median, and it is set equal to zero otherwise. μ_i, η_t, and $\theta_{j,k}$ denote borrower, time, and lender-region fixed effects, respectively. $\varepsilon_{i,j,k,t}$ denotes the idiosyncratic error term.

The coefficient β_1 measures how the terms of new loans to borrower i from MFI j change when the borrower graduates to a CL in regions where the MFI faces low competition from CLs, while β_2 measures the differential changes in regions where the MFI faces high competition from CLs. Effectively, β_2 measures the spillover effects for graduates due to local competitive effects (i.e., MFI j may offer more attractive terms to borrower i in regions where it has lost many other borrowers to CLs). The third coefficient, β_3, measures the spillover effects of competition on stayers (i.e., this includes both borrowers who graduated at a later time and borrowers who never graduated).

The results, reported in Table 7, show that in areas where MFIs face high competition from CLs (i.e., where they lost a large fraction of their borrowers to CLs), both graduates and staying borrowers receive improved loan terms from their inside MFIs. In particular, after borrowers graduate to CLs, new loans from inside MFIs are on average 6.7 percent smaller in size if the MFI faces low competition. However, when competition from CLs is high, new loans to graduating borrowers are, on average, 5.5 percent larger (-0.067+0.122). They are also cheaper and have longer maturities, through they are slightly more likely to require collateral, suggesting that MFIs may compensate for the extra risk (of larger and longer maturity loans) by increasing collateral requirements. Finally, we also find that competition carries significant spillover benefits to staying borrowers: when their inside MFI faces a high degree of competition from CLs, new MFI loans to staying borrowers are also larger and have longer maturities.

[Insert Table 7 approximately here]

Overall, our results indicate that competition from CLs led MFIs to improve loan terms for both graduates and staying borrowers. In line with the contestable market theory, our findings suggest that competitors may not need to remain in the market for pricing benefits to persist (Baumol, 1982). Incumbent MFIs may have strategically engaged in limit pricing to deter CLs from (re)entering the market (Gaskins, 1971).[15]

V. Conclusion

This paper provides new evidence on how bank entry reshaped microfinance markets, highlighting both the benefits and risks associated with increased competition. Our analysis demonstrates that while banks entering microfinance markets improve borrower outcomes by offering larger, cheaper loans with longer maturities, these benefits extend beyond the graduating borrowers. Competitive pressures force MFIs to improve loan terms for staying borrowers as well, leading to broader market-wide benefits.

Despite the short-lived presence of commercial lenders in the microfinance market, their entry led to persistent improvements in loan terms, especially in borrowing costs and the use of

[15] In additional tests reported in the Online Appendix, we also examine whether increased competition from CLs affected the composition of borrowers entering the formal financial sector. The results show that faced with increased competition from CLs, MFIs expanded lending to "first-time" formal borrowers, suggesting a "crowding-out" effect on informal credit.

joint liability. This suggests that competitive pressures—even from temporary entrants—can deliver lasting benefits. However, our findings also reveal that entry into these markets is not without risks. When entrants do not adapt their lending practices to the microfinance environment, they face stronger adverse selection problems.

Our results offer valuable insights for governments and financial regulators seeking to promote financial inclusion. Facilitating entry into microfinance markets—through initiatives such as subsidized credit programs and credit registries that mandate information sharing between MFIs and CLs—can enhance competition and improve borrowers' access to better loan terms. However, policymakers must remain cautious about the risks of aggressive competition, including potential over-indebtedness and market instability. Ensuring that entrants adopt appropriate lending and risk management practices can help mitigate these risks while maximizing the benefits of competition.

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FIGURE 1

Graduation from MFIs to CLs

The figure shows the number of MFI-to-CL loans as a fraction of MFI loans issued in each month from January 1995 to June 2004.

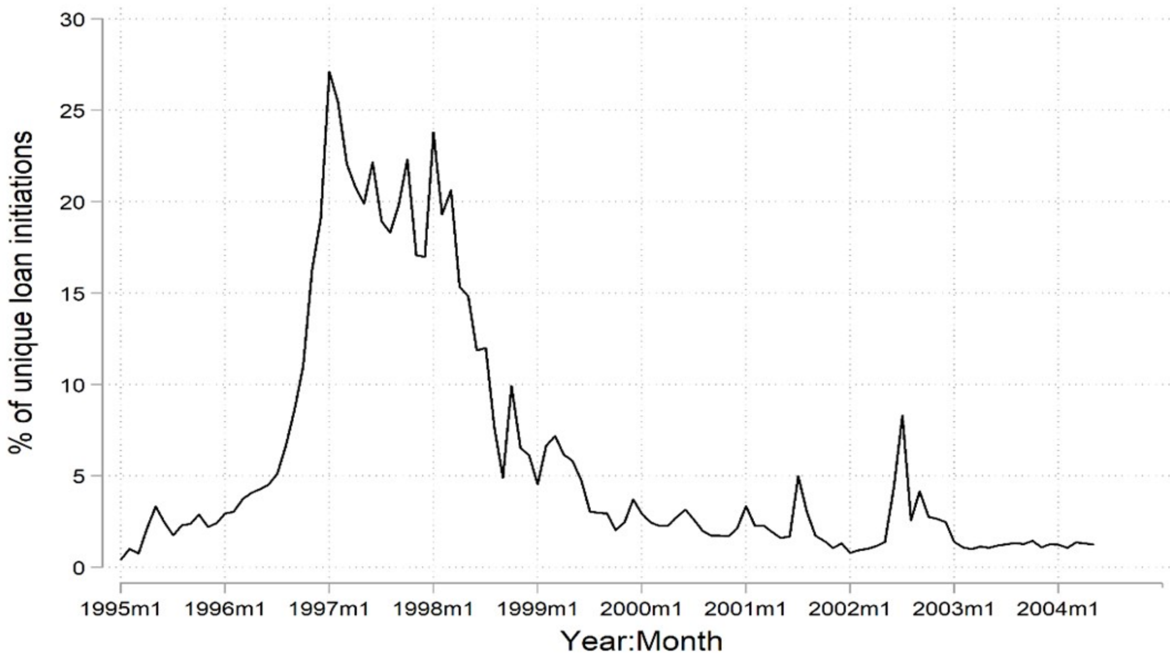
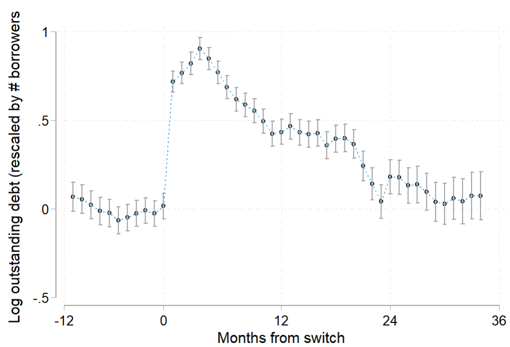


