Default risk and multiple bank relations among microenterprises*

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Abstract

Do multiple bank relations increase or reduce the credit risk of very small and opaque firms? While sustained borrowing from a single lender can solve the information problem these firms are subject to and increase their credit quality, multiple bank relations can provide them with more flexibility, in particular when debt contracts focus on repayment discipline. Utilizing credit bureau and client panel data from an Ecuadorian bank specialized on loans to microenterprises, we find that while multi-banking is more common than a single banking relationship, it is associated with an increase in long-term default risk by up to 22%. However, this association appears to be driven by endogeneity: employing a novel instrumental variable estimator suitable for duration data, and using disruptions in the personal lending relation between clients and loan officers as source of exogenous variation, we find that multiple bank relations are a response to, rather than a cause of increased default risk. The finding is supported by several checks for robustness and exogeneity of the instruments. Thus, multiple bank relations can be a rational response by borrowers to rigid debt contracts, but at the same time they are primarily deployed by clients with a higher ex-ante credit risk.

Keywords: relationship lending, microfinance, multi-borrowing, loan default, credit risk, competition, survival analysis, pseudo-observations

JEL-codes: C36, C41, G20, G21, G32, L25, L26, O16

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1 Introduction

Should small and opaque firms maintain multiple bank relations or do they rather benefit from holding a single bank relation? While multiple bank relations may provide financial flexibility needed by a firm to manage a volatile cash flow, they may at the same time create short-term maturity mismatches and thereby compromise the firm's liability management; on the other hand, a single relationship lender can better address the firm's actual credit constraints and promise future access to credit, while the firm risks to be locked in by the lender in its debt finance. In this study, we investigate whether multiple bank relations affect the probability of default of informationally opaque microenterprises borrowing from a relationship lender, drawing on administrative data from an Ecuadorian bank specialized on microfinance products.

Informational frictions in financial intermediation markets are considered one of the main forces behind credit-rationing of small and opaque firms (Stiglitz and Weiss, 1981). Relationship lenders attempt to overcome these frictions by making costly efforts in collecting private information about a firm through repeated interactions with the firm over time, allowing them to extract a monopoly rent from the firm (Rajan, 1992).[1] Informed debt financing offers returns both to the firm and the lender: the firm can get a higher loan amount than it would get from uninformed lenders, while the lender gains an edge over competitors. Relationship lenders may therefore have a vested interest to be the exclusive lender to these firms (Degryse et al., 2016a). In addition, various studies show that lenders face a higher equilibrium default risk when firms sequentially borrow from other sources (Bizer and DeMarzo, 1992; Bennardo et al., 2015; Parlour and Rajan, 2001). Empirically, mutual benefits of the relationship lending model for both borrowers and lenders are amply documented, e.g. in the context of credit for small firms (Petersen and Rajan, 1994; Berger and Udell, 1995; Berg and Schrader, 2012; Beck et al., 2018; Rosenfeld, 2014), and more recently retail bank customers (Agarwal et al., 2018; Puri et al., 2017). Petersen and Rajan (1994), in particular, suggested that firms maintaining a single bank relationship are less credit-constrained than those diversifying their debt sources. Several studies, however, argue that multiple bank relations can also provide benefits for small firms, for instance by reducing the

[1] Another potential strategy from lenders is to offer a menu of incentive-compatible loan contracts to firms, thereby achieving a certain degree of self-selection among firms (Gale and Hellwig, 1985). This preserves competitiveness between lenders but essentially shuts out from the credit market borrowers that are too risky ex-ante, such as opaque microenterprises.

lender's bargaining power, or by insuring against illiquidity of the lender (Ongena and Smith, 2000; Detragiache et al., 2000; Degryse et al., 2011; Elsas et al., 2004).

While microenterprises account for the lion share of the labor force in emerging or developing countries, including in much of Latin America (Pagés, 2010), they constitute the low end of the firm spectrum in terms of opacity and are therefore particularly finance-constrained. Lenders to this kind of firms face increased credit risk both ex-ante and ex-post: since business performance indicators derived from systematic book-keeping are often absent, let alone audited, the risk of adverse selection is high; and since businesses are not typically registered legal entities, compounding the verification of loan use, the risk of moral hazard is high, too. Microfinance providers, specifically targeting this class of firms, have adapted their lending model to address these fundamental information problems. Firstly, borrowers get relatively small loans when they borrow for the first time, but larger and more useful loans with each loan renewal, which is known as the dynamic incentives model (Shapiro, 2015). Second, loans are non-revolving and loan officers visit clients on a regular basis (e.g., monthly) to collect installment payments. In an environment of weak legal debt enforcement, effectively preventing loan collateralization or the use of covenants, both features are meant to increase the repayment discipline among borrowers (Morduch, 1999). In addition, geared towards a lasting business relationship and the acquisition of soft information about the client over time, they manifest the lenders' relationship lending approach. At the same time, however, these features provide incentives for borrowers to complement the loan with other debt sources; either to increase the overall loan amount, or to synthetically create a line of credit and thereby increase flexibility in the timing of their financing needs.

In the microfinance context, multiple bank relations have long been regarded as hazardous both for lenders and borrowers due to their potential to overstrain borrowers' debt capacity (McIntosh et al., 2005; Guha and Roy Chowdhury, 2013; Vogelgesang, 2003; McIntosh and Wydick, 2005). Sequentially borrowing from different lenders is mainly seen as a result of deficient information sharing mechanisms in the market. Accordingly, the establishment of a credit bureau has been attested positive effects in helping reduce these information asymmetries (de Janvry et al., 2010; Behr and Sonnekalb, 2012). Our study provides an interesting setting in this regard: being an early adopter of an enabling policy environment for credit information-sharing, Ecuador in 2011 was ranked as the single best country (out of 55 emerging markets) in terms of quality and market coverage of credit bureaus, according to an industry report published by the *Economist Intelligence Unit*.[2] Under such conditions of relatively complete information-sharing between lenders, it is *a priori* not clear whether multiple bank relations exert adverse effects on microenterprises or lenders, as lenders can take this information into account in their screening process. Further, this setting makes our study more comparable to studies on small firm financing in developed financial intermediation markets, where lenders can typically observe each other's lending decisions.

One inherent problem of isolating the effect of bank relations on loan outcomes is that they are endogenous to the borrower's financial situation. Any attempt to directly estimate the effects of multiple bank relations on loan outcomes using observational data is therefore confounded by factors underlying a client's choice to multibank. We address this caveat by leveraging dyadic information about loan officers and their contact with clients over a loan cycle as source of exogenous variation in the uptake of additional bank relations. Specifically, we exploit information about loan officers rotating to other clients as well as loan officers quitting the bank. We provide several statistical checks to validate that changes in the customer-loan officer relation are sufficiently exogenous to the clients' ex-ante probability to default. We then implement a novel instrumental variable estimator developed by Kjaersgaard and Parner (2016), suitable for right-censored duration data and drawing on the concept of "pseudo-observations", to explore the causality in the effect of clients' use of multiple bank relations on their ex-post credit risk. We compare the findings from the IV approach with those obtained by running a Cox regression on the hazard to default (cf. Agarwal et al., 2018), where the multivariate association between multiple bank relations and default risk is estimated directly, which we refer to as naïve estimator since it ignores the endogeneity.

Our findings indicate that multiple bank relations are more common than a single bank relation; 62% of clients in our sample make use of multiple banking at some point. At any given point in time, borrowers maintain on average 1.7 bank relations, and 2.3 financial relations overall (also including financial cooperatives and consumer credit). Results from the naïve estimator indicate that clients with multiple bank relations are more likely to default on their loans, and in particular are more likely to end up in long-term arrears lasting for more than 12 months. Each additional bank

[2]For the annually issued reports, see http://www.eiu.com/landing/Global-Microscope (accessed on July 30, 2018). The rating for the highest credit bureau score reads: "Credit bureaus provide comprehensive information on the whole range of transactions and also include positive information about borrowers (on-time payment history etc.) and adequate protections for borrowers and lenders."

relation, starting from two and onward, is associated with a near-linear increase in default risk. However, these results appear to be driven by endogeneity: the results from the pseudo-observation IV approach, where the uptake of new bank relations is instrumented by disruptions in the loan officer-client relationship, indicate that causality in fact goes the other way. More precisely, instrumented multiple bank relations reduce the chance of client default both in the short and in the long term and thus do not appear to *per se* cause a higher credit risk. To address concerns that non-randomness in the sample composition might drive the results, we run several robustness checks on different subsets of clients, all of which are supportive of the finding. The results imply that multiple bank relations are mainly deployed by clients who would have an increased ex-ante default risk, even in case they would not make use of multiple bank relations; they are also consistent with the reasoning that multiple bank relations are a response by borrowers to the higher default risk. On the other hand, some clients signal the need for a more flexible financial management, in particular a line of credit, which is not offered by the relationship lender in our study. Field et al. (2013) find that a more flexible repayment schedule can stimulate entrepreneurship among microborrowers, but in contrast to our findings they report that it comes at the cost of increased default risk. Finally, we also find that, all else equal, the longer the relationship that borrowers maintain with the relationship lender, the less likely they are to start a new outside bank relation, and the less likely they are to default, which corroborates the benefits of relationship lending.

Our study is related to different aspects of small business finance studied in the literature. While a large body of literature has studied relationship lending, the "relation" often remains a black box (Puri et al., 2017). A variety of indicators has been put forward to identify a lending relationship, including the length of relationship, breadth of relationship, being the lead lender, granting a line of credit, or the subjective assessment of bank CEOs (Petersen and Rajan, 1994; Puri et al., 2017; Agarwal et al., 2018; Berger and Udell, 1995; Degryse and Ongena, 2007; Boot and Thakor, 2000; Rosenfeld, 2014). More recently, Karolyi (2018) pointed at the importance of personal (firm executive-loan officer) as opposed to institutional (firm-bank) relationships. Our study feeds into this line of research by explicitly focusing on the role of the loan officer acting as "repository" of soft information (Berger and Udell, 2002) and personal link in the lending relationship between the bank and its clients. Methodologically, our approach to study disruptions in this relationship is related to studies by Fisman et al. (2017) and Drexler and Schoar (2014). Fisman et al. (2017) use loan officer rotation as source of exogenous variation to induce exogenous matching of loan officers and borrowers with respect to their cultural background. Drexler and Schoar (2014) directly estimate effects of loan officer leaves on loan outcomes. In contrast to these studies, we are interested in the intermediate effect of loan officer dynamics, first inducing exogenous variation in clients' use of multiple bank relation, *before* those may exert an effect on loan outcomes.

The remainder of the article is organized as follows. Section 2 discusses the views on multiple bank relations both in the small firm as well as in the microfinance literature, and relates them to the context of this study. Section 3 describes the dataset and the methodology used. Section 4 reports and discusses the results, including several robustness checks and validity checks for instrument exogeneity. Section 5 concludes.

