DISCUSSION PAPER SERIES

DP13905
(v. 2)

Collateral and Asymmetric Information in Lending Markets

Vasso Ioannidou, Nicola Pavanini and Yushi Peng

FINANCIAL ECONOMICS

INDUSTRIAL ORGANIZATION

CEPR

Collateral and Asymmetric Information in Lending Markets

Vasso Ioannidou, Nicola Pavanini and Yushi Peng

This Discussion Paper is issued under the auspices of the Centre's research programmes:

- Financial Economics
- Industrial Organization

Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

The Centre for Economic Policy Research was established in 1983 as an educational charity, to promote independent analysis and public discussion of open economies and the relations among them. It is pluralist and non-partisan, bringing economic research to bear on the analysis of medium- and long-run policy questions.

These Discussion Papers often represent preliminary or incomplete work, circulated to encourage discussion and comment. Citation and use of such a paper should take account of its provisional character.

Collateral and Asymmetric Information in Lending Markets

Abstract

We study the benefits and costs of collateral requirements in bank lending markets with asymmetric information. We estimate a structural model of firms' credit demand for secured and unsecured loans, banks' contract offering and pricing, and firm default using credit registry data in a setting where asymmetric information problems are pervasive. We provide evidence that collateral mitigates adverse selection and moral hazard. With counterfactual experiments, we quantify how an adverse shock to collateral values propagates to credit supply, credit allocation, interest rates, default, bank profits, and document the relative importance of banks' pricing and rationing in response to this shock.

Vasso Ioannidou - v.ioannidou@lancaster.ac.uk
Lancaster University and CEPR

Nicola Pavanini - n.pavanini@tilburguniversity.edu
Tilburg University and CEPR

Yushi Peng - yushi.peng@bf.uzh.ch
University of Zurich

Collateral and Asymmetric Information in Lending Markets[*]

Vasso Ioannidou[†] Nicola Pavanini[‡] Yushi Peng[§]

August 2020

Abstract

We study the benefits and costs of collateral requirements in bank lending markets with asymmetric information. We estimate a structural model of firms' credit demand for secured and unsecured loans, banks' contract offering and pricing, and firm default using credit registry data in a setting where asymmetric information problems are pervasive. We provide evidence that collateral mitigates adverse selection and moral hazard. With counterfactual experiments, we quantify how an adverse shock to collateral values propagates to credit supply, credit allocation, interest rates, default, bank profits, and document the relative importance of banks' pricing and rationing in response to this shock.

JEL-classification: D82, G21, L13

Keywords: Asymmetric information, Structural estimation, Credit markets, Collateral

---

[†]Lancaster University and CEPR, v.ioannidou@lancaster.ac.uk

[‡]Tilburg University and CEPR, n.pavanini@tilburguniversity.edu

[§]University of Zürich and SFI, yushi.peng@bf.uzh.ch

1 Introduction

A vast theoretical literature studies the benefits and costs of collateral in debt contracts. On the positive side, collateral is argued to increase borrowers' debt capacity and access to credit, by mitigating both ex ante and ex post asymmetric information problem in credit markets. Since Stiglitz and Weiss (1981), the theoretical literature motivated collateral as a screening device to attenuate adverse selection (Bester 1985, Besanko and Thakor 1987*a*), and as a way of reducing various ex post frictions such as moral hazard (Boot and Thakor 1994), costly state verification (Gale and Hellwig 1985), and imperfect contract enforcement (Albuquerque and Hopenhayn 2004).[1] On the negative side, apart from limiting borrowers' use of the pledged assets, collateral is often blamed for amplifying the business cycle (Bernanke and Gertler 1989, Kiyotaki and Moore 1997). Appreciating collateral values during the expansionary phase of the business cycle fuel a credit boom, while their subsequent depreciation weakens both the demand and supply of credit, leading to a deeper recession. This "collateral channel" is viewed as one of main drivers of the Great Depression (Bernanke 1983), and a key factor behind the 2007-2009 financial crisis in the United States (Mian and Sufi 2011, 2014).