FIGURE 2

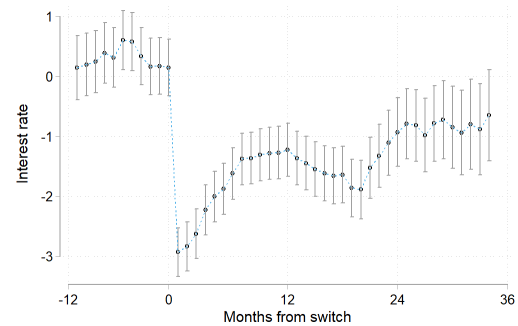
Long-term Credit Outcomes: MFI-to-CLs vs. MFI-to-MFI

This figure compares the credit outcomes of MFI-to-CL graduates to the credit outcomes of matched MFI-to-MFI switchers between $t = -12$ to $t = 36$. Each graph reports the estimated DiD coefficients of specifications of equation (2) and their 95% confidence intervals using the matched sample of borrowers in Panel B of Table 3. We report results for *Log*(TOTAL_OUTSTANDING_LOANS), INTEREST_RATE, MATURITY, COLLATERAL (% of loans), and JOINT_LIABILITY (% of loans).

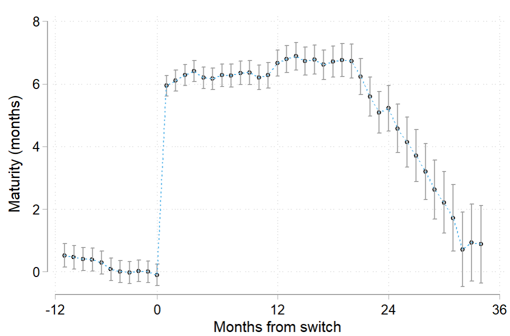
TOTAL_OUTSTANDING_LOANS



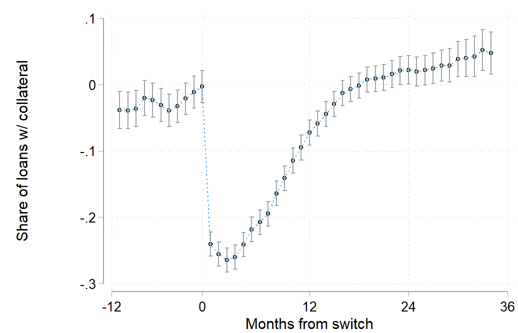
INTEREST_RATE



MATURITY



COLLATERAL



JOINT_LIABILITY

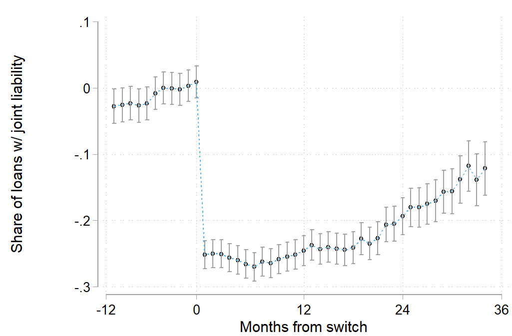


TABLE 1

Graduation and Switching Rates

The table presents the number of new loans and unique borrowers from MFIs and CLs between January 1995 and June 2004. It also reports the number and percentage of borrowers who moved from MFIs to CLs and those who switched within the same lender type (MFI-to-MFI or CL-to-CL).

Type of Loan	Loans (1)	Borrowers (2)
New loans		
From MFIs	860,715	709,196
From CLs	1,007,818	506,143
MFI-to-CL loans	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 loans	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 loans	173,050	112,452
As a % of all MFI	20.11%	15.86%
As a % of all CL	17.17%	22.22%

TABLE 2

Loan Characteristics and Lending Models: MFIs vs. CLs

This table presents summary statistics on the characteristics of loans issued by MFIs and CLs to existing customers between January 1995 and June 2004. The summary statistics are calculated at the loan origination level. Loan amounts are expressed in thousands of USD. INSTALLMENT_LOAN is a dummy variable set equal to 1 if loan type is an installment loan and 0 otherwise. FIXED_TERM_LOAN is a dummy variable set equal to 1 if loan type is a fixed-term loan and 0 otherwise. CREDIT_CARD_LOAN is a dummy variable set equal to 1 if loan type is a credit card loan and 0 otherwise. ADVANCE_CHECKING_A/CS is a dummy variable set equal to 1 if loan type is an advance from a checking account and 0 otherwise. MORTGAGE_LOAN is a dummy variable set equal to 1 if loan type is a mortgage loan and 0 otherwise. The definitions of all other variables are provided in Appendix Table A1. ***, **, * indicate whether differences in the mean of the two groups are statistically significant at the 1%, 5%, and 10% levels, respectively.

	MFIs		CLs	
Loan Characteristics	Mean	Std	Mean	Std
AMOUNT	2,236 ***	3,224	6,012	7,369
AMOUNT_PER_BORROWER	987 ***	1,588	5,549	7,082
INTEREST RATE (%)	37.47 ***	9.00	25.88	11.62
MATURITY	12.17 ***	11.15	19.97	23.38
COLLATERAL	0.15 ***	0.36	0.20	0.40
VALUE_TO_LOAN_RATIO	2.06 ***	2.43	2.18	110.58
PERSONAL_GUARANTEES	0.29 ***	0.45	0.44	0.50
FOREIGN_CURRENCY_USD	0.44 ***	0.50	0.86	0.35
NUMBER_OF_BORROWERS	2.25 ***	1.26	1.19	1.62
JOINT_LIABILITY	0.65 ***	0.48	0.11	0.32
Loan type:				
INSTALLMENT_LOAN	0.86 ***	0.34	0.57	0.49
FIXED_TERM_LOAN	0.13 ***	0.34	0.18	0.39
CREDIT_CARD_LOAN	0.00 ***	0.00	0.12	0.32
ADVANCE_CHECKING_A/CS	0.00 ***	0.00	0.10	0.30
MORTGAGE_LOAN	0.01 ***	0.08	0.02	0.16
Observations	602,981		411,617	