2 Multiple bank relations and the information problem in credit markets

2.1 Small firms versus microenterprises

While asymmetric information is ubiquitous in financial intermediation, it particularly affects small and credit-constrained firms who bear the costs of their opacity (Berger and Udell, 1995). In a seminal treatise on the value of bank relationships, Petersen and Rajan (1994) suggest that loans from a single relationship lender are beneficial for small firms and lead to, perhaps counter-intuitively, *improved* credit availability compared to multiple bank relations. The rationale is that young and small firms have a disadvantage in signalling their risk as there is little or no information publicly available about them. Investors would therefore charge an opacity premium. A relationship lender by contrast, characterized by its efforts to acquire "soft" information through multiple interactions with the firm over time (Boot, 2000), can estimate the appropriate quantity and price of capital that is in line with the the firm's risk profile and growth perspectives.

Detragiache et al. (2000) however contend that in reality most firms, including small ones, obtain credit from more than one lender. Relying on a single relationship lender not only provides benefits but also involves costs, for instance the unavailability of future credit in case the lender runs out of liquidity. This may particularly be a concern in the case of small and specialized lenders that are credit-constrained themselves. In addition, maintaining multiple bank relations may be a firm's strategy to avoid holdup costs arising due to an information monopoly of the lender (Ongena and Smith, 2000). Elsas et al. (2004) further suggest that borrowing from a relationship lender needs not preclude multiple bank relationships of a firm; instead, firms may prefer to *complement* loans from a relationship lender with loans from transaction-based lenders, for instance in order to mitigate bargaining power of the former. Neuberger and Räthke (2009), using a sample of German microenterprises, find that multiple bank relations are a response to credit constraints for those enterprises. In the same vein, Degryse et al. (2011) suggest that small firms maintain multiple bank relations as insurance against relationship discontinuations due to mergers or liquidations of their lenders. Berg and Schrader (2012) are more in line with the findings of Petersen and Rajan (1994) mentioned above, noting that credit constraints of microenterprises in Ecuador were lowered by longer bank-borrower relationships; yet, in their study the authors do not take multiple bank relations of clients into account. Studying multiple bank relations from a supply-side approach, Carletti et al. (2007) show theoretically that lenders, too, may reap benefits from sharing the lending, because it allows them to cut back their monitoring efforts. In their model, the attractiveness of multiple bank lending increases in the cost of monitoring a borrower's project and in the degree to which the lender is credit-constrained itself; both are factors that reinforce the applicability of the model to the setting of our study.

Most studies that focus specifically on borrowers from microfinance institutions come to the conclusion that multiple borrowing leads to adverse loan outcomes, and identify the information problem between borrowers and lenders as the main culprit. When capital markets are competitive but lenders are subject to moral hazard as they cannot observe the borrowers' loan use, borrowers will increasingly multi-borrow and as a result increase their probability to default (Guha and Roy Chowdhury, 2013; McIntosh and Wydick, 2005). Using data from the microlender FINCA in Uganda, McIntosh et al. (2005) find that repayment rates drop where competition increases. While Vogelgesang (2003) finds a lower incidence of default in more competitive areas in the Bolivian microfinance market, she also reports multiple loans as a determinant for increased default risk. Shapiro (2015) takes a different angle and studies multi-borrowing when borrowers face dynamic incentives to repay a loan. He shows theoretically that if borrowers who are credit-constrained use multiple loans, they will eventually default.

2.2 Are microenterprises like small firms?

Like other Latin American countries, Ecuador represents a mature microcredit market. This means it has become more similar to, and vertically integrated with, banking markets (in terms of customer overlap) as well as financial markets in general (in terms of lenders' funding sources) (D'Espallier et al., 2017). Such markets are characterized by a number of microfinance institutions that have transformed into banks and shifted their lending methodology from group loans[3] to individual loans, as a result of, and at the same time reinforcing, the commercialization of the markets, as particularly observed in parts of Latin America (Christen, 2001; Shapiro, 2015). Borrowers from these institutions resemble in certain aspects small and opaque firms in more developed markets, although important differences remain.

Similar to small firms, microfinance borrowers have been found to be subject to severe credit constraints (de Mel et al., 2008; Banerjee and Duflo, 2014). In individual microlending, credit constraints are in fact incorporated in the lending model namely by giving dynamic incentives to repay: borrowers will obtain larger and more useful loans only upon repaying previous loans. In the absence of institutions that can cost-efficiently sanction non-repayment, this device has proven to be a useful loan enforcement mechanism (Shapiro, 2015). At the same time though, it potentially delays the availability of the optimal credit amount to future loan disbursements, and may therefore be detrimental to those borrowers who need to make a relatively large and non-divisible investment in the first place. These borrowers face incentives to multi-borrow from several lenders rather than to wait for the availability of larger future loans from a single lender.

One main difference between microenterprises targeted by microfinance lenders and small firms is that the former are often informal, i.e. their business is not legally registered. This implies that a borrower's household and business are combined in a single entity without separated liabilities. Loans are more exposed to moral hazard since the fungibility of money makes it very difficult to verify the borrowers' loan use. In addition, the inherently risky cash flow often forces borrowers to compensate business losses out of their private pockets, as their assets are not shielded by limited liability.

[3]In the group loan methodology, characteristic for the early days microcredit model and popularized by later Peace Nobel laureates Muhammad Yunus and his Grameen Bank, borrowers, mostly women, form groups of joint liability; typically, loans are tiny and lenders know little about the borrowers' businesses.

In the present study, we use loan defaulting as indicator for financial distress, assessed through administrative data. Adding a new feature to the measurement, we distinguish between different spells of defaulting to capture different degrees of severity of financial distress. Importantly, we also make the assumption that lending contracts successfully limit strategic default. Borrowers have an incentive to default strategically when the discounted value of outstanding debt exceeds the costs of non-repayment.[4] The latter, similar to what Diamond (1984) calls the bankruptcy penalty, may include both pecuniary and non-pecuniary costs, including for instance sanctioning costs and the expected costs of foregone future access to credit. As mentioned before, a common device to prevent strategic default is to provide dynamic repayment incentives. Another important factor is the perceived cost of sanctioning. A recent microfinance industry report pointed at large differences in loan recollecting practices across countries, ranging from clients fleeing their village in fear of being imprisoned, as observed in Uganda, to clients whose main perceived risk in not repaying is to lose their clean record in the credit bureau, as observed in Peru (Solli et al., 2015). The existence of a credit bureau has been found to reduce moral hazard both in microcredit and retail banking markets when borrowers are aware that they will not only lose access to future credit from the lender whose loan they default on, but in most cases from *any* formal lender (de Janvry et al., 2010; Behr and Sonnekalb, 2012; Vogelgesang, 2003).

2.3 The Ecuadorian banking market

The institutional landscape of Ecuador's financial system underwent a severe contraction in the late 1990s when the country suffered an economic and bank crisis during a phase of political instability. Fourteen banks including the country's largest, Filanbanco, were liquidated, and surviving institutes experienced significant profit cuts and a sharp increase in nonperforming loans (Quispe-Agnoli and Whisler, 2006). Banco Solidario, at the time Ecuador's only licensed microfinance bank, withstood the crisis better than most commercial institutes in terms of loan performance and deposit stability (Marulanda, 2006). After some unsuccessful government interventions, the crisis' turning point was reached when then-president Jamil Mahuad replaced a hyperinflated Sucre by the US Dollar as national currency in 2000. The dollarization helped the financial system regain the confidence of both investors and local depositors.

[4]See Bond and Rai (2009) for an analytic discussion of strategic defaults in the context of microcredit.

Additionally fostered by rising oil prices, the net oil-exporting economy started to recover.

During the phase of macroeconomic expansion, and supported by more comprehensive regulations for the practice of microfinance in 2002, the microfinance sector embarked on a growth path and gradually increased its significance in the overall economy. This can in part be attributed to the revival of credit and saving cooperatives, which likewise weathered the 2000 crisis remarkably well; plenty of financial cooperatives, also known as credit unions, exist in Ecuador, reflecting the long-standing importance of the cooperative model in Latin America (Westley and Shaffer, 1999). In the first six years under the left-leaning administration of Rafael Correa who became Ecuador's president in 2007, they increased their microfinance lending volume by nearly twice the rate of banks (Weisbrot et al., 2013). Actively supported by both the government and international nonprofit organizations, many of them also obtained a license and became regulated by financial authorities. Following a different business model than banks, cooperatives are member-owned institutions and their funds principally come from their depositors, who technically are equity-holders (Hansmann, 2000). Often, although not necessarily always, cooperatives operate in geographically narrow areas and may be characterized by social ties between their members.

The growth in the microfinance industry was accompanied by a commercialization of the sector also observed in other Latin American countries, going along with pushes towards financial inclusion.[5] On the one hand, several "downscaling" banks extended their services with microfinance products; for instance, Banco Pichincha and Banco Guayaquil, two major Ecuadorian banks, both developed sizable microfinance departments over the time. On the other hand, "upscaling" microfinance NGOs transformed into licensed banks or non-bank financial institutions (D'Espallier et al., 2017; Christen, 2001). In Ecuador's financial sector, banks to date operate in a highly competitive environment, as measured by international standards: Beck et al. (2013b) locate Ecuador in the top quintile in terms of competition in the banking market. Due to its integration into the formal financial system, the microfinance sector has opened up to the competition observed in the banking sector.

As in other Latin American countries, consumer credit has been introduced in Ecuador during the 1990s following the Chilean example, where specialized agencies

[5]Between 2011 and 2014, estimated bank account penetration in Ecuador has increased from 37% to 46% (Demirgüç-Kunt et al., 2015)

and international banks had earlier established consumer finance on a large scale (Marulanda, 2006; Madeira, 2017). Based on standardized and quantitative credit scoring models, consumer credit is a type of transactional lending and tied to wages rather than to fluctuating income generated by self-employment, and therefore requires a certain degree of formality in the labor market. On the other hand, in a study on South African microfinance clients, Karlan and Zinman (2010) attest a positive effect of pay-day consumer lending on borrowers' welfare, and find that it lifts borrowers' credit constraints. Due to their distinct features, we treat both consumer credit and loans from financial cooperatives as separate categories in our empirical specification to find associations with default risk.

3 Data and Methodology

3.1 Data sources

The data for this study has been provided by Banco D-MIRO (D-MIRO in the following), a regulated Ecuadorian bank headquartered in Guayaquil, Ecuador's largest city and business hub. D-MIRO was initiated in 1997 as a project by an international NGO, but in 2011 transformed into its current form as full-fledged bank. Through its network of 13 branches, operating along the coastal part of the country, it offers individual loans as well as savings accounts and insurance products to its clients. Loans may start from US$ 400 (in rare cases below) and can reach up to US$ 20,000, repaid in monthly installments. Loans are not collateralized but are required to be signed by a co-debtor. Upon a client's first loan application, loan officers assess the client's entrepreneurial activity with due diligence; thereafter they frequently visit the client to collect loan repayments and to disburse new loans, and also to verify the business performance. The lending model of D-MIRO makes it a typical relationship lender extending credit to small and opaque firms, as described by Petersen and Rajan (1994).

The dataset at hand covers all clients that had an active relationship with D-MIRO at any time between April 2012 and March 2016. The cleaned dataset includes 84,648 individuals, in total making up 721,892 quarterly observations. For this period, detailed information is available about the day a loan is disbursed, the outstanding amount including interest at the end of a quarter, and the loan cycle. For delinquent loans, the data records the days passed since a payment was missed and the current overdue amount. In addition to that, at the beginning of a new loan cycle, detailed information is collected by loan officers about the financial situation of the client, including a multi-dimensional poverty assessment and a household balance sheet. While in countries with formalized labour markets microenterprises are usually defined as firms with up to nine employees, clients' businesses in our sample are truly "micro": 71% of the clients reportedly run their business on their own (although many may not count their family members), and only about 0.5% of clients contract more than 5 employees.