The extant empirical literature provides sharp micro-evidence on the impact of collateral on the demand and supply of credit, analyzing each individually by holding the other constant. Several studies show that increases in exogenous collateral values give firms access to more and cheaper credit for longer maturities (Benmelech, Garmaise and Moskowitz 2005, Benmelech and Bergman 2009), while exogenous drops in collateral values lead to higher loan rates, tighter credit limits and lower monitoring intensity (Cerqueiro, Ongena and Roszbach 2016). The associated changes in credit supply are found to have a significant impact on firm outcomes, such as investment (Chaney, Sraer and Thesmar 2012, Gan 2007) and entrepreneurship (Schmalz, Sraer and Thesmar 2017). Changes in collateral values are also shown to induce similar and contemporaneous changes in households' consumption, which further undermine firms' profits, and hence demand and access to credit (Mian and Sufi 2011, 2014). While these results provide evidence consistent with the expected role of collateral in credit markets with information frictions, they do not fully shed light on the underlying mechanisms and interactions, as they do not separately identify the role of demand and supply channels.

We fill this gap in the empirical literature on collateral by bringing the costs and benefits of collateral into a unified micro-founded structural framework of credit demand and supply. This approach allows us to test key assumptions and predictions of the theoretical literature that underlie the benefits of collateral, and to study how a shock to collateral values affects both the demand and supply of credit in the presence of asymmetric information frictions. We contribute to the literature on three key dimensions. First, by modeling firms' demand for secured and unsecured credit and subsequent loan repayment, we provide micro-founded evidence of the benefits of collateral under both the ex ante and ex post theories, estimating structural parameters that measure the effectiveness of collateral in mitigating both sets of frictions. Second, by modeling banks' loan supply of both collateralized and uncollateralized loans, we are able to separately

---

[1]Other important theoretical contributions include Besanko and Thakor (1987*b*) and Chan and Kanatas (1985) on ex ante frictions, Boot, Thakor and Udell (1991), Aghion and Bolton (1997), Holmstrom and Tirole (1997) on moral hazard, Banerjee and Newman (1993), Cooley, Marimon and Quadrini (2004) on imperfect contract enforcement, and Townsend (1979), Williamson (1986), Boyd and Smith (1994) on costly state verification.

quantify the role of credit demand and credit supply within the collateral channel, accounting for their inter-action. We do so by simulating a counterfactual scenario where the value of the pledged assets deteriorates, and measure the effect of this shock on banks' expected profits, their offering and pricing of secured and unsecured loans, and borrowers' loan demand and default. Third, by allowing banks to respond to a collat-eral value shock through both pricing and rationing, we can document the relative importance of these two margins at determining the effectiveness of collateral as a screening and monitoring device.

We estimate our empirical framework using the detailed credit registry data of Bolivia for the period be-tween March 1999 and December 2003. Besides extensive data availability through a comprehensive credit registry, Bolivia provides a good setting for analysis for two main reasons. First, the Bolivian credit market is characterized by deep informational asymmetries between borrowers and lenders, where the informational inefficiencies highlighted by the extant literature are likely to be important. In fact, even for our sample of mostly large and less risky firms, there is very little reliable information other than what is available through the credit registry. This happens because during the sample period there was no private credit bureau and the vast majority of Bolivian firms do not have audited financial statements (Sirtaine, Skamnelos and Frank 2004). This aspect is particularly useful in the context of our model, as it minimizes differences in the available information between the bank and the econometrician. Second, during the period of analysis the Bolivian credit market did not undergo any deregulation wave or phenomena such as loan sales and securi-tization. Banks in the sample are operating in steady-state under the traditional "originate and hold" model, allowing us to more closely approximate the bank and borrower incentives modeled in the related literature.