TABLE 3

Comparison of the Terms of MFI-to-CL Graduation Loans

This table compares the loan terms received by MFI borrowers who graduate to CLs (MFI-to-CL loans) with: (i) the terms on their last loans from their inside MFIs before graduating (Panel A), and (ii) the terms received by similar borrowers who switched within MFIs (Panels B and C). Panels A and B match loans using Coarsened Exact Matching (CEM), while Panel C employs Random Forest (RF). Standard errors, reported in parentheses, are clustered at the provider-month level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dependent Variables							
	Log(AMOUNT)	INTEREST_RATE	MATURITY	COLLATERAL	VALUE_TO_LOAN	JOINT_LIABILITY	PERSONAL_GUARANTEES	USD
	1	2	3	4	5	6	7	8
A. MFI-to-CL vs. Inside MFI (CEM)								
$D_{i,t}$	0.520***	-3.205***	12.676***	-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
Matching variables								
REGION	Y	Y	Y	Y	Y	Y	Y	Y
LOAN_TYPE	Y	Y	Y	Y	Y	Y	Y	Y
Borrower fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
B. MFI-to-CL vs. MFI-to-MFI (CEM)								
$D_{i,t}$	1.127***	-2.377***	15.688***	-0.375***	-98.963***	-0.441***	0.423***	0.672***
	(0.105)	(0.915)	(0.879)	(0.075)	(19.565)	(0.067)	(0.074)	(0.024)
Total Obs	24,563	24,563	24,563	24,563	24,563	24,563	24,563	24,563
MFI-to-CL	10,139	10,139	10,139	10,139	10,139	10,139	10,139	10,139
MFI-to-MFI	14,424	14,424	14,424	14,424	14,424	14,424	14,424	14,424
C. MFI-to-CL vs. MFI-to-MFI (RF)								
$D_{i,t}$	1.008***	-9.094***	12.675***	-0.120***	-36.338***	-0.426***	0.148***	0.785***
	(0.094)	(0.789)	(1.144)	(0.038)	(11.557)	(0.070)	(0.049)	(0.016)
Total Obs	12,852	12,852	12,852	12,852	12,852	12,852	12,852	12,852
MFI-to-CL	8,271	8,271	8,271	8,271	8,271	8,271	8,271	8,271
MFI-to-MFI	4,581	4,581	4,581	4,581	4,581	4,581	4,581	4,581
Matching/control variables								
MONTH_YEAR	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	Y	Y	Y	Y	Y	Y	Y	Y
MULTIPLE_INSIDE_LENDERS$_{t=-1}$	Y	Y	Y	Y	Y	Y	Y	Y
TOTAL_OUTSTANDING_LOANS$_{t=-1}$	Y	Y	Y	Y	Y	Y	Y	Y
WORST_CREDIT_RATING	Y	Y	Y	Y	Y	Y	Y	Y
OBSERVABLE_BORROWER_RISK	Y	Y	Y	Y	Y	Y	Y	Y

TABLE 4

Comparison of the Terms of MFI-to-CL Graduation Loans: Banks vs. FFPs

This table compares the loan terms received by MFI borrowers who graduate to CLs (MFI-to-CL loans) of different regulatory forms. We include an interaction term which splits the treatment group into borrowers that graduate to FFPs (base level) versus borrowers that graduate to commercial banks. We match loans using Coarsened Exact Matching (CEM). Standard errors, reported in parentheses, are clustered at the provider-month level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dependent Variables							
	Log(AMOUNT)	INTEREST_RATE	MATURITY	COLLATERAL	VALUE_TO_LOAN	JOINT_LIABILITY	PERSONAL_GUARANTEES	USD
	1	2	3	4	5	6	7	8
MFI-to-CL vs. MFI-to-MFI								
$D_{i,t}$	0.790***	1.908**	13.746***	-0.395***	-103.400***	-0.387***	0.442***	0.659***
	(0.115)	(0.808)	(1.330)	(0.075)	(19.549)	(0.079)	(0.074)	(0.025)
$D_{i,t} \times Commercial\ Bank$	0.885***	-11.262***	5.124***	0.053***	11.698***	-0.143***	-0.049***	0.034***
	(0.081)	(0.956)	(1.414)	(0.015)	(2.552)	(0.053)	(0.016)	(0.009)
Total Obs	24,563	24,563	24,563	24,563	24,563	24,563	24,563	24,563
MFI-to-CL	10,139	10,139	10,139	10,139	10,139	10,139	10,139	10,139
MFI-to-MFI	14,424	14,424	14,424	14,424	14,424	14,424	14,424	14,424
Matching variables								
MONTH_YEAR	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	Y	Y	Y	Y	Y	Y	Y	Y
MULTIPLE_INSIDE_LENDERS$_{t=-1}$	Y	Y	Y	Y	Y	Y	Y	Y
TOTAL_OUTSTANDING_LOANS$_{t=-1}$	Y	Y	Y	Y	Y	Y	Y	Y
WORST_CREDIT_RATING	Y	Y	Y	Y	Y	Y	Y	Y
OBSERVABLE_BORROWER_RISK	Y	Y	Y	Y	Y	Y	Y	Y

TABLE 5

Ex ante Borrower Risk: Observable vs. Unobservable

This table compares the ex ante risk profile of MFI borrowers who graduate to CLs (MFI-to-CL) to staying (Inside MFI) or switching borrowers within MFIs (MFI-to-MFI) using different specifications of equation (1), where the dependent variable is OBSERVABLE_BORROWER_RISK (columns (1)-(3)) or UNOBSERVABLE_BORROWER_RISK (columns (4)-(7)). Standard errors, reported in parentheses, are clustered at the provider-month level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	DV=OBSERVABLE_BORROWER_RISK			DV=UNOBSERVABLE_BORROWER_RISK			
	1	2	3	4	5	6	7
A. MFI-to-CL vs. Inside MFI							
$D_{i,t}$	-0.010**	-0.010**	-0.026***	0.102***	0.100***	0.089***	0.089***
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)
Total Obs	110,108	109,370	108,164	110,108	109,370	103,872	101,657
MFI-to-CL	14,821	14,774	14,565	14,821	14,774	14,378	14,262
Inside MFI	95,287	94,596	93,599	95,287	94,596	89,494	87,395
B. MFI-to-MFI vs. Inside MFI							
$D_{i,t}$	-0.010**	-0.020***	-0.022***	0.052***	0.052***	0.047***	0.046***
	(0.005)	(0.006)	(0.006)	(0.003)	(0.003)	(0.004)	(0.004)
Total Obs	111,182	105,470	98,005	111,182	105,470	83,332	81,935
MFI-to-MFI	15,814	15,753	15,481	15,814	15,753	15,205	15,057
Inside MFI	95,368	89,717	82,524	95,368	89,717	68,127	66,878
C. MFI-to-CL vs. MFI-to-MFI							
$D_{i,t}$	-0.001	-0.010	0.004	0.046***	0.044***	0.068***	0.068***
	(0.004)	(0.011)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)
Total Obs	30,602	30,051	28,483	30,602	30,051	25,780	25,299
MFI-to-CL	14,821	14,637	13,317	14,821	14,637	10,950	10,757
MFI-to-MFI	15,781	15,414	15,166	15,781	15,414	14,830	14,542
Matching variables							
MONTH_YEAR	Y	Y	Y	Y	Y	Y	Y
REGION		Y	Y		Y	Y	Y
INSIDE_LENDER		Y	Y		Y	Y	Y
MULTIPLE_INSIDE_LENDERS$_{t=-1}$			Y			Y	Y
TOTAL_OUTSTANDING_LOANS$_{t=-1}$			Y			Y	Y
WORST_CREDIT_RATING						Y	Y
OBSERVABLE_BORROWER_RISK							Y