For each D-MIRO client, the internal bank information is complemented with data from Equifax, an internationally operating credit agency. This information is purchased by the bank on a running basis. The data covers credit information from all Ecuadorian commercial banks as well as a large number of saving and credit cooperatives and other financial or non-financial companies granting consumer credit. The richness in information allows to differentiate between different types of lenders: "commercial banks" comprise all banks operating in Ecuador and reporting to the credit bureau, such as the country's largest commercial bank, Banco Pichincha, or the most significant microfinance institute, Banco Solidario. In total, we use information on 42 institutes, which also includes a few regulated non-bank financial institutes, the *sociedades financieras*. Further, 137 different credit and savings cooperatives make up the "cooperative" category. Finally, 200 other sources of credit recorded are aggregated to the "other" category, which includes companies granting consumer credit as well as many shops selling on credit. For each loan, end-of-the-quarter information is available from the credit bureau about the total outstanding loan and for the part of the loan that is delinquent. For each financial relation, only aggregated information is available, or put differently, we do not observe how many loans a client may have with a particular bank. We therefore focus on the number of different financial relationships rather than the number of different loans.

3.2 A naïve Cox estimator of the probability to default

We construct a naïve estimator that estimates a direct but potentially confounded effect of the number of bank relations on the ex-post probability to default. To this end, we model the clients' probability to default through its hazard function, denoted by $\lambda(t)$.[6] Modelling the default probability conditional on past performance rather than

[6] The hazard is defined as the likelihood to default at a certain point in time, given a clean repayment performance until this point. Let T be a positive random variable denoting the time

unconditionally has been shown to improve estimates for firm bankruptcy compared to static models such as probit when panel data is available (Shumway, 2001). We estimate determinants of the default hazard via a Cox regression, as done in previous studies (e.g. Agarwal et al., 2018; Goedecke, 2018). The model assumes a proportional effect of each covariate $x_j, j = 1, ..., J$ on the hazard at any given point in time t. To separate effects by the source of a loan, we distinguish between bank loans, cooperative loans, and consumer loans, as explained earlier. We denote the numbers of the three different credit sources by x_1, x_2 and x_3, and denote a vector of control variables by $\mathbf{z}$. The model then specifies as

$$\lambda(t|\mathbf{x}_t, \mathbf{z}_t) = \lambda_0(t) \exp\left(\sum_{j=1}^{3} \beta_j x_{jt} + \mathbf{z}_t' \gamma\right) \tag{2}$$

with $\lambda_0(t)$ being the so-called baseline hazard at time t, which is simply the hazard function conditional on each covariate equalling zero. When a client still has some outstanding balance at the end of our observed period, or when a client closes the relationship with D-MIRO after paying off a loan, an observation is considered censored. Censoring, which produces an upward bias in the estimated hazard if ignored (Kiefer, 1988), is taken into account in the estimation of the Cox model.

We use a set of control variables that includes characteristics of the D-MIRO loan, the borrower's household and the borrower's business. An important control variable is a client's loan cycle in the relation with D-MIRO, which captures the effect of the relationship lending model. The longer the relationship lasts, the better the institution should be able to gauge future repayment capacity, and the better should the client's credit history indicate her future repayment behavior, in line with the benefits suggested by relationship lending (Petersen and Rajan, 1994). Next, we consider overall leverage, defined as the percentage to which a client's assets are financed through liabilities. Liabilities here is the total of outstanding loan amounts plus interest captured by the credit bureau. It therefore includes commercial bank loans, cooperative loans and consumer credit. Information on clients' assets are assessed by loan officers during

that elapses between loan disbursement and loan default. Then, given that duration t elapsed since loan disbursement, the hazard can be expressed as

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{Pr(t \leq T < t + \Delta t \,|\, t \leq T)}{\Delta t} = \frac{f(t)}{1 - F(t)} \tag{1}$$

their initial client visits and updated each time a client enters a new loan cycle. The inclusion of the leverage variable enables us to distinguish between effects of how *many* loans clients use, compared to how *much* they borrow in total. Further, we control for the clients' total assets, as well as for the size of the current loan at D-MIRO. Finally, we account for a number of client characteristics. To control for the poverty status of the client, we include the so-called poverty scorecard index in the model, which assigns a score based on ten dimensions capturing the living standard of the household. It is repeatedly evaluated by the loan officers with every new loan cycle. Further control variables are the client's sex, age, the occupational sector, and the highest educational degree obtained. Finally, sets of dummies are added to the models to control for business quarter and for branch fixed effects.

3.3 Instrumenting multiple bank relations with loan officer-client dynamics

A. The pseudo-observation IV estimator for duration data

While the standard Cox regression is a suitable approach to measure the association between bank relations and default controlling for other observed factors, it does not measure a causal effect of bank relations. The factors underlying a client's choice to start another bank relationship are not independent from the client's ex-ante risk to default, thereby creating an endogeneity bias. We address this issue using an instrumental variable approach recently developed by Kjaersgaard and Parner (2016), fitted to the context of a Cox regression model.

In the classic instrumental variable design within a linear regression framework, the endogenous independent variable is regressed on a set of instruments that need to fulfill two conditions: first, they must be sufficiently correlated with the endogenous independent variable, and second, they must be independent from the error term of the structural equation. However, the concept cannot be easily applied when the dependent variable is censored, as is generally the case with survival data. Kjaersgaard and Parner (2016) developed an approach to overcome this problem by using so-called pseudo-observations, which represent a given client's *expected* default probability at a given time t. To understand the mechanics behind this approach, consider two steps: First, an unbiased estimate of the probability distribution of default is constructed, which the sample is assumed to be randomly draw from. Second, each observation's contribution to the estimated probability distribution is calculated. These contributions are dubbed pseudo-observations. They are continuously distributed and uncensored (i.e. complete) estimates of the expected default risk, and can be used in lieu of the observed, but discrete and censored default incidence.

The construction of the pseudo-observations is laid out in the following. Let the observed and possibly censored time-to-event observations in the sample be $T_1, ..., T_n$, and define a parameter θ such that

$$\theta = E\left[f(T)\right] \tag{3}$$

with $f(\cdot)$ being a real-valued, unspecified function. In our case, following Andersen et al. (2003), we are interested in the Kaplan-Meier estimator where $f(T) = I(T > t)$, such that $\theta = E\left[I(T > t)\right] = S(t)$ becomes the survival function. Then, the i-th pseudo-observation is constructed as

$$\widehat{\theta}_i = n \cdot \widehat{\theta} - (n-1) \cdot \widehat{\theta}_{-i}, \qquad i = 1, ..., n \tag{4}$$

where $\widehat{\theta}_{-i}$ denotes the estimate for θ based on all observations except the i-th, which is also known as "leave-one-out" estimator. n is the sample size after aggregating the data on the loan level. The incompletely observed $T_1, ..., T_n$ are then replaced by the complete, and estimated, pseudo-observations $\widehat{\theta}_1, ..., \widehat{\theta}_n$.

To implement the approach in our sample, we first aggregate the dataset in such a way that one observation corresponds to one client–loan cycle combination. After aggregation, the possible loan outcomes per observation are loan amortization, defaulting on the loan, or censoring (that is, the outcome is unobserved). In the next step, the survival function is estimated from the time-to-event data via the Kaplan-Meier estimator. Finally, each time-to-event observation is transformed based on its contribution to the estimated survival function. Each transform is therefore a function of the entire sample. The pseudo-observations are unbiased estimates under certain assumptions as discussed below, and serve as dependent variable in a standard instrumental variable framework, such as two-stage least squares (2SLS) or generalized methods of moments (GMM).

In analogy to the Cox model where the dependent variable is the hazard to default, in the pseudo-observation approach the dependent variable is the cumulative incidence function $C(t) = 1 - S(t)$, where the incidence is default.[7] A necessary assumption for unbiasedness of the pseudo-observations is that censoring is independent of both the outcome and the independent variables. If we considered default as the single possible outcome, every loan cycle without default would be counted as censored; however, the end of a loan cycle clearly is no random event and is obviously not independent from whether or not a default occurs. Therefore, in calculating the cumulative incidence function, we consider loan amortization at the end of a loan cycle as a competing event to default, in the sense that the two events are mutually exclusive (Fine and Gray, 1999). To implement the instrumental variable approach, we employ a two-step generalized methods of moments (GMM) estimator, which requires fewer distributional assumptions than the 2SLS estimator.[8] The endogenous variable in the IV approach is defined as the number of *new* bank relationships started by a client within a loan cycle, where a financial relation with a given lender is considered new when a client obtains a loan for the first time from this lender. To retain the total number of bank relationships in the model, we include a variable capturing the initial number of other bank relations, observed at the point in time when a client transacts with D-MIRO for the first time.

B. Using disruptions in the relationship between loan officer and client as instrument

We instrument the number of new bank relations by two variables that describe the dynamics of disruptions in the business relationship between loan officers and clients up to one year prior to, or during a new loan cycle. The first variable captures the number of loan officers changes a client faces because of internal loan officer rotation; this means that the loan officer who is substituted does not quit the bank but is usually (though not necessarily) relocated to other clients. The second variable captures the number of loan officers that stop serving a client because they leave the bank. Both variables and their suitability as instruments are discussed in the following.

[7] The exact equivalent of the Cox model is in fact the complementary log-log transform, defined as $\log(-\log(1 - S(t)))$ (Kiefer, 1988). However, the pseudo-observations of the survival function, while being unbiased estimates, are not restricted to the interval $[0, 1]$ (Andersen and Perme, 2010). For cases where they fall outside this range, the complementary log-log transform is thus undefined. Since in our case this scenario applies to a large number of observations, we instead employ the cumulative incidence function $C(t) = 1 - S(t)$.

[8] However, we also performed all IV regressions using the 2SLS method, which produced nearly identical results.