On the demand side, we estimate a structural model of borrowers' demand for credit where firms choose their preferred bank, and conditional on this choice they select a secured or unsecured loan and how much to borrow. We model imperfect competition among lenders allowing banks to be differentiated products and borrowers to have preferences for bank characteristics other than the contract terms offered. We also model borrowers' default on these loans. We let borrowers have heterogeneous preferences for loan interest rates and collateral requirements, and we allow their unobserved heterogeneity in price and collateral sensitivity to be jointly distributed with unobservable borrower characteristics that determine whether they default on their loans. This follows the approach of the empirical literature on testing for asymmetric information (Chiappori and Salanié 2000, Einav, Jenkins and Levin 2012), allowing us to test for the empirical relevance of both the ex ante and ex post channels of collateral, and to separately quantify adverse selection and moral hazard. The first channel predicts a negative correlation between borrowers' sensitivity to collateral and their default unobservables, which implies that riskier firms have greater disutility from pledging collateral than safer ones, and hence determines the extent to which collateral can mitigate adverse selection. The second channel predicts a negative effect of collateral on default risk, which implies that when firms pledge collateral their incentives to default on a loan are reduced, consistent with collateral mitigating moral hazard. We interpret a positive correlation between borrowers' price sensitivity and their default unobservables as evidence of adverse selection, since riskier borrowers are less price sensitive and thus more likely to take credit. Finally, we interpret a positive causal effect of loan interest rate on default as additional evidence of moral hazard.

On the supply side, we allow banks to offer borrower-specific contracts, in the form of secured and unsecured loans, to ration borrowers by offering only one of the two or none, and to compete Bertrand-Nash on interest rates to attract borrowers. We let borrowers have private information about their unobservable (to

both the lender and the econometrician) default risk, which implies that each bank offers the same interest rate to observationally equivalent borrowers. Specifying banks' borrower-specific profit functions we derive the equilibrium pricing equations for both secured and unsecured loans for each lender, and use these to back out their marginal costs. We then use the combination of demand, default, and supply models to conduct counterfactual policy experiments, where we simulate how shocks to collateral values influence the demand and supply of credit and banks' expected profits. This allows us to study the propagation of the collateral channel in the presence of asymmetric information, and to investigate the relative importance of banks' pricing and rationing response to a shock to collateral values.

We estimate our model using loan-level data from the Bolivian credit register. The credit registry includes detailed contract and repayment information on all loans originated in Bolivia. We have data for the period 1999-2003 and focus on commercial loans granted by commercial banks as in Berger, Frame and Ioannidou (2011). This allows us to keep the set of lenders and borrowers homogenous and focus on a class of loans where collateral is (only) sometimes pledged, as predicted by the theoretical literature. The sample includes term loans (installment and single payment), which account for 92% (85%) of the total value (number) of commercial loans to firms in the registry.[2] We mostly avoid modeling the evolution of borrower-lender relationships over time, to minimize the asymmetry of information about borrowers' quality between the econometrician and banks (Petersen and Rajan 1994, Berger and Udell 1995, Degryse and Van Cayseele 2000). We therefore focus on firms that take a loan for the first time within our sample period, and track their loan originations for their first 18 months in the sample. Crucially, these are the borrowers for which information frictions might be most severe, and collateral requirements might be most effective. One challenge we face is that we only observe the loans a borrower finally chooses, but not the whole set of offers available to the borrower. We therefore need to predict the set of contracts that are available to each borrower as well as the interest rate offered. Exploiting multiple lending relationships that each borrower has, we use fixed effects models and a propensity score matching method to predict the available contracts and the missing interest rates. The advantage of using borrower fixed effects is that it controls for borrowers' information that is observable to banks but not to the econometrician. In the estimation of the structural model, we provide an identification strategy to address potential price and collateral endogeneity concerns in both our borrowers' demand and default models.

We find evidence consistent with both the ex ante and ex post theories of collateral, and quantify their empirical relevance. Consistent with the presence of adverse selection, we find a positive and significant correlation of 0.10 between borrowers' price sensitivity and their default unobservables, implying that riskier borrowers are indeed less price sensitive and hence more likely to demand a loan than safer borrowers. In accordance with the ex ante theories that collateral mitigates adverse selection, we find a negative and significant correlation of -0.42 between borrowers' sensitivity to collateral and their default unobservables, which suggests that riskier borrowers tend to have a higher disutility from pledging collateral, and are therefore less likely to demand a secured loan compared to safe borrowers, allowing collateral to serve as a screening device. Furthermore, we find that riskier borrowers have a higher marginal rate of substitution of collateral for price – a key assumption in the ex ante theories, which to the best of our knowledge has never been verified before. Consistent with the presence of moral hazard, we also find a positive and significant

---

[2]We do not include mortgage or credit card loans as they are either always secured or always unsecured.

causal effect of loan interest rates on default. Our estimates indicate that a 10% increase in loan interest rates raises the average default probability of a loan by 16.7%. Finally, in accordance with the ex post theories that pledging collateral mitigates moral hazard, we find a negative and significant causal effect of collateral on default, indicating that on average posting collateral decreases the probability of default by 27.6%.