TABLE 6

Unobservable Borrower Risk and CLs' Lending Technologies

This table compares MFI-to-CL loans to MFI-to-MFI loans in terms of unobservable borrower risk. We estimate specifications similar to equation (1), where the dependent variable is UNOBSERVABLE_BORROWER_RISK and $D_{i,t}$ is a dummy variable equal to 1 for MFI-to-CL loans and 0 for MFI-to-MFI loans. To examine the role of lending technologies in mitigating adverse selection, we classify CLs based on their observed lending practices. ADAPTIVE_CL is a dummy variable set equal to 1 for CLs using joint liability for more than a quarter of their new loan originations; 0 otherwise. HIGH_COLLATERAL_USE is a dummy variable set to 1 for non-adaptive CLs (i.e., where ADAPTIVE_CL=0) that use collateral for more than 15% of their new loan originations; 0 otherwise. Standard errors, reported in parentheses, are clustered at the provider-month level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	DV=UNOBSERVABLE_BORROWER_RISK			
	Type of CLs		Type of Non-Adaptive CLs	
	ADAPTIVE_CL=1	ADAPTIVE_CL=0	HIGH_COLLATERAL_USE=1	HIGH_COLLATERAL_USE=0
MFI-to-CL vs. MFI-to-MFI	1	2	3	4
$D_{i,t}$	0.046***	0.074***	0.036*	0.078***
	(0.012)	(0.008)	(0.019)	(0.008)
Total Obs	12,374	22,937	11,693	21,968
MFI-to-CL	2,189	8,550	728	7,822
MFI-to-MFI	10,185	14,387	10,965	14,146
Matching Variables				
MONTH_YEAR	Y	Y	Y	Y
REGION	Y	Y	Y	Y
INSIDE_LENDER	Y	Y	Y	Y
MULTIPLE_INSIDE_LENDERS$_{t=-1}$	Y	Y	Y	Y
TOTAL_OUTSTANDING_LOANS$_{t=-1}$	Y	Y	Y	Y
WORST_CREDIT_RATING	Y	Y	Y	Y
OBSERVABLE_BORROWER_RISK	Y	Y	Y	Y

TABLE 7

Spillover Effects on MFI Loan Terms for Graduates and Stayers

This table presents estimates from equation (3), analyzing how competition from CLs affected MFI loan terms for borrowers who graduated to CLs and those who remained with MFIs. $\text{POST}_{i,t}$ equals 1 after borrower i obtains a graduation loans for the first time and equals zero otherwise. The variable $\text{HC}_{j,k,t}$ indicates whether MFI j faces a high degree of competition from CLs in region k. The variable is predetermined and calculated at the lender-region-month level using the fraction of MFI j borrowers in region k who graduated to CLs in the previous 6 months (i.e., $t-1$ to $t-6$). To facilitate the interpretation of the estimated coefficients, $\text{HC}_{j,k,t}$ is set equal to 1 if this fraction is greater than the sample median, and it is set equal to zero otherwise. Finally, $\text{HC}_{j,k,t} \times$ (1 - $\text{POST}_{i,t}$) measures the spillover effects of competition on stayers (i.e., this includes both borrowers who graduated at a later time and borrowers who never graduated). Standard errors, reported in parentheses, are clustered at the provider-month level. Log(AMOUNT) represents the logarithm of loan amount per borrower (in thousands of USD). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dependent variables			
	Log(AMOUNT)	INTEREST_RATE	MATURITY	COLLATERAL
Period-Region	1	2	3	4
$\text{POST}_{i,t}$	-0.067***	-0.024	0.310**	-0.024
	(0.016)	(0.166)	(0.137)	(0.016)
$\text{HC}_{j,k,t} \times \text{POST}_{i,t}$	0.122***	-0.688***	0.768***	0.038*
	(0.020)	(0.202)	(0.179)	(0.022)
$\text{HC}_{j,k,t} \times$ (1 - $\text{POST}_{i,t}$)	0.037***	-0.011	0.475***	0.005
	(0.012)	(0.123)	(0.107)	(0.012)
Total Obs	896,504	896,506	806,337	896,506
R-squared	0.814	0.780	0.745	0.765
Controls				
BORROWER FE	Y	Y	Y	Y
LENDER-REGION FE	Y	Y	Y	Y
MONTH_YEAR FE	Y	Y	Y	Y

A. Appendix

TABLE A1

Variable Names and Definitions

This table reports the names and definitions of all variables used in the empirical analysis.

Variable Names	Definitions
Borrower characteristics	
TOTAL_OUTSTANDING_LOANS	Total amount of outstanding loans in USD
INSIDE_LENDER	Lenders with whom a borrower had a loan in the previous 12 months. We match on the identity of borrowers' most recent inside lender prior to their graduation/switching loan.
MULTIPLE_INSIDE_LENDERS	1 if borrower has loans from more than one inside lender at time t, and 0 otherwise
OBSERVABLE_BORROWER_RISK	1 if at time t the borrower had overdue payments on outstanding loans in the previous 2 months or prior defaults; 0 otherwise
UNOBSERVABLE_BORROWER_RISK	1 if at time t the borrower had overdue payments on outstanding loans in the previous 3 to 12 months but not in the last 2 months; 0 otherwise
WORST_CREDIT_RATING	Borrower's worst credit rating over the past 2 months with any lender. Risk rating from 1 (lowest risk) to 5 (highest risk)
Loan characteristics	
LENDER	Identity of the lender that originated the loan
MONTH_YEAR	Month and year of loan origination
REGION	Region where the loan was originated
AMOUNT	Loan amount at origination, measured in USD
AMOUNT_PER_BORROWER	Loan amount divided by the number of joint borrowers (in USD)
CREDIT_RATING	Risk rating from 1 (lowest risk) to 5 (highest risk)
INTEREST_RATE	Annualized contractual interest rate at origination
MATURITY	Loan term in months, from origination to maturity
COLLATERAL	1 if backed by collateral at origination; 0 otherwise
VALUE_TO_LOAN_RATIO	Collateral value divided by loan amount at origination
PERSONAL_GUARANTEES	1 if secured by personal guarantees; 0 otherwise
FOREIGN_CURRENCY_USD	1 if denominated in USD; 0 otherwise
NUMBER_OF_BORROWERS	Total number of individuals jointly borrowing
JOINT_LIABILITY	1 if borrowers share joint repayment responsibility; 0 otherwise
LOAN_TYPE	Loan type: 1 = Installment loan, 2 = Fixed term loan, 3 = Credit card loan, 4 = Advance checking account, 5 = Mortgage loan
Ex-post loan performance	
NPL	1 if the loan had overdue payments exceeding 30 days anytime post-origination; 0 otherwise
DEFAULT	1 if the loan was downgraded to default status or written off anytime post-origination; 0 otherwise
EX_POST_REPAYMENT_PROBLEMS	1 if the graduation or switching loan experienced overdue payments, downgraded to default, or written off anytime post-origination; 0 otherwise