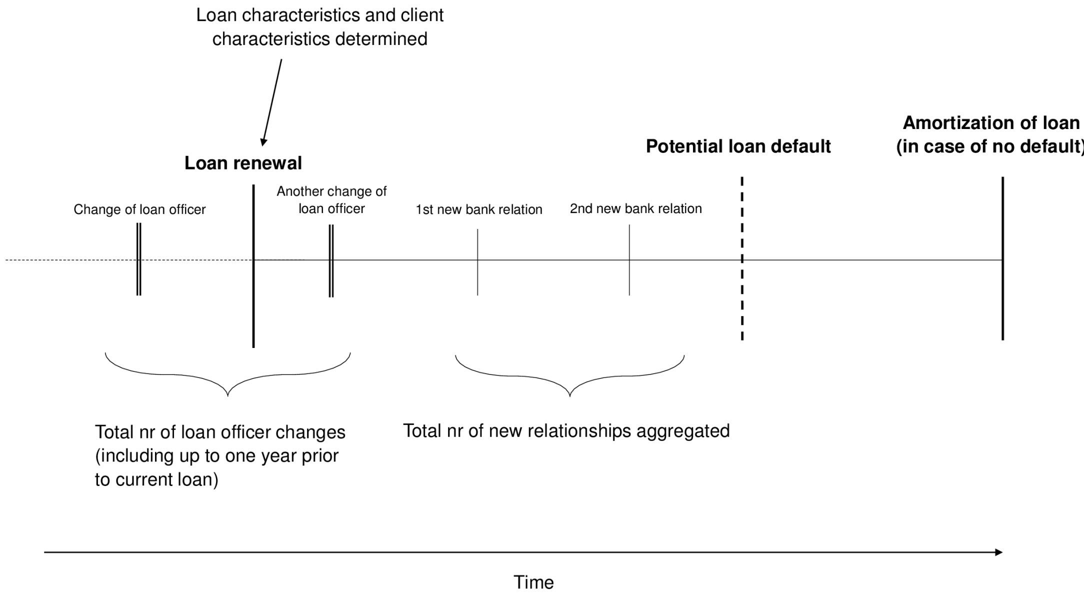


Figure 1: Order in which the information contained in one observation is determined in the IV approach

First, the order of outcomes matters, since any change in the loan officer-client link can be used as a meaningful instrument only if it occurs *before* the client may or may not start another bank relation (and, of course, before any potential default may be recorded). The instruments are therefore constructed such that they sum all loan officer changes for one client, starting from one year before and up to the point when the client may start a new bank relation. Figure 1 illustrates the chronological order of the outcome determination for all variables.

The rationale behind the instruments is that client-bank relationships are effectively created and preserved by the loan officer, who enjoys substantial autonomy in the credit allocation process. Several studies have confirmed the important role of the loan officer in credit allocation and as the main link between the bank and the customer (Fisman et al., 2017; Beisland et al., 2017; Agier and Szafarz, 2013; Beck et al., 2013a). In the relationship lending model where the bank acquires soft information about borrowers by interacting with them, the loan officer serves as "repository" of this information (Berger and Udell, 2002). In the same vein, Karolyi (2018) finds that personal borrower-lender constellations matter much more for lending relationships than institutional relations. Clients benefit from the soft information accumulated by loan officers in several ways: for instance, officers over time adapt their visit schedule to the clients' convenience, acquire first-hand knowledge about the clients' business performance, can take clients' private situation and related expenses into account in their timing of repayment collections, and can build mutual trust helping to assess the clients' honesty in reporting her financial situation, all of which creates a positive value of the lending relationship for the borrower. This in turn implies that a change in the loan officer can, all else equal, be perceived as costly by the client, which may provide an incentive for the client to contract a loan from another lender.

This reasoning is empirical supported when looking at the correlation between loan officer changes and new bank relations started by clients in our sample. Figure 2 plots the percentage of clients contracting outside bank loans against the number of loan officer re-assignments they experienced at D-MIRO. The figure shows that the more re-assignments client experience, the more likely they are to start another bank relation. Naturally, clients that advance to higher loan cycles are more likely to experience a loan officer change at some point simply because the time period in which a change may occur is longer. Therefore, we also show the percentages of new bank relations only for those clients that are at least in their second loan cycle at D-MIRO (dashed line). The patterns of both lines are fairly similar, confirming the overall conclusion that loan officer changes go along with a higher incidence of clients starting outside bank relations.

Besides the requirement that instruments are strong predictors of the endogenous variable, the second main assumption for instrument validity is conditional exogeneity of the instruments with the dependent variable, in our case the clients' ex-ante probability to default. The two instrumental variables we consider, officer rotation and officers leaving the bank, can be expected to differ in this regard. To begin with the former, loan officer rotation is largely conditioned by internal re-assignments of districts which a loan officer is in charge of. For logistical reasons, loan officers mainly remain within a prescribed area which enables them to visit several client a day (nonetheless loan officers typically spend a substantial amount of time travelling from one client to another, often more than one hour). Re-assignments to different clients take place for instance when a new officer joins a branch, when another officer quits the bank, or, less frequently, when a loan officer is relocated from one branch to another. In these cases, loan officers may be assigned to different clients simply because the boundaries of the prescribed area they are in charge of change.

Turning to the second instrumental variable, we observe in total 170 cases of leaves among the 288 loan officers captured over the four years that span our sample period.

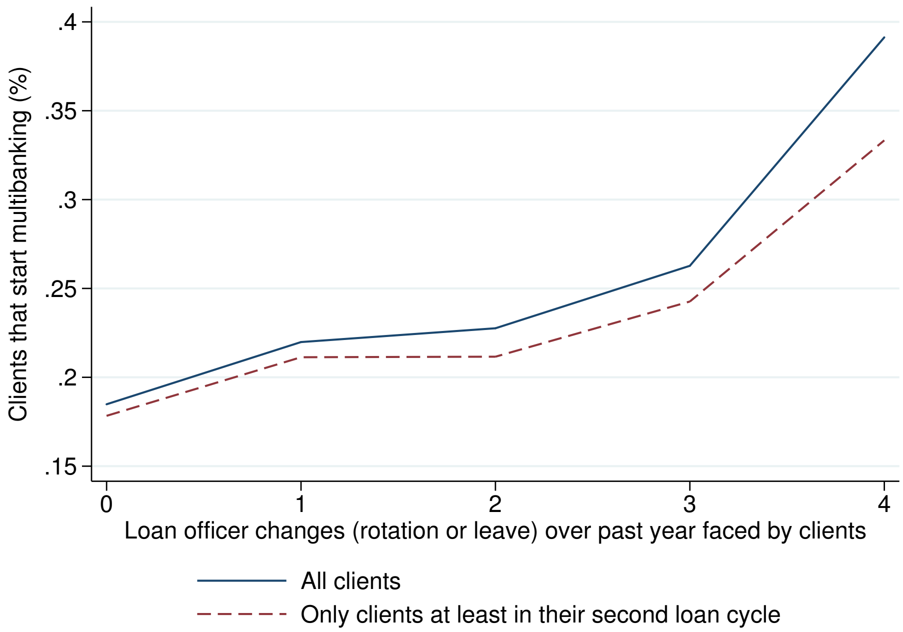


Figure 2: Loan officer changes and new bank relations of clients

The vast majority of leaves (135) are accounted for by resignations of loan officers, while the second most common reason for leave is layoffs (15).[9] Loan officers that resign typically leave for professional reasons, e.g. they may move on with their career, although we do not observe their further development. The assumption that loan officer layoffs are independent of loan performance is not easily justifiable; in particular, the probability to be fired might be correlated with the ex-ante credit risk of borrowers selected by an officer, or the officer's skills to enforce repayment. We shall return to a more general discussion and empirical checks of the exogeneity of the instruments in Section 4.5, where we also show that the observed credit risk of borrowers does not have explanatory power in determining layoffs once the number of borrowers served by an officer is controlled for.

[9] The remaining reasons are expiration of fixed-term contract (10 cases), internal re-assignment of duties (9) and death of the officer (1).

4 Results

4.1 Sample statistics

Table 1 summarizes key sample statistics. Panel A shows distributional figures on client characteristics. On average, 8.5 quarterly data points are available per client, thus covering a period of two years and one month. While clients' debt on average exceeds assets by a factor of 2.47, half of the clients are leveraged by not more than 80% on average, suggesting considerable right-skewness caused by some outliers.[10] Clients' total assets on average amount to about US$10,000, although the median is only about US$4,700. D-MIRO loans average at US$2,840. At the mean, clients have progressed to the third loan cycle, and on average 18 monthly loan repayments are scheduled per loan cycle, thus amounting to one and a half years. 57% of D-MIRO clients are women, which reflects the (yet weak) lending preference to women that is characteristic to the microfinance business. The poverty index, scaled from zero to 100 with larger values indicating higher well-being, is centred around 62 in the sample. Clients are on average 42 years old, but range from as young as 17 up to 79. In terms of formal educational attainment, most clients (56%) have completed secondary education. Finally, the majority of the clients (57%) earn their main income in small-scale retail activities, mostly as petty traders.

Panel B of Table 1 displays information on the frequency of defaults. In total, 19% of clients turn into arrears of at least 30 days at some point. If we only consider arrears longer than a year, the percentage of clients in default is still 7%. Long term defaults cut into the bank's profits considerably stronger: as shown in the second column, far more loans in long-term arrears end up being written off (44%) compared to short-term arrears (17%), while as shown in the third column, the amount of bad debt is on average higher for loans defaulted on in the long term ($743) compared to the short term ($531). Besides the financial costs, long term bad debt also incurs higher operational costs, as it binds more labour capacity needed for recollection attempts.

Table 2 illustrates the prevalence of multiple borrowing in the sample. The average client maintains 0.76 *additional* bank relations over the observed sample period, which

[10] E.g., the alarming maximum leverage of 48 times should not be taken literally: while liabilities obtained through the credit bureau are relatively comprehensive, it is likely that self-reported assets are—in some cases probably severely—under-reported, yielding substantially skewed leverage values. To mitigate right-skewed measurement error in the leverage variable, the log leverage is used in all empirical models.

Table 1: Sample statistics

Panel A. Client characteristics

Variable	Observations	Mean	Std. dev.	Median	Min	Max
Quarters available per client	84,508	8.54	5.1	8.0	1	18
Leverage (debt-to-asset ratio)[a]	83,569	2.47	5.0	0.8	0	48
Total assets[a]	83,662	10,047.40	13,857.9	4,683.1	0	92,110
Loan size D-MIRO	84,508	2,843.20	2,740.6	2,131.6	150	20,004
Loan cycle[a]	83,765	2.95	2.4	2.0	1	13
Total installments[a]	84,207	17.90	6.0	18.0	5	36
Female client	84,508	0.57	0.5	1.0	0	1
Poverty index	68,993	62.01	11.8	61.0	0	97
Age	84,508	41.76	11.7	41.0	18	79
Education:	84,508					
No completed degree		2.2%				
Primary		36.9%				
Secondary		55.9%				
Post-secondary		5.0%				
Sector of self-employment:	84,476					
Retail/Petty trading		56.8%				
Services		11.7%				
Manufacturing		8.0%				
Logistics		7.7%				
Accommodation/Catering		5.0%				
Agriculture		4.7%				
Construction/Supply		3.2%				
Professional		2.2%				
Other		0.7%				

Panel B. Client default statistics

	Percentage	Loans eventually written off	Amount defaulted on
Short term arrears	19.2%	16.8%	$531.72
Medium term arrears	13.4%	23.7%	$648.19
Medium-long term arrears	10.2%	31.0%	$718.62
Long term arrears	7.1%	44.2%	$743.87

Data source: Banco D-MIRO. *Notes:* Panel A shows descriptive statistics per client, observed over the period March 2012 to July 2016. Time-varying variables are first averaged within clients, and then between clients. Panel B depicts the percentage of clients who at some point default, the percentage of their loans that are eventually written off the bank's balance sheet, and their latest observed overdue debt (including written off amounts). Short term arrears, medium term arrears, medium-long term term arrears and long term arrears are arrears $\geq$ 30 days, $\geq$ 3 months, $\geq$ 6 months, and $\geq$ 12 months, respectively.

[a] trimmed at the 99th percentile.