We use the estimates of our structural model, together with our supply side framework, for counterfactual policy experiments. We simulate the effects of a 40% drop in collateral values on credit supply, credit allocation, interest rates, and banks' expected profits.[3] This exercise allows us to study the propagation of the collateral channel across various credit, borrower, and bank outcomes, and to understand the relative effectiveness of banks' pricing and rationing as alternative or complementary strategies to respond to the shock. If we let banks' respond to the drop in collateral value only through pricing, we find a 2.1% median increase in interest rates, a 1.5% median increase in default probabilities, and a median 4.4% and 5.0% decrease respectively for expected borrowers' demand and banks' profit. When we instead allow banks to respond to the shock with both pricing and rationing, we find that 39% of the loan contracts have become unprofitable and hence are not offered by banks anymore. This rationing allows banks to reduce significantly their price response relatively to the previous case. We are also able to investigate whether collateral is an effective screening device, by regressing our model-predicted probability of choosing a secured loan on a set of controls, including unobserved borrower risk, backed out from our estimation. We find that collateral is effective at screening under the baseline level of collateral value, as one standard deviation increase in borrower's unobserved risk leads to a 0.5 percentage points increase in her probability of choosing a secured loan. When we shock collateral values with a 40% drop we find that if banks only respond to the shock via pricing, collateral becomes ineffective as a screening device, but if banks can use both pricing and rationing, collateral is almost as effective as in the baseline scenario. Rationing allows in fact banks to reject borrowers whose assets were most severely affected by the shock, for whom collateral would not achieve an effective screening anymore, while still offering secured and unsecured loans to the least affected borrowers, for whom instead the screening role of collateral is still preserved.

We contribute mostly to three broad strands of literature. First, we provide new supportive evidence of the ex ante and ex post theories of collateral. Existing work provides reduced form evidence consistent with theoretical predictions of both sets of theories. Consistent with the ex post theories that banks require collateral from observably riskier borrowers, several studies document that the incidence of collateral is positively related to observable borrower risk.[4] Evidence for the ex ante theories is instead scarce, as borrowers' unobservable risk is typically not observable to the econometrician and difficult to disentangle from ex post frictions. A rare exception is Berger, Frame and Ioannidou (2011), who exploit an information sharing feature of the Bolivian credit registry, using borrowers' historical performance that is unobservable to lenders but observable to the econometricians as a proxy of borrowers' private information.[5] Their findings support

---

[3]A 40% drop in collateral values is similar in magnitude to drops in collateral values documented in the literature during economic downturns, such as the burst of the Japanese assets price bubble that caused land prices in Japan to drop by 50% between 1991 and 1993 (Gan 2007), the early 30% drop of the Case-Shiller 20-City Composite Home Price Index in the U.S. during the 2007-2009 financial crisis, and the increase in average repo haircut on seven categories of structured debt from zero to 45% between August 2007 and December 2008 (Gorton 2010).

[4]For example Berger and Udell (1990), Blackwell and Winters (1997), Machauer and Weber (1998), John, Lynch and Puri (2003), Jiménez and Saurina (2004), Brick and Palia (2007), Berger, Frame and Ioannidou (2011), Godlewski and Weill (2011).

[5]Relatedly, Berger, Espinosa-Vega, Frame and Miller (2011) take advantage of the adoption of an information-enhancing loan

both sets of theories and indicate that ex post frictions are empirically dominant. The structural approach in this paper allows us to go beyond testing the two sets of motives for pledging collateral to additionally assessing whether collateral is effective in mitigating the associated frictions.