A. Online Appendix

A. Additional Figures and Tables

FIGURE A.1

Definitions of Borrower Transitions: Graduating and Switching

This figure illustrates the definitions of switching and graduating, as well as the distinctions between inside loans/lenders and outside loans/lenders. At time $t = 0$, an MFI borrower obtains a new loan (loan 2) from a lender (lender 2) with whom they had no outstanding loans in the previous 12 months. Lender 2, which can be either an MFI or a CL, is referred to as an outside lender. If lender 2 is an MFI, loan 2 is classified as an MFI-to-MFI switching loan. If instead lender 2 is a CL, loan 2 is classified as an MFI-to-CL graduation loan. The horizontal solid line for lender 2 indicates the loan spell of loan 2, while the dashed line before $t = -12$ shows that the borrower may have had a prior loan from lender 2 that ended more than 12 months earlier. At $t = 0$, the borrower has outstanding loans from at least one inside lender (loan 1 from lender 1 and possibly loan 3 from lender 3). These are referred to as inside loans, and lenders 1 and 3 are classified as inside lenders. Additionally, the figure illustrates that after taking a loan from an outside lender at $t = 0$, the borrower may continue to receive new loans (loans 4 and 5) from their initial inside lenders.

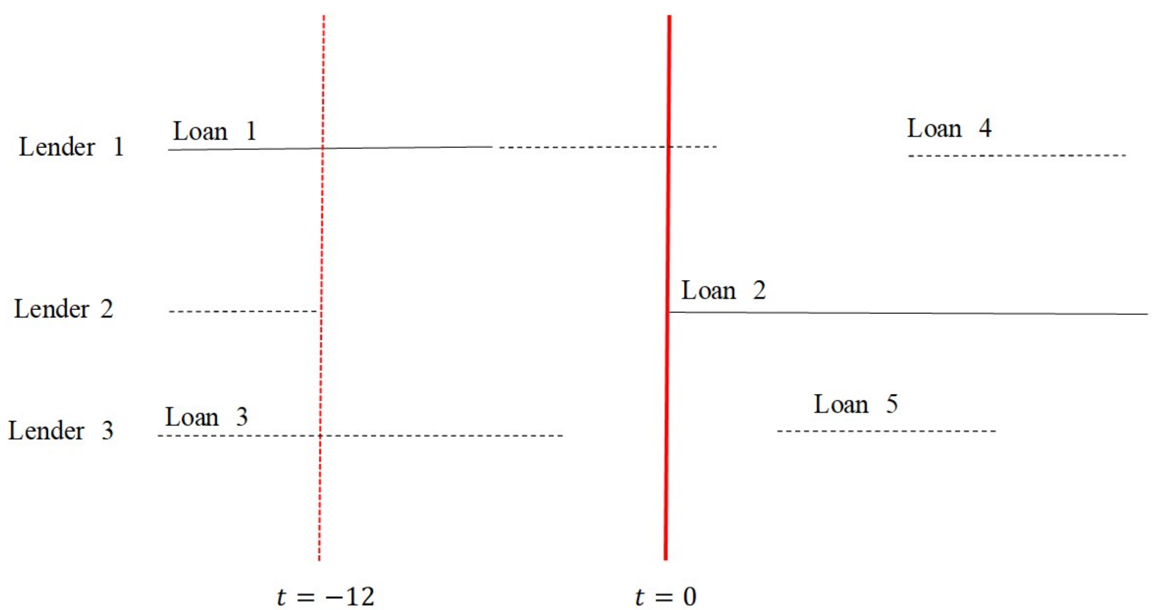


FIGURE A.2

Random Forest Diagnostic Plots for Loan Term Analysis

This figure depicts the receiving operating characteristic curve (ROC) and area under the curve (AUC) metric for the Random Forest (RF) model used in our loan term analysis (in Table 3, Panel C). The ROC is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. It is created by plotting the true positive rate against the false positive rate at various threshold settings. The AUC provides an aggregate measure of performance across all possible classification thresholds.

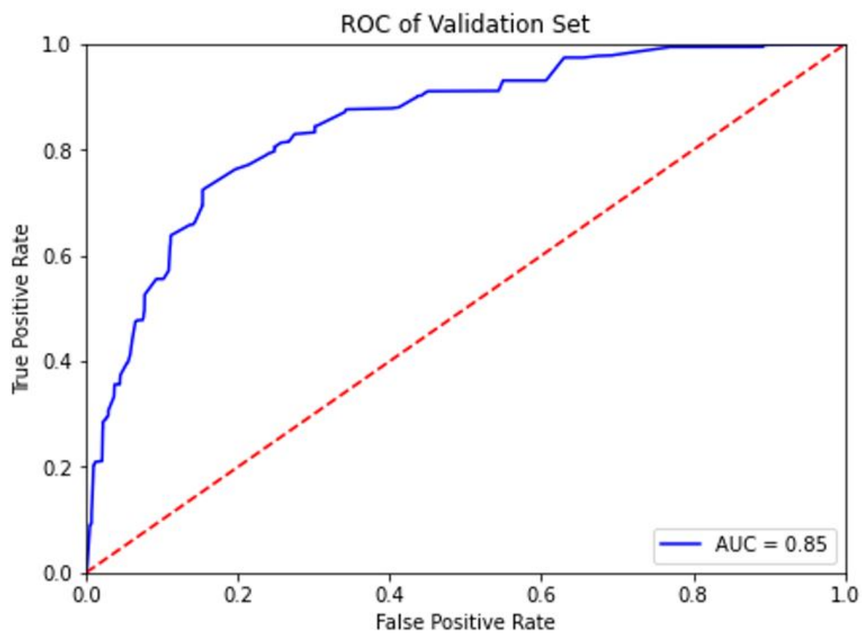
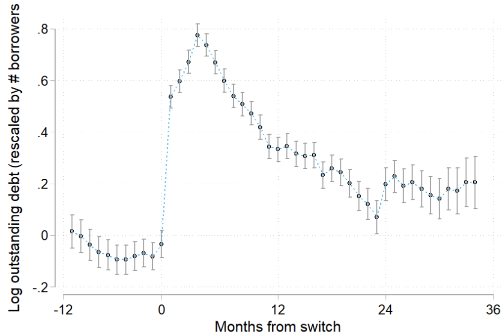