Table 2: Financial relations with other institutes

	Avg. number of lending relations per client in sample period	Avg. outstanding debt, per financial relation	% of clients with at least one additional relation in sample period	Avg. number of new relations per client-cycle in sample period	% of clients starting at least one relation in sample period
Bank relations	0.76	$ 1,986	61.7%	0.20	32.6%
Fin. coop. relations	0.09	$ 2,800	12.1%	0.06	7.7%
Consumer credit	0.51	$ 396	62.4%	0.38	45.4%
Any financial relation	1.36	$ 1,360	81.7%	0.64	59.9%

Data source: Equifax Ecuador. *Note:* The numbers are average statistics about additional bank relations of D-MIRO clients over the period March 2012 to July 2016. Loans from D-MIRO are not included in the statistics.

in total makes 1.76 bank relations including D-MIRO. Few clients are members of a credit and savings cooperative, with less than one in ten observations. In contrast, consumer credit is common: if we randomly draw two client-quarter combinations out of our sample, one of them will on average entail an outstanding consumer loan. Indeed, 62% of all clients use consumer credit at least once over the entire observed period. Roughly the same percentage of clients takes some bank loan, while no more than 12% of clients at some point have taken a loan from a financial cooperative. Cooperatives exhibit the highest average outstanding balances, with clients having an average outstanding debt of $2,800 at one cooperative. Outstanding debt at commercial banks averages at $1,986. Consumer credit on average is much smaller, amounting to $396 on average, reflecting the many lower-end products sold on credit by small shops, which are included in this category.

The last two columns of Table 2 reveal the dynamics of clients' formal financial relations. On average, a new outside bank relation is contracted in one out of five D-MIRO loan cycles. Similarly, 0.38 new consumer loans are taken. Of course, the average values do not capture that some clients will generally make use of several different financial relations while others retain a single bank relation. This is however addressed in the last column, which shows that new relations are common across the board: 60% of clients start at least one new financial relation throughout the observed sample period, and about 33% start at least one new bank relation.

As Figure 3 shows, the average number of bank relationships remained stable at about 0.75 on average throughout the entire sample period; if anything, the trend

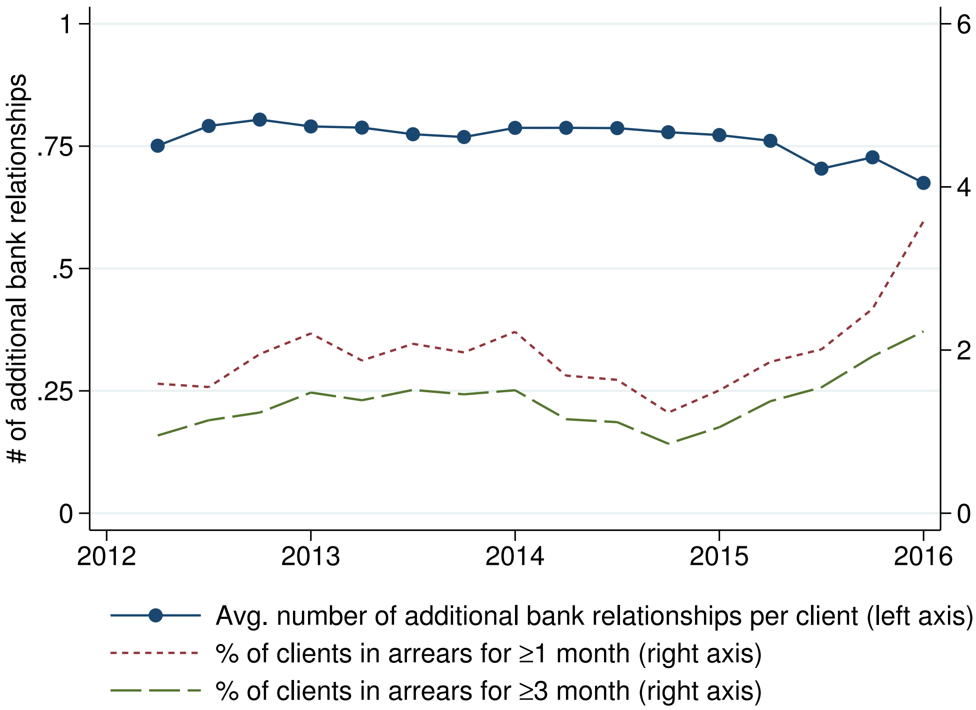


Figure 3: Financial relationships and defaults over time. *Sources:* Banco D-MIRO, Equifax Ecuador

slightly decreases during the second half of 2015. At the same time, defaults lasting for at least 30 days fluctuated around 2% from 2012 until the end of 2014, when an upward-sloping trend set off that culminated in a default rate of nearly 4% in 2016. A similar pattern can be observed for defaults lasting for a minimum of six months. The increase in default rates likely reflects the economic recession the country experienced since 2014.

4.2 Results from the naïve estimator

Table 3 displays the coefficients from the Cox regression model of borrowers' defaulting behaviour on the number of financial relationships and individual characteristics. The five models presented differ in the definitions of what constitutes a default, where the default "severity" increases from left to right: while in the first model any non-repayment of at least 30 days is counted as default, the last model requires arrears in excess of 12 months to define a default.[11] Loans that are written off the banks' balance

[11] This definition implies that clients who repay their overdue debt partially still qualify as defaulters.

sheet in the meantime continue to count towards the length of default. Exponentiated coefficients are displayed, which correspond to the hazard ratios of the independent variables.

For all four models we find that an additional bank relation is associated with higher odds of a subsequent default. The first model, considering arrears of 30 days or more, indicates an increase in the chance of defaulting of 22.7% per additional relation. The numbers for longer arrears remain high and significant, varying between 20.1% and 22.3%. Financial cooperatives, in contrast, are associated with a considerably higher default risk, increasing the likelihood to default in the long term by up to 55%. Other outstanding loans, which are essentially consumer loans, significantly increase chances to default, too. Their effect is lower than that of cooperatives, but higher than that of banks; for long term arrears the increase is 30.2%, which implies a 8 percentage points higher chance of long term default stemming from consumer loans as compared to bank loans.

Other things equal, more leveraged clients turn, perhaps surprisingly, less often into arrears. The size of the coefficient shrinks somewhat for longer arrears, but it remains negative. This implies that, given the number of different loans, smaller average loans from other institutions go along with a higher chance of default. This in turn is mirrored by the effect of the D-MIRO loan size: here too, a smaller loan is associated with a higher default probability, everything else equal and no matter the length of default. Further, clients with a higher value of fixed assets default less often. In all models, a longer relationship with D-MIRO substantially lowers the chances of defaulting by about 16.4% (short arrears) to 20.2.% (long term arrears) per loan cycle. This is consistent with the mechanisms of the relationship lending model, where learning effects about the borrower's repayment capacity and the accumulation of soft information manifest over time in a higher credit quality (Petersen and Rajan, 1994). Within one loan cycle, clients are more likely to turn into short term arrears the closer they are to loan maturity. In contrast, clients tend to turn into long term arrears the earlier on in the cycle they default, which implies that they carry on a growing debt burden over several missed installments. The poverty index, reflecting the client's overall living standard, significantly affects the default likelihood in the sense that poorer clients (corresponding to lower values of the index) have a higher chance to default. Women are found to default less often than men (23% less for long term arrears), corroborating similar findings from previous studies (de Janvry et al., 2010).

Table 3: Hazard ratios of defaulting from the naïve Cox estimator

	Length of default			
	short	medium	medium/long	long
# of bank relations	1.227***	1.205***	1.201***	1.223***
	(18.26)	(14.22)	(12.16)	(10.63)
# of fin. cooperative relations	1.448***	1.450***	1.508***	1.549***
	(17.33)	(15.09)	(14.44)	(10.89)
# of consumer loans	1.258***	1.252***	1.277***	1.302***
	(17.50)	(14.57)	(13.79)	(11.63)
Leverage (log)	0.754***	0.814***	0.819***	0.810***
	(−12.74)	(−8.19)	(−7.18)	(−6.08)
Remaining installments	0.968***	0.992***	1.007**	1.029***
	(−14.53)	(−3.30)	(2.70)	(9.19)
Total assets (log)	0.782***	0.815***	0.826***	0.839***
	(−18.86)	(−13.34)	(−10.89)	(−7.36)
Loan size (log)	0.801***	0.721***	0.678***	0.600***
	(−10.46)	(−12.97)	(−13.26)	(−13.08)
Loan cycle	0.836***	0.827***	0.817***	0.798***
	(−19.53)	(−16.82)	(−15.03)	(−12.84)
Poverty index	0.995***	0.994***	0.994***	0.994***
	(−5.89)	(−6.09)	(−5.43)	(−3.94)
Female client	0.857***	0.811***	0.794***	0.769***
	(−7.23)	(−8.35)	(−8.03)	(−7.20)
Age	0.984***	0.984***	0.982***	0.980***
	(−16.19)	(−14.20)	(−13.92)	(−12.30)
Fixed effects[a]	Yes	Yes	Yes	Yes
χ^2 likelihood ratio	7694.96	5047.13	3486.01	2518.80
LR test p-value	0.000	0.000	0.000	0.000
# of defaults	10,186	7,451	5,711	3,552
Total N	433,243	436,910	439,526	444,111

Data source: Banco D-MIRO and Equifax Ecuador. *Notes:* The table shows results from Cox regressions of default risk (using different spells of arrears) on the number of bank relations and other independent variables. The reported numbers are hazard ratios (exponentiated coefficients). Unit of observation is client-quarter. Short term arrears, medium term arrears, medium-long term term arrears and long term arrears are arrears $\geq$ 30 days, $\geq$ 3 months, $\geq$ 6 months, and $\geq$ 12 months, respectively. z-statistics in parentheses. *, ** and *** represent significance at 5%, 1% and 0.1% levels. Standard errors are clustered on the client level.
[a] Fixed effects on occupation, education, branch, and quarter level.