Second, we contribute to the empirical literature on the collateral channel. One line of papers in this area focusses on how exogenous variation in collateral values influences credit supply by exploiting exogenous variation in commercial zoning regulations (Benmelech, Garmaise and Moskowitz 2005), asset redeployability of airline fleets (Benmelech and Bergman 2008, 2009), regulatory changes affecting creditor seniority (Cerqueiro, Ongena and Roszbach 2016, 2019), or rich credit register data (Luck and Santos 2019). A related line of papers in this area traces the effects of exogenous shocks to collateral values on firms' investment (Chaney, Sraer and Thesmar 2012, Gan 2007), employment (Ersahin and Irani 2018), and entrepreneurship (Adelino, Schoar and Severino 2015, Corradin and Popov 2015, Kerr, Kerr and Nanda 2015, Schmalz, Sraer and Thesmar 2017). A smaller set of papers studies the broader effects of collateral shocks. For example, Benmelech and Bergman (2011) study how drops in collateral values, arising from negative externalities of bankrupt firms on their non-bankrupt competitors, amplify industry downturns. A more recent line of papers in this area also studies the amplifying role of the housing net worth channel during the recent financial crisis. House price appreciation prior to the financial crisis triggered significant increases in existing homeowners' consumer demand and leverage (Mian and Sufi 2011), while the subsequent collapse in house prices during the financial crisis led to decreases in consumer demand, which in turn weakened further the real economy, especially in the non-tradeable sectors (Mian and Sufi 2014). We are closer to the first line of papers in this area, as we focus on the effect of the collateral channel on firms' debt capacity and access to credit. Our structural approach allows us to trace the impact of shock to collateral values, accounting for feedback effects between banks' and borrowers' behavior. Differently from the papers listed above – that exploit identification strategies holding either credit demand or supply constant – our structural framework can decompose the collateral channel into its demand and supply effects. Moreover, our approach also allows us to capture spillover effects of a shock to collateral values from secured to unsecured loan rates and demand, a channel previously unexplored by the extant literature. We find that spillover effects on unsecured loan rates are of similar magnitude to direct effects on loan rates of secured loans.

Third, we contribute to the recent strand of literature on empirical models of asymmetric information using both reduced form and structural methods (Karlan and Zinman 2009, Adams, Einav and Levin 2009, Einav, Jenkins and Levin 2012). Our modeling approach is closest to Crawford, Pavanini and Schivardi (2018), who focus on the interaction between asymmetric information and imperfect competition in the context of Italian unsecured credit lines. We share a similar identification method by combining credit demand for differentiated products and ex post debt performance. We generalize their approach by considering both secured and unsecured loans, allowing for multi-dimensional bank screening through both interest rates and collateral requirements. More generally, we contribute to the growing literature using structural methods from empirical industrial organization to model financial markets, with applications to deposits (Ho and Ishii 2011, Egan, Hortaçsu and Matvos 2017, Honka, Hortaçsu and Vitorino 2017), corporate loans (Crawford, Pavanini and Schivardi 2018), mortgages (Benetton 2019, Robles-Garcia 2019), insurance (Koijen and Yogo 2016), and investors' demand for assets (Koijen and Yogo 2019).

_____

underwriting technology, showing that after its introduction lower collateral incidence is consistent with the ex ante channel.

The paper is organized as follows. Section 2 provides a data description and institutional details. Section 3 presents the structural model. Section 4 describes the econometric framework, including price prediction and identification strategies. The estimation results are presented in Section 5. Section 6 presents the counterfactuals, and Section 7 concludes.

2 Data and Descriptive Evidence

We make use of the data from Central de Informatión de Riesgos Crediticios (CIRC), the public credit registry of Bolivia, provided by the Bolivia Superintendent of Banks and Financial Entities (SBFE) between January 1998 and December 2003. The SBFE requires all formal (licensed and regulated) financial institutions operating in Bolivia to record and share information on their loans.[6] This aims to facilitate the supervision of the financial sector and reduce the otherwise pervasive information asymmetries in the Bolivian credit markets. Besides the information shared through the credit registry or through a bank-firm relationship, banks have very limited reliable information about borrowers. For example, during the sample period there was no other comprehensive private credit bureau operating in the country (De Janvry, Sadoulet, McIntosh, Wydick, Luoto, Gordillo and Schuetz 2003) and the vast majority of firms in the registry did not have audited financial statements (Sirtaine, Skamnelos and Frank 2004).