FIGURE A.3

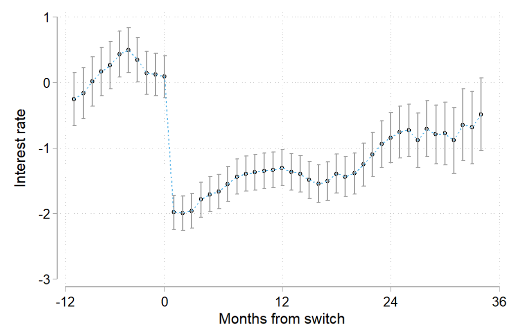
Long-term credit outcomes: with Borrower Fixed Effects

This figure compares the credit outcomes of MFI-to-CL graduates to the credit outcomes of matched MFI-to-MFI switchers between $t = -12$ to $t = 36$. Each graph reports the estimated DiD coefficients of equation (2) with borrower fixed effects, μ_i, and their 95% confidence intervals using the matched sample of borrowers in Panel B of Table 3. We report results for Log(TOTAL_OUTSTANDING_LOANS), INTEREST_RATE (%), MATURITY (months), COLLATERAL (% of loans), and JOINT_LIABILITY (% of loans).

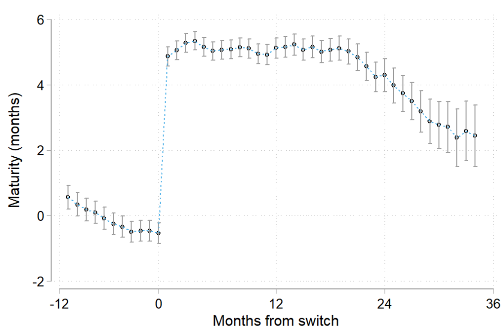
TOTAL_OUTSTANDING_LOANS



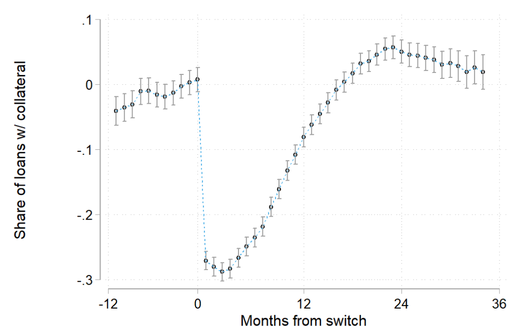
INTEREST_RATE



MATURITY



COLLATERAL



JOINT_LIABILITY

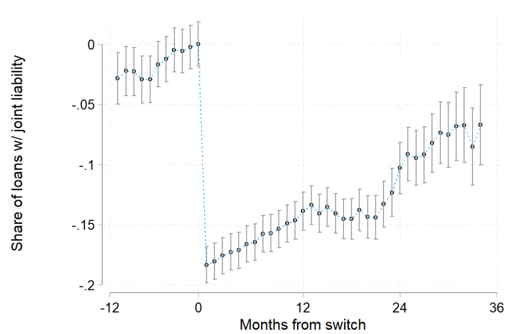


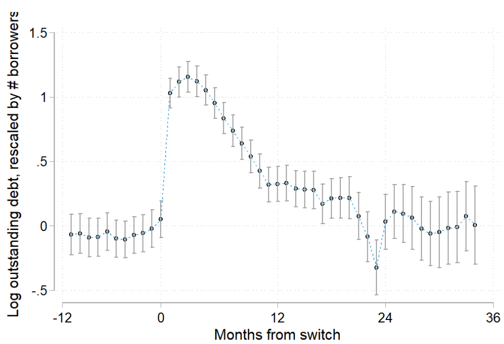
FIGURE A.4

Long-term Credit Outcomes: With vs. Without Repayment Problems

This figure reports the estimated coefficients of specifications of equation (2) and their 95% confidence intervals. We report results for Log(TOTAL_OUTSTANDING_LOANS), INTEREST_RATE (%), MATURITY (months), COLLATERAL (% of loans), and JOINT_LIABILITY (% of loans). In Panel A, we compare outcomes for MFI-to-CL graduates who had repayment problems (EX_POST_REPAYMENT_PROBLEMS=1) on their graduation loan. In Panel B, we compare outcomes for MFI-to-CL switchers who did not have any repayment problems on their graduation loan. The comparison group in both cases is MFI-to-MFI switching loans to similar (matched) borrowers. The sample period covers graduation and switching loans from January 1996 and December 1998 and any additional loans for these borrowers between January 1995 to December 2001.