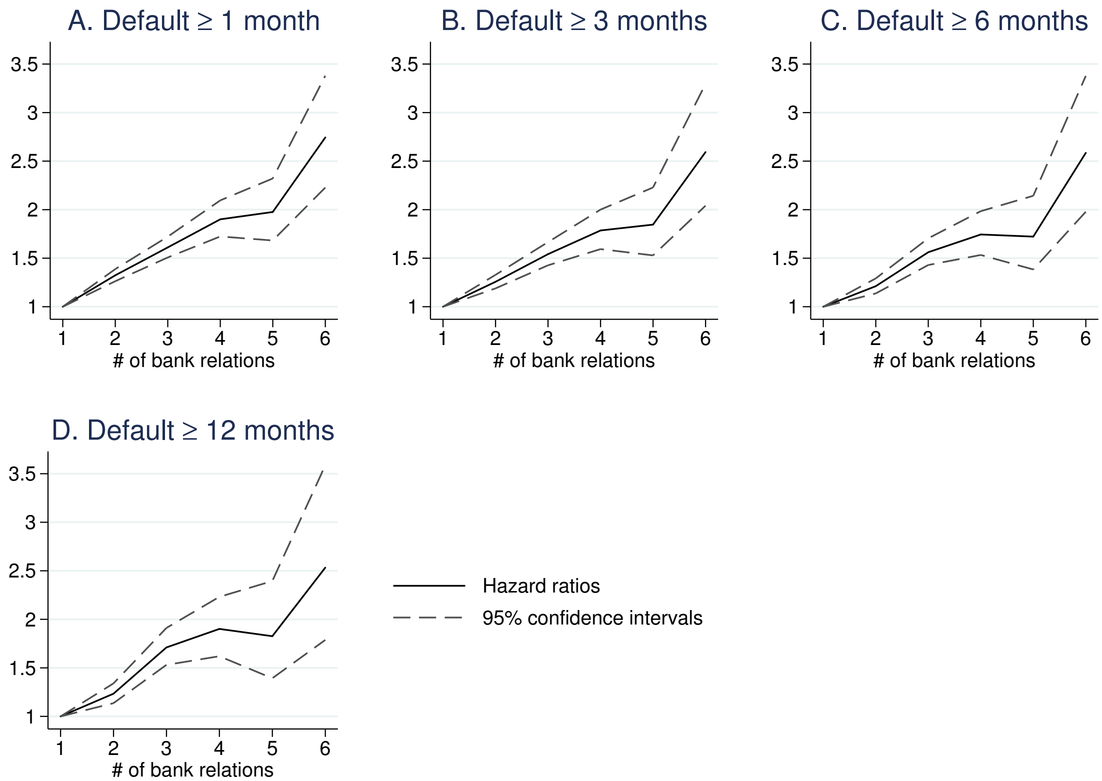


Figure 4: Nonlinear associations between bank relations and default risk

Data source: Banco D-MIRO and Equifax Ecuador. *Notes:* The five graphs depict hazard ratios (=exponentiated coefficients) of the number of bank relations obtained from regressions of default risk on the number of bank relationships and control variables. The graphs correspond to the five models reported in Table 3, where variable "# of bank relations" is replaced with dummies for each level (from 1 = single bank relation, to 6 = five or more additional bank relations.

Finally, age is negatively associated with the likelihood to default across all models (again as in de Janvry et al., 2010).

The results obtained so far present average or "lumped" associations between one additional bank relation and default risk, irrespective of how many bank relations a client already maintains. As an additional analysis, we relax this restriction in the following, allowing us to detect potential non-monotonicity in the associations between the number of bank relations and default risk. To this end we replace the number of bank relations with five dummy variables for each level, ranging from one up to five or more other bank relations, where the reference category is that a client maintains a single bank relation with D-MIRO. Except for this change, we run the same five models as previously. We focus on the coefficients of the inserted dummies and do not tabulate the entire table, but we note that overall the point estimates are very close to the ones obtained in Table 3.

The results are presented graphically in Figure 4, where the four graphs correspond to the five models shown in Table 3. All graphs depict a fairly linear, increasing association between the number of bank relations and the hazard to default until up to four bank relations, while a kink is observed between four and five bank relations.[12] Overall, increasing associations between the number of bank relations and default risk are thus in line with the linear association obtained in the Cox regressions in Table 3. In particular, for any number of relationships the 95% confidence intervals cover estimates strictly larger than one.

Taken together, the results suggest that each additional bank relation contracted by a client goes along with a higher probability of a default in the short, medium, and long run. However, as mentioned before, one inherent difficulty in estimating the effect of multiple bank relations on default is that the number of bank relations a client contracts is obviously not random. The results obtained so far are thus by nature descriptive, and no causal claims can be inferred from the number of bank relationships to credit risk. Importantly, causality might be reversed, that is default risk, caused for instance by financial distress or temporary illiquidity of the borrower, may induce clients to use a new loan to payoff a previous one. We address the endogeneity in the next section using the instrumental variable approach.

4.3 Results from the IV estimator

We explore the causality in this section by instrumenting the uptake of new bank relations by loan officer rotation on the client level. We draw on the instrumental variable approach suggested by Kjaersgaard and Parner (2016), in which censored duration data are transformed into uncensored pseudo-observations.

Table 4 reports the results of the IV GMM estimator, where the expected default risk estimated via the pseudo-observations approach is the dependent variable. It is regressed on the number of new bank relations during a loan cycle, which is instrumented by the number of new loan officers a client faces due to rotation, and the number of new officers due to loan officers leaving the bank. As before, the four different estimations use different definitions of default, depending on the duration of

[12]However, relatively few clients maintain more than four bank relations, which renders the estimates for those coefficients less precise, which is also reflected in the wider confidence intervals.

Table 4: Instrument GMM estimation of loan default

	Second stage: Default length				First stage
	short run	medium run	med.-long run	long run	
# new bank relations	-1.791^{***}	-1.511^{***}	-1.139^{***}	-0.528^{***}	
	(0.420)	(0.353)	(0.268)	(0.135)	
Loan officers rotating					0.0112^{*}
					(0.004)
Loan officers quitting					0.0202^{***}
					(0.005)
Loan cycle	-0.0208^{***}	-0.0166^{***}	-0.0127^{***}	-0.00619^{***}	-0.00708^{***}
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
Total installments	0.0139^{***}	0.0107^{***}	0.00785^{***}	0.00405^{***}	0.00419^{***}
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
# initial bank relations	-0.0540^{**}	-0.0471^{**}	-0.0340^{**}	-0.0118^{*}	-0.0422^{***}
	(0.019)	(0.016)	(0.012)	(0.006)	(0.003)
Leverage (log)	0.515^{***}	0.428^{***}	0.319^{***}	0.138^{***}	0.304^{***}
	(0.128)	(0.108)	(0.082)	(0.041)	(0.007)
Total assets (log)	0.260^{***}	0.220^{***}	0.167^{***}	0.0745^{***}	0.155^{***}
	(0.066)	(0.055)	(0.042)	(0.021)	(0.004)
Loan size (log)	-0.0744^{***}	-0.0544^{***}	-0.0386^{***}	-0.0181^{***}	-0.0252^{***}
	(0.015)	(0.012)	(0.009)	(0.005)	(0.005)
Poverty index	-0.00251^{***}	-0.00198^{***}	-0.00138^{***}	-0.000572^{**}	-0.00105^{***}
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Female client	0.0530^{**}	0.0424^{**}	0.0324^{**}	0.0131^{*}	0.0391^{***}
	(0.018)	(0.015)	(0.012)	(0.006)	(0.004)
Age	-0.00388^{***}	-0.00304^{***}	-0.00234^{***}	-0.00127^{***}	-0.00112^{***}
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.811^{***}	-1.650^{***}	-1.285^{***}	-0.588^{***}	-1.234^{***}
	(0.530)	(0.445)	(0.338)	(0.170)	(0.056)
Fixed effects[a]	Yes	Yes	Yes	Yes	Yes
Observations	72,319	72,319	72,319	72,319	72,319
F-stat. model fit	9.154	7.349	7.724	13.832	
J-test p-val.	0.900	0.799	0.719	0.314	
Weak idtf. F stat.					10.244
Under idtf. LM stat.					20.499
Under idtf. p-val					0.000

Data source: Equifax Ecuador and Banco D-MIRO. *Notes:* Unit of observation is a client-loan cycle. Standard errors shown in parentheses. Short term arrears, medium term arrears, medium-long term term arrears and long term arrears are arrears ≥ 30 days, ≥ 3 months, ≥ 6 months, and ≥ 12 months, respectively. Standard errors in parentheses. *, ** and *** represent significance at 5%, 1% and 0.1% levels. Standard errors clustered on the client level.
[a] Fixed effects on occupation, education, branch, and quarter level.

arrears. In all four models, we find that coefficients of the instrumented additional bank relations are consistently negative and significant at the 1% level for short, medium, or long lasting defaults. This implies that additional bank relations do not *per se* cause financial distress, but rather suggests that causality rather runs the other way. In fact, to the extent that the instrumental variable approach isolates the exogenous part of new bank relations taken up, a new bank relation reduces borrowers' credit risk. In addition to this, the number of initial bank relations (at the time when a client first transacts with D-MIRO), similarly exposes negative coefficients. As found before, clients in higher loan cycles are less likely to default, age decreases the chance of default, and clients with lower living standards are more likely to default.

In addition, the first stage estimates reveal interesting patterns. We note that although the relations between the excluded instruments and the endogenous variable need not be causal to fulfill the assumptions of instrument validity, they do provide insights for why clients may start a new bank relation that are in line with relationship lending theory. First, a client who faces a new loan officer at D-MIRO is more likely to subsequently contract a loan from another bank, all else equal. This is consistent with the borrower's perceived costs associated with a rupture in the business relationship with a loan officer, and is similarly found in the study of Drexler and Schoar (2014). The loss of the knowledge depository accumulated by the previous loan officer creates costs for the borrower that, other things equal, increase her propensity to contract another lender. Second, all else equal, clients in higher loan cycles are less likely to start another bank relation. This is consistent with the idea that borrowers benefit from a single bank relation only after the relationship has successfully been built over time (Petersen and Rajan, 1994; Puri et al., 2017). Taken together, these two results illustrate the mechanics of relationship lending: the more frequent the interactions between loan officers and clients, and the longer the period over which they last, the more likely they create ties that may benefit the borrower, and the less likely the client will contract a loan from a competitor.

Table 4 also reports several model statistics that allow to assess the statistical performance of the instruments. Specifically, it shows the cluster-robust F statistic from the Kleibergen-Paap rank test, testing for the presence of unacceptably large bias caused by instrument weakness, the Lagrange multiplier test for under-identification, and Hansen's $J-$test statistic for overidentification of the instruments. The tests for weak and under-identification are based solely on the first stage results and are therefore only reported once (since the first stage regressions in all specifications are equivalent). The weak identification statistic indicates that we can reject at the 5% level the null that the coefficients are biased by more than 20% (critical value: 8.75). Similarly, under-identification, i.e. the null hypothesis that the endogenous variable is not identified by the two instrumental variables, can be rejected at the 1% level. Finally, the $J-$test statistics, testing the null that the two instruments are correctly excluded from the second stage, cannot be rejected, which statistically supports our assumption of conditional instrument exogeneity.

4.4 Robustness checks of the results

We provide a couple of alterations to the main IV approach reported in the previous section in order to test the results for robustness. Specifically, we run the same models as in Table 4, but for different client subsets in order to address some caveats of the instrument exogeneity. The first alteration only considers experienced borrowers, namely those that are at least in their third loan cycle at D-MIRO. Since one loan cycle at D-MIRO runs on average over 18 months, many of these clients have borrowed for at least three years. While this specification substantially reduces sample size, it has the advantage of providing a cleaner sample that is more homogeneous in the sense that all clients have shown a good repayment performance over (at least) two cycles, and also in that the chance of facing a a loan officer change is more evenly distributed. In contrast, clients who drop out from the bank after one loan cycle have a lower chance of experiencing a loan officer change simply because of a shorter borrowing period.

A second alteration takes into account the different roles that banks may play in borrowers' financing decisions. When firms borrow from multiple banks, they may often perceive one of the banks as their main lender and other lenders rather as complements (Degryse and Ongena, 2007). While we have limited information on clients' length and depth of relations with other banks, we proxy the clients' main lending institutions by taking into account which bank they borrow from first: clients who do not have any outstanding loan from outside lenders at the time when they first transact with D-MIRO will likely consider D-MIRO as their main lender. Thus, in the second alteration we only focus on clients that do not have any other bank relation at the time they borrow from D-MIRO for the first time.

Finally, we consider a specification that drops those clients from the sample who already had a lending relationship with D-MIRO at the beginning of our sample period (third quarter of 2012). While likely only a mild caveat to the assumption of exogenous

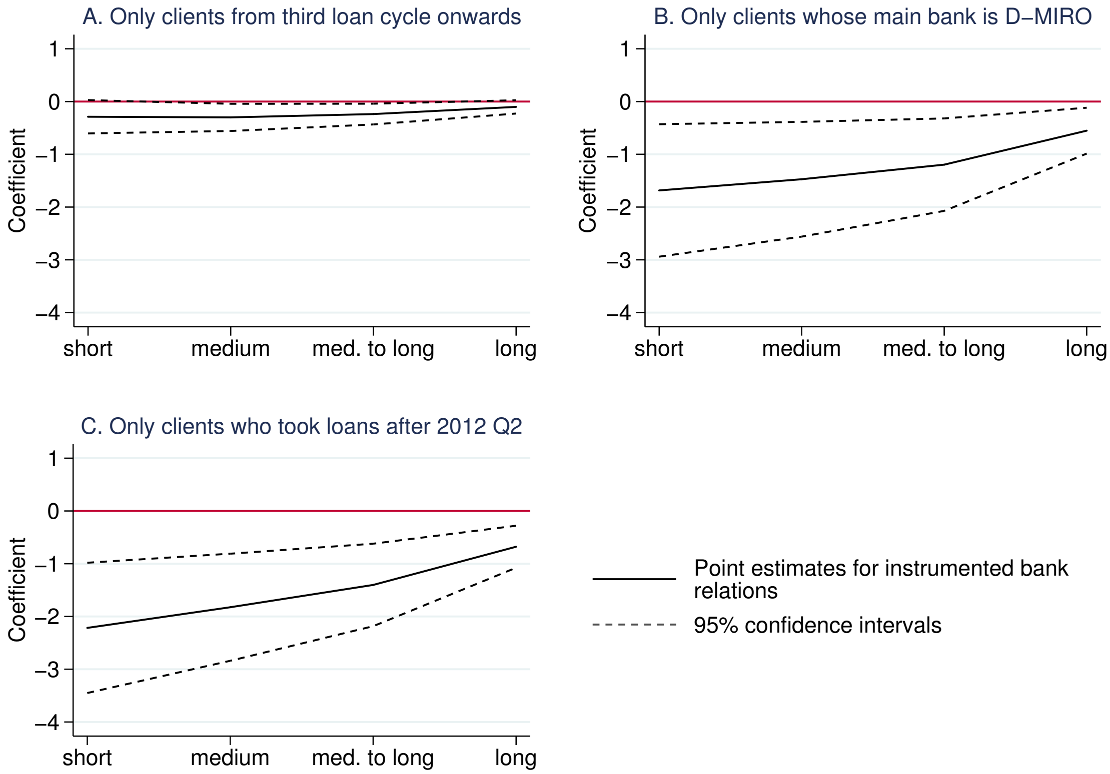


Figure 5: Effects of instrumented additional bank relations on default risk, using different client subsets

Notes: The graphs depict point estimates and confidence intervals from IV-GMM regressions where the dependent variable is expected default risk (as measured by pseudo-observations) for different lengths of arrears. Excluded instruments and control variables are the same as in Table 4, but the models use different subsets of clients: Model A only considers clients borrowing in their third or a higher loan cycle. Model B only considers clients whose first lender is D-MIRO. Model C only considers clients whose first loan at D-MIRO falls in our sample period (2012 Q2 to 2016 Q3).

instruments, it could be argued that these clients cause some additional self-selection in the sample. For instance, consider two clients who take a loan from D-MIRO in mid-2010, that is two years before our sample period begins. If only one of the two clients subsequently takes follow-up loans, this client will enter our data from her second loan onward. In contrast, the other client who starts borrowing at the same time but does not renew the loan thereafter will not be observed at all.

We apply all three alterations to the same models as in Table 4, but only report the parameters of interest: the coefficients from the instrumented number of additional bank relations, the first stage regression coefficients of the excluded instruments, and

Table 5: Additional model statistics and first stage results for the robustness checks from Figure 5

	(1) Model A	(2) Model B	(3) Model C
Loan officers rotating	0.0183*	0.00631	0.0111*
	(0.008)	(0.006)	(0.005)
Loan officers quitting	0.0317***	0.0174**	0.0187**
	(0.009)	(0.007)	(0.006)
N	20,011	41,244	55,156
Under-identification p-value	0.000	0.017	0.001
Kleibergen-Paap weak id. test stat	8.785	4.056	6.763
J-test p-value short arrears	0.312	0.496	0.926
J-test p-value medium arrears	0.326	0.565	0.960
J-test p-value med-long arrears	0.233	0.548	0.854
J-test p-value long arrears	0.428	0.365	0.283

Data source: Equifax Ecuador and Banco D-MIRO. *Notes:* Table shows model statistics for the three sets of models corresponding to Fig. 5: Model A only considers clients borrowing in their third or a higher loan cycle. Model B only considers clients whose first lender is D-MIRO. Model C only considers clients whose first loan at D-MIRO falls in our sample period (2012 Q2 to 2016 Q3). Standard errors, clustered on the client level, are shown in parentheses. *, ** and *** represent significance at 5%, 1% and 0.1% levels.

model statistics. The results are collected in Figure 5 and Table 5. Figure 5 graphically depicts the effects of the instrumented additional bank relations on default risk, broken down by the length of arrears. Panel A, considering only clients from their third loan cycle onwards, retains the the results obtained in the main IV specification according to which additional bank relation reduce default risk, although the effects shrink in magnitude, and for both short and long arrears the 95% confidence bands in fact cover a null effect (yet on a small margin). It should be noted, however, that the much smaller sample size means less variation in additional bank relations induced through loan officer changes, and thus lower statistical power to detect significant results. The two other alterations likewise confirm the previously obtained results: panel B, which only considers clients whose first bank is D-MIRO essentially reproduces the results in magnitude only with somewhat wider confidence bands, and panel C, where only clients are considered that entered the sample during our observed period, even produces stronger effects than the original IV specification.

The model statistics, displayed in Table 5, largely support instrument validity for the alterations. The under-identification test statistics is significant at 5% in all three alterations. For the second alteration (panel B of Figure 5), the Kleibergen-Paap test statistic indicates that instrument weakness might create a bias in the IV estimates;

this mirrors the statistically insignificant coefficient for rotating officers in the first stage of Model B. Yet, the second stage coefficients of additional bank relations, as shown in Figure 5, are numerically very close to those found in the main IV specification in Table 4. Finally, the $J-$test statistics in all three alterations and for any duration of arrears do not indicate a violation of instrument coherency.

In summary, we therefore conclude that the results are robust and not spuriously caused by a specific composition or selection of clients in the sample.

4.5 Exogeneity of the instruments

While neither loan officer rotation nor the hiring and firing of loan officers are random events, instrument validity requires them to be sufficiently exogenous to ex-ante loan default risk, conditional on observables. Therefore, in this section we undertake some empirical checks to validate our assumption of instrument exogeneity. To this end, we again (as in the robustness checks in Section 4.4) restrict the sample to a subset of clients that remain in D-MIRO's borrower pool at least until their third loan cycle. We classify this subsample into three categories: in the first one, clients will never experience a loan officer change during our observed period; in the second one, clients' loan officers will at some point rotate to other clients; and in the third one, clients' loan officers will leave the bank at some point. Exogeneity of the disruptions in the loan officer-client relationship postulates that the three subsets of clients should be similar *ex-ante*, i.e. before any such disruption occurs.

Table 6 displays an ex-ante comparison of the three client subsets to test whether the postulation holds. The results broadly confirm that clients are similar with respect to observable characteristics ex-ante, at the beginning of their first cycle. None of the variables exhibit a significant difference between clients whose loan officer will remain the same throughout the sample period compared to those who face a change, either because the loan officer rotates away or because she might leave the bank. In particular, the number of initial other bank relations, at the time when a client for the first time obtains a loan from D-MIRO, is similar across the three subsets, ranging from .50 for clients who will continue to be served by the same loan officer, to .54 for clients who will experience a loan officer rotation.

In addition, we take a closer look at the dynamics of loan officer internal rotation and employment at D-MIRO over time. Figure 6 visualizes these dynamics. While both loan officer rotation rates (Figure 6a) and officer turnover rates (Figure 6b) are

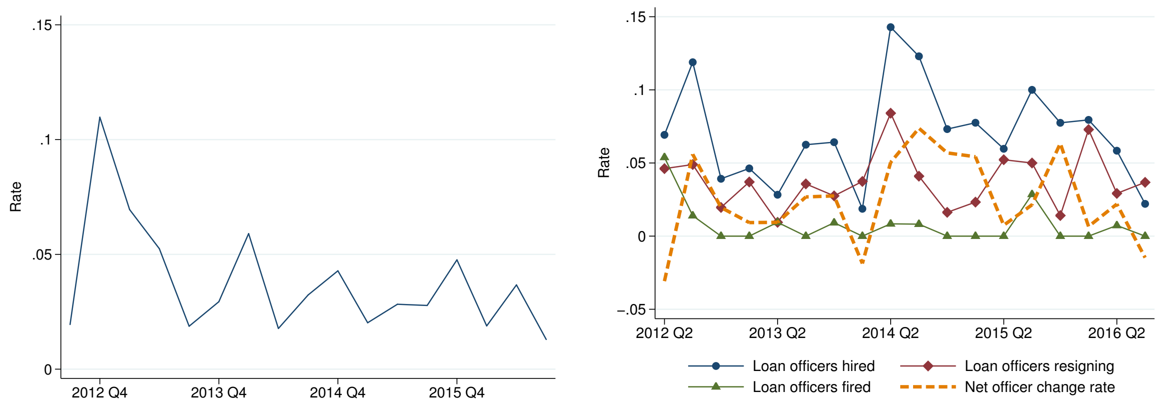
Table 6: Ex ante comparison of clients who will experience change of loan officer vs clients who won't

	Average values at beginning of relationship			Wald test p-value	
	Loan officer never changes (1)	Loan officer will rotate (2)	Loan officer will quit (3)	(1) vs (2)	(1) vs (3)
Installments of first loan	12.53	12.45	12.57	0.201	0.774
	(0.05)	(0.05)	(0.13)		
Initial other bank relations	0.50	0.54	0.53	0.146	0.379
	(0.01)	(0.02)	(0.03)		
Log leverage	1.00	0.97	0.94	0.221	0.090
	(0.01)	(0.02)	(0.03)		
Log assets	6.80	6.84	6.88	0.388	0.169
	(0.02)	(0.03)	(0.05)		
Log DMIRO loan size	7.04	7.02	7.02	0.385	0.530
	(0.01)	(0.01)	(0.02)		
Poverty index	59.43	58.98	60.21	0.204	0.116
	(0.22)	(0.28)	(0.45)		
Female client	0.59	0.60	0.61	0.259	0.237
	(0.01)	(0.01)	(0.02)		
Age	38.16	38.58	38.54	0.233	0.466
	(0.21)	(0.29)	(0.47)		
N	3,053	1,631	579		

Data source: Equifax Ecuador and Banco D-MIRO. *Notes:* Standard errors in parentheses. The figures are average values for clients at the beginning of their relationship with D-MIRO, i.e. before any loan officer relocation might occur. The analysis is restricted to borrowers who remain with D-MIRO for at least three loan cycles, to obtain a 'clean' sample.

at healthy levels from an organizational perspective and never exceed 15%, they vary considerably over the sample period. Figure 6 also shows that D-MIRO was on average expanding its workforce over the sample period, with the net officer employment rate being positive in every quarter except for 2012 Q2, 2014 Q1 and 2016 Q3. Overall, there does not appear to be any systematic trend that would indicate any shift of either bank employment policies or internal rotation policy to change.