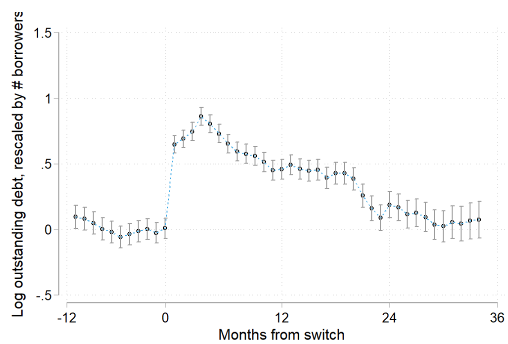
A. Graduates w/ NPL or DEF

TOTAL_OUTSTANDING_LOANS

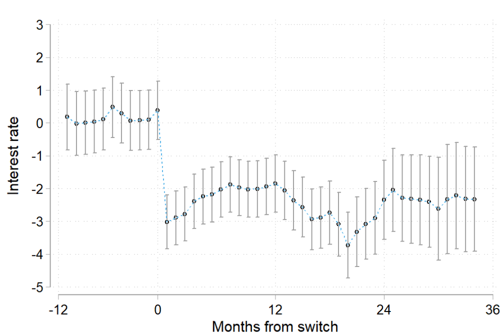


B. Graduates w/o NPL or DEF

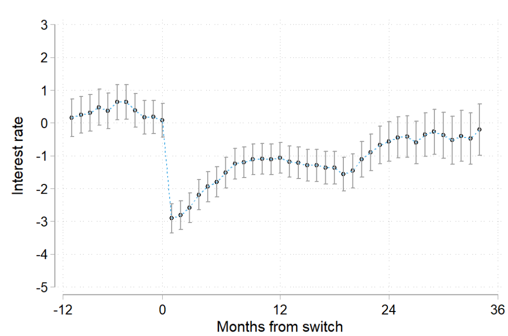
TOTAL_OUTSTANDING_LOANS



INTEREST_RATE



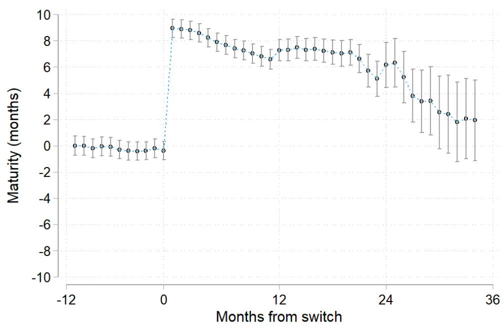
INTEREST_RATE



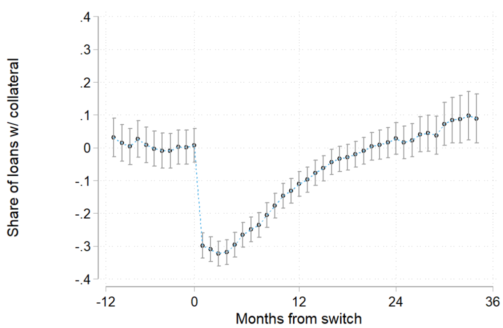
(Continued on next page)

A. Graduates w/ NPL or DEF

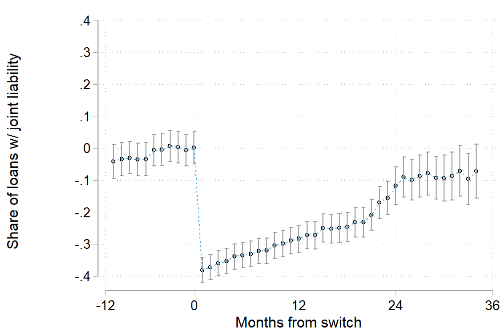
MATURITY



COLLATERAL

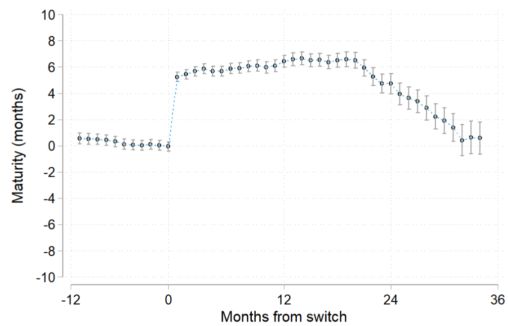


JOINT_LIABILITY

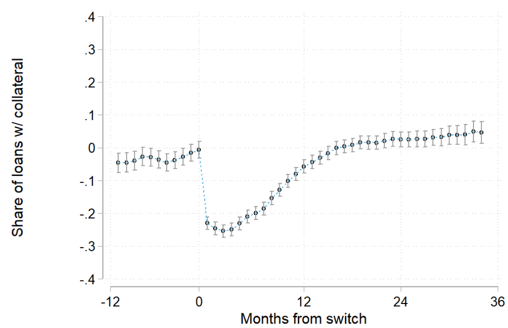


B. Graduates w/o NPL or DEF

MATURITY



COLLATERAL



JOINT_LIABILITY

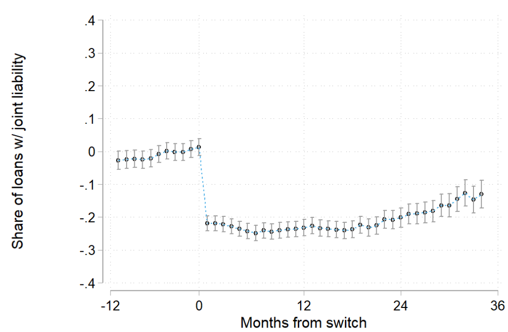


TABLE A.1

Borrower Risk by Lender Type: Banks vs. FFPs

This table compares the ex ante risk profile of MFI borrowers who graduate to CLs (MFI-to-CL) to staying (Inside MFI) or switching borrowers within MFIs (MFI-to-MFI) using different specifications of equation (1), where the dependent variable is OBSERVABLE_BORROWER_RISK or UNOBSERVABLE_BORROWER_RISK. Columns (1) and (3) report results for banks (i.e., MFIs and CLs that are legally banks). Columns (2) and (4) report corresponding results for FFPs (both MFIs and CLs that are legally FFPs). Standard errors, reported in parentheses, are clustered at the provider-month level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	OBSERVABLE_BORROWER_RISK		UNOBSERVABLE_BORROWER_RISK	
	Banks	FFPs	Banks	FFPs
	1	2	3	4
A. MFI-to-CL vs. Inside MFI				
$D_{i,t}$	-0.047***	-0.061***	0.057***	0.160***
	(0.011)	(0.024)	(0.018)	(0.012)
Total Obs	70,231	23,950	61,507	22,051
MFI-to-CL	5,313	2,828	4,866	2,296
Inside MFI	64,918	21,122	56,641	19,755
B. MFI-to-MFI vs. Inside MFI				
$D_{i,t}$	-0.051***	-0.179***	0.003	0.025*
	(0.016)	(0.046)	(0.023)	(0.015)
Total Obs	57,893	20,159	19,844	7,896
MFI-to-MFI	6,551	5,321	5,785	3,991
Inside MFI	51,342	14,838	14,059	3,905
C. MFI-to-CL vs. MFI-to-MFI				
$D_{i,t}$	-0.004	0.002	0.070***	0.079***
	(0.009)	(0.013)	(0.010)	(0.010)
Total Obs	10,907	12,179	9,658	11,079
MFI-to-CL	3,566	4,869	2,810	4,160
MFI-to-MFI	7,341	7,310	6,848	6,919
Matching Variables				
MONTH_YEAR	Y	Y	Y	Y
REGION	Y	Y	Y	Y
INSIDE_LENDER	Y	Y	Y	Y
MULTIPLE_INSIDE_LENDERS$_{t=-1}$	Y	Y	Y	Y
TOTAL_OUTSTANDING_LOANS$_{t=-1}$	Y	Y	Y	Y
WORST_CREDIT_RATING			Y	Y
OBSERVABLE_BORROWER_RISK			Y	Y