Next, we address the issue that the fact that a loan officers quits the bank—in particular for those who are fired—might be correlated with the ex-ante credit risk of clients in the borrower pool they manage. To check whether this is the case, we run a Cox regression on the loan officer level that predicts the officer dropout. The results can be found in Table A.1 in the appendix. While we find that in a simple bivariate



(a) Loan officer rotation rate by quarter (b) Hiring and firing rates

Figure 6: Loan officer employment dynamics at D-MIRO

model, the share of non-performing loans in an officer's borrower pool is significantly correlated with dropout, the correlation drops sharply and becomes insignificant once the number of new clients served by the loan officer in the preceding quarter is controlled for. This shows that the scale of productivity used by the bank's management to assess loan officers' performance is primarily measured by the number of clients she is able to cater to, rather than the ex-post loan performance. In addition, we note that only few loan officers are actually fired (15 out of 287, or 5%), further mitigating the risk of confounding the instrumental variable estimation.

We undertake a similar check for loan officer rotation, where we look at the determinants of the rate by which an officer rotates away from clients. We include the same variables as in the Cox specification on officer dropout, but now run a fixed effects panel regression on the loan officer-quarter level (see Table A.2 in the appendix). We find insignificant effects of the share of non-performing loans across the board, no matter whether 30 days or 90 days non-performing loans are considered. Among the control variables, the officer's stock of clients significantly predicts rotation positively. This illustrates how areas designated to specific officers are re-defined in ways that balance out the number of clients in each loan officer's portfolio. In contrast, we find no statistical evidence that the average loan performance within an officer's portfolio would play any significant role in the re-assignment of officers to clients. Altogether, the checks are thus supportive of our assumption that disruptions in the loan officer-client relationships are conditionally exogenous of their clients' ex-ante default risk.

4.6 Discussion of the findings

Overall, our results point at different ways in which clients make use of outside bank relations. On the one hand, some clients may have a need for more flexible liability management, in particular a line of credit, which is purposefully not granted by the relationship lender in our study as to not compromise repayment discipline. For these clients, multiple bank relations reduce credit risk, where improved debt management may be one of the channels which translate to lower default risk. On the other hand, the "misuse" of multiple bank relations quantitatively dominates the positive effect of improved liability management and better credit risk, which results in an increased probability to default for the majority of those clients who resort to outside loans. Explanations for the increased credit risk include taking out a loan to pay off an outstanding loan from a different lender, which involves an unsustainable accumulation of debt due to compound interest, or the diversion of funds, for instance towards consumption purposes, both of which reflect moral hazard. While this underlines the elevated risk of moral hazard microlenders face when issuing loans intended for business purposes but with few options to monitor loan use, we note that the overall incidence of default remains rather low, ranging from 1.8% to 3.8% on average over the observed quarters, which shows that the discipline-based lending approach generally has its intended effect. In addition, methodologically our results show the importance of controlling for endogeneity in the effect of maintaining multiple bank relations.

Noteworthily, in our study multiple bank relations are frequent despite relatively complete information-sharing mechanisms between lenders through an existing credit bureau. Previous studies find that a credit bureau is an effective tool to cope with a lack of information-sharing between lenders and in addition exerts disciplining effects on the demand side that reduce moral hazard (de Janvry et al., 2010; Behr and Sonnekalb, 2012; Bennardo et al., 2015). Our results indicate that a credit bureau does not prevent multi-borrowing, as suggested for instance by McIntosh et al. (2005) or Bennardo et al. (2015). Although often assumed otherwise in the context of microlenders (McIntosh et al., 2005; Guha and Roy Chowdhury, 2013), it may be the case that lenders prefer to share the lending once information-sharing occurs. As theoretically shown by Carletti et al. (2007), lending institutions may enjoy a net benefit from multiple borrowing among their clients when they share the costs of monitoring opaque borrowers. Their model predicts that the benefits of sharing the monitoring are higher when lenders have low equity, expected returns of the borrowers' projects are low, monitoring is costly, borrowers are more opaque, and disclosure and accounting standards in the market are generally slack. All of these conditions tend to apply to the setting in our study, which is situated in Ecuador, an emerging market, and explain why multiple borrowing need not be perceived negatively from the lenders' perspectives.

Another relevant aspect of our study concerns competition in the lending market. Although we do not directly measure the extent to which competition varies during our sample period, we note that banks in Ecuador have been found to operate under a competitive environment by international standards (Beck et al., 2013b). Previous studies find ambiguous effects of competition on relationship lenders. Both Boot and Thakor (2000) and Degryse and Ongena (2007) find that competition in the inter-banking markets tends to increase lenders' propensity to rely on the relationship lending model, whereas Petersen and Rajan (1995) suggest that concentrated markets offer more favorable conditions for relationship lenders (and their borrowers). One argument put forward by the latter is that only a monopoly lender has incentives to extend credit to risky and opaque firms due to the opportunity to extract future rents, while by doing so, the lender improves the firm's credit quality, in turn helping the firm to tap into other debt sources. This scenario is likely relevant in our study too: a lender specifically targeting opaque microenterprises, who may ex-ante have low prospects of obtaining funds elsewhere, helps these borrowers to build a credit history over time, which may eventually give the borrower access to larger loans from arm's length competitors. This could eventually not only lead to multibanking, but even to clients fully abandoning the relationship lender, in particular when they hit the credit ceiling imposed by the lender. Yet, the significantly negative coefficient for the loan cycle obtained in the first stage regressions from the IV-GMM specification suggests that the relationship lending model mitigates such effects: the longer clients stay with the bank, the less likely they have other bank relationships, and the less likely they are to default on a loan.

Should a relationship lender then worry about its borrowers maintaining multiple bank relations? Based on our results, the answer to this is both yes and no. No, because multiple bank relations are in fact so common that more clients have them than not, whereas the average default rate of clients remains generally low, which suggests that under normal economic conditions, the magnitude of the association between bank relations and default is moderate. However, the answer is yes because multiple bank relations may signal either repayment problems on behalf of the client, or the need for more flexibility in financing decisions. An important recommendation for lenders is thus to identify clients who make use of multiple bank relations as a response to limitations in the products provided by the relationship lender. This may include a line of credit, grace periods of repayment, or access to multiple accounts. In fact, other studies have precisely used the availability of a line of credit or the number of accounts to identify relationship lenders (Berger and Udell, 1995). It may therefore be particularly in the provision of services where competition can make a dent in the demand for loans of the relationship lender. In this respect, banks whose lending model is focused on repayment discipline although loans are intended for business purposes may have to adjust their product line in order to remain competitive to lenders who offer more flexible loans.

5 Conclusion

In our sample of clients from an Ecuadorian relationship lender specialized on loans to microenterprises, we find that multiple bank relationships are more common than single-banking. 62% of borrowers in our sample use multiple bank relations at least once, and at a given point in time borrowers maintain on average 1.7 bank relationships. A naïve estimator not accounting for endogeneity yields a monotonous and positive association between the number of bank relations and clients' probability to default. Yet, this association appears to be driven by endogeneity: instrumenting the uptake of additional bank relations by disruptions in the loan officer-client relationship as instrument, we find evidence that multiple bank relations can reduce credit risk. We interpret this as indicating reverse causality, or put differently: borrowers with higher ex-ante credit risk tend to rely more on multiple bank relations, while some borrowers signal the need for more flexible financing and improve their credit risk through the use of multiple bank relations. The latter are, however, outnumbered by the former.

As is the case with every IV estimator, our results hinge on the use of specific instruments. While we undertake several statistical checks that support our assumption of conditional exogeneity of the instruments, similar empirical exercises that assign the number of bank relations quasi-experimentally can provide additional insights in how bank relations affect borrowers' credit risk. Another interesting research angle is to study to which extent multiple bank relations, and interbank competition more general, induce clients to switch their lender. Other avenues for future research include the interaction of formal credit use and informal credit use, which we do not observe in our study, but which has been found to play a role in financial decision-making of borrowers in other emerging market contexts (Degryse et al., 2016b).

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Appendices

A Additional checks for the exogeneity of loan officer dynamics

Table A.1: Cox regressions on loan officer dropout

	(1)	(2)	(3)	(4)
30 days default rate	6.583***	0.904		
	(6.66)	(−0.29)		
90 days default rate			6.021***	0.725
			(5.52)	(−0.83)
Nr of new clients		0.968***		0.967***
		(−6.36)		(−6.52)
Nr of clients		1.000		1.000
		(0.46)		(0.45)
Pseudo R^2	0.016	0.081	0.011	0.081
Observations	1,929	1,929	1,929	1,929
χ^2	44.4	67.0	30.5	64.2

Notes: Unit of observation is loan officer per quarter. The figures reported are hazard ratios, e^{β}, obtained from a Cox regression model where the event (failure) is a loan officer's leave from the bank, irrespective of the reason. 30 (90) days default rate denotes the share of nonperforming loans after 30 (90) days in a loan officer's loan portfolio. Nr of new clients denotes the nr of new clients assigned to an officer (both new and existing clients) in the quarter before the leave outcome is realized. Nr of clients denotes the size of a loan officer's client portfolio in the quarter before the leave outcome is realized. *, ** and *** represent significance at 5%, 1% and 0.1% levels. $t-$statistics are shown in parentheses. Standard errors are clustered on the loan officer level.

Table A.2: Fixed effects panel regressions on client rotation rate per loan officer

	(1)	(2)	(3)	(4)
30 days default rate	0.001	−0.044		
	(0.081)	(0.088)		
90 days default rate			−0.016	−0.052
			(0.101)	(0.108)
Nr of new clients		−0.014		−0.014
		(0.019)		(0.019)
Nr of clients		0.018***		0.018***
		(0.005)		(0.005)
Constant	3.547***	−1.186	3.634***	−1.216
	(0.627)	(1.564)	(0.574)	(1.550)
Observations	1802	1802	1802	1802
Within R^2	0.000	0.010	0.000	0.010
Between R^2	0.023	0.007	0.021	0.007

Notes: The table presents fixed effects estimates for determinants of the rotation rate of loan officers; rotation rate characterizes the rate in a given quarter by which a loan officer rotates away from D-MIRO clients that will continue to be served by another loan officer. 30 (90) days default rate denotes the share of nonperforming loans after 30 (90) days in a loan officer's loan portfolio. Nr of new clients denotes the nr of new clients assigned to an officer (both new and existing clients) in the quarter before the leave outcome is realized. Nr of clients denotes the size of a loan officer's client portfolio in the quarter before the leave outcome is realized. Unit of observation is loan officer per quarter. Standard errors are shown in parentheses. *, ** and *** represent significance at 5%, 1% and 0.1% levels.