TABLE A.2

Ex-Post Repayment Problems and Ex-ante Borrower Risk

This table reports estimation results from probit regressions testing whether the ex-ante borrower risk indicators, OBSERVABLE_BORROWER_RISK and UNOBSERVABLE_BORROWER_RISK, predict repayment problems (i.e., overdue payments, defaults, or write-offs), captured by the dependent variable EX_POST_REPAYMENT_PROBLEMS, for graduation or switching loans. Standard errors, reported in parentheses, are clustered at the provider-month level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	DV=EX_POST_REPAYMENT_PROBLEMS	
Ex-ante borrower risk	1	2
OBSERVABLE_BORROWER_RISK	0.220***	0.217***
	(0.023)	(0.023)
UNOBSERVABLE_BORROWER_RISK	0.152***	0.148***
	(0.017)	(0.017)
Total Obs	97,416	97,416
R-square	0.078	0.083
Control Variables		
LENDER FE	Y	Y
REGION FE	Y	Y
MULTIPLE_INSIDE_LENDERS$_{t=-1}$	Y	Y
TOTAL_OUTSTANDING_LOANS$_{t=-1}$	Y	Y
WORST_CREDIT_RATING	Y	Y
Average INTEREST RATE$_{t=-1}$		Y
Average MATURITY$_{t=-1}$		Y
Max. COLLATERAL$_{t=-1}$		Y
Max. PERSONAL_GUARANTEE$_{t=-1}$		Y
Max. JOINT_LIABILITY$_{t=-1}$		Y

TABLE A.3

Loan Characteristics: Adaptive vs. Non-Adaptive CLs

This table presents summary statistics on graduation loans from CLs to MFI borrowers from 1996 to 2001. CLs are classified as adaptive if joint liability loans constitute more than 25% of their MFI-to-CL loans and as non-adaptive if this share is below 25%. Summary statistics are calculated at loan origination, with loan amounts expressed in thousands of USD. INSTALLMENT_LOAN is a dummy variable set equal to 1 if loan type is an installment loan and 0 otherwise. FIXED_TERM_LOAN is a dummy variable set equal to 1 if loan type is a fixed-term loan and 0 otherwise. CREDIT_CARD_LOAN is a dummy variable set equal to 1 if loan type is a credit card loan and 0 otherwise. ADVANCE_CHECKING_A/CS is a dummy variable set equal to 1 if loan type is an advance from a checking account and 0 otherwise. MORTGAGE_LOAN is a dummy variable set equal to 1 if loan type is a mortgage loan and 0 otherwise. The definitions of all other variables are provided in Appendix Table A1.

	Adaptive CLs		Non-Adaptive CLs	
Loan Characteristics	Mean	Std	Mean	Std
AMOUNT	2,863	3,688	2,630	3,584
AMOUNT_PER_BORROWER	1,361	2,127	2,477	3,446
INTEREST RATE (%)	32.5	9.47	34.34	10.4
MATURITY	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_USD	0.92	0.27	0.95	0.22
NUMBER_OF_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
ADVANCE_CHECKING_A/CS	0.00	0.04	0.03	0.17
MORTGAGE_LOAN	0.00	0.07	0.01	0.08
Observations	11,762		33,008	

B. Competition and spillovers on the informal sector

In additional tests, we examine whether increased competition from CLs influenced the composition of borrowers entering the formal financial system. Specifically, we assess whether MFIs became more likely to lend to "first-time" borrowers—defined as those without a prior loan recorded in the credit registry—as competitive pressures from CLs intensified. Since these first-time borrowers likely relied on informal credit before entering the formal sector, this analysis provides an indirect test of whether competition from CLs helped "crowd out" informal lending, and whether this effect reversed as CLs later retrenched. Using all MFI loans between 1996:01 and 2001:12, we estimate:

$$
\begin{aligned}
Y_{i,j,k,t} &= \alpha + \beta_1 \mathrm{POST}_1 + \beta_2 \mathrm{POST}_2 \\
&\quad + \beta_3 \mathrm{HC}_{j,k,t} \times \mathrm{POST}_1 \quad + \beta_4 \mathrm{HC}_{j,k,t} \times \mathrm{POST}_2 + \theta_{j,k} + \varepsilon_{i,j,k,t},
\end{aligned}
\tag{4}
$$

where $Y_{i,j,k,t}$ equals one if a loan to borrower i originated by MFI j in region k during period t is to a first-time borrower, and zero otherwise. We define first-time borrowers as those with no loans recorded in the registry during the period from January 1995 to December 1995, which establishes pre-sample credit histories. The dummy variables POST_1 and POST_2 divide the sample window into three distinct phases. POST_1 equals one during the period of rapid CL entry and heightened competition (1996:07–1999:06). POST_2 equals one during the period of CL market withdrawal (1999:7–2001:12). The omitted period (1996:01–1996:06) serves as the pre-competition baseline.

As before, $\mathrm{HC}_{j,k,t}$ indicates whether MFI j faces a high degree of competition from CLs in region k, based on the fraction of its borrowers who graduated to CLs in the previous six months. $\theta_{j,k}$ indicate lender-region fixed effects. The coefficients β_3 and β_4 measure how the likelihood of lending to first-time borrowers changes due to competition from CLs during the boom and retrenchment phases, respectively.

The results, reported in Table B.1, show that during the period of intense competition from CLs (POST_1), MFIs were 6.3 percentage points more likely to originate loans to first-time borrowers in regions facing high competitive pressure. This suggests that competition from CLs may have crowded out informal lending by drawing previously informally financed borrowers into the formal credit market. In contrast, during the retrenchment phase (POST_2), this pattern weakens as competitive pressures eased.

These results complement our earlier findings, showing that the entry and exit of CLs not only affected the terms of credit of graduating and staying MFI borrowers, but also the extent to which borrowers transitioned from the informal to the formal sector.

TABLE B.1

Competition and outreach to first-time formal borrowers

This table presents estimates from Equation (4), analyzing how competition affected the composition of borrowers entering the formal financial system. The dependent variable is FIRST_TIME_FORMAL_BORROWER, which is a dummy variable set to equal one if a loan is to a borrower who appears in the credit registry for the first time, and zero otherwise. We use the period from January 1995 to December 1995 to establish borrowers' credit histories prior to the sample period. The variables POST_1 and POST_2 divide the sample window into three distinct phases. POST_1 equals one during the period of rapid CL entry and heightened competition (1996:07–1999:06), and zero otherwise. POST_2 equals one during the period of CL market withdrawal (1999:7–2001:12), and zero otherwise. The omitted period (1996:01–1996:06) serves as the pre-competition baseline. $\text{HC}_{j,k,t}$indicates whether MFI j faces a high level of competition from CLs in region k, based on the fraction of its borrowers who graduated to CLs in the previous six months. $\theta_{j,k}$ captures lender-region fixed effects to control for time-invariant unobserved heterogeneity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Period-Region	DV=FIRST_TIME_FORMAL_BORROWER
POST_1	0.019
	(0.022)
POST_2	0.006
	(0.016)
$\text{HC}_{j,k,t} \times \text{POST}_1$	0.063**
	(0.031)
$\text{HC}_{j,k,t} \times \text{POST}_2$	0.041
	(0.030)
LENDER-REGION FE	Y
Total Obs	1,033,485
R-squared	0.037