For each loan, we observe the identity of the bank originating the loan, the date of loan origination, the maturity date, the loan amount, the loan interest rate,[7] the type and estimated value of collateral securing a loan as well as ex-post loan performance information (i.e., overdue payments or defaults). Information on type of credit is only available as of March 1999. We thus begin our sample in March 1999 and use the earlier information from January 1998 to identify pre-existing bank-borrower lending relationships.[8] Borrowers information includes a unique identification number that allows us to track borrowers across banks and time, an industry classification code, the region where the loan was originated, the borrowing firms' legal structure, current and past bank lending relationships, the borrowers' internal credit rating with each bank, and current and past credit history (i.e., overdue payments or default with any bank in the registry).[9]

The credit registry includes loans from commercial banks as well as other non-bank financial institutions (e.g., microfinance institutions, credit unions, mutual societies, and general deposit warehouses). To keep the set of lenders and borrowers homogenous in terms of financial structure, regulation and lending technologies, we focus exclusively on commercial loans granted by commercial banks. Typically only the larger and better firms in Bolivia have access to the commercial banks. A large number of micro firms have access only to the informal sector and microfinance institutions. During the sample period, there are 12 commercial banks operating in Bolivian, half of which are foreign owned.[10] There are several types of commercial credit

---

[6]After written authorization from a prospective borrower, banks can access the registry to obtain a credit report containing information on all outstanding loans and the borrower's past repayment history (e.g., current overdue payments and past defaults).

[7]We have access to a single variable for interest rate that is the combination of APR and fees, and are unable to separate the two.

[8]We do not have access to data prior to January 1998, so we cannot identify pre-existing relationships before that time.

[9]For confidentiality reasons borrowers' identifiers were altered, preventing us to match firms to any publicly available database.

[10]We exclude ABN AMRO as it left the Bolivian market in November 2000 and in the year prior to formally exiting the market it only originated a very small number of loans. We also exclude Banco Boliviano Americano that failed two months after the beginning of our sample period (in May 1999). The 12 banks in our sample are: Banco Santa Cruz (Foreign), Banco Industrial, Banco Nacional de Bolivia, Banco Mercantil, Banco de Credito de Bolivia (Foreign), Banco de la Union, Banco Economico,

contracts in the data, including credit cards, overdrafts in the current account, credit lines, term loans (either instalment or single payment), and mortgage loans. As in Berger, Frame and Ioannidou (2011) we focus on term loans, for which collateral is only sometimes pledged. We thus exclude all other types of products that are always uncollateralized (e.g., credit cards, overdrafts in the current account, and credit lines) or always secured (e.g., mortgage loans and discount documents). Focusing on a fairly homogenous type of credit that is sometimes secured or unsecured helps reduce concerns that the presence or absence of collateral is symptomatic of complementary types of credit used by the firm for different purposes (e.g., term loans and credit lines). The terms loans we focus on account for about 92% (85%) of the total value (number) of commercial loans to firms. This yields a sample of 32,274 loan originations (i.e., loans originated sometime during the sample period) to 2,676 unique firms, including new loans to new or existing customers.

In order to minimize the information asymmetry on borrowers' private information between the econometrician and banks, we follow the literature on testing for asymmetric information (Chiappori and Salanié 2000) and focus only on firms that enter the formal credit market for the first time, for which banks have no previous credit records. This leads to a sample of 561 new borrowers that we track for the first 18 months since their initial loan origination, resulting in 1,650 loans used for the estimation of the structural model. Hence, on average, we use around 3 loans per borrower, because focusing only on the first loan would result in a too small sample of 561 loans.[11] As we explain in more detail in Section 4, we need to predict interest rates for loan contracts offered to borrowers but not chosen. For this exercise, we use a larger sample to achieve higher statistical power by including borrowers who entered the credit register no more than 6 months before the beginning of our sample. This larger sample consists of 9,400 loan originations to 1,421 borrowers, among which are the 561 borrowers in our restricted sample that enter the credit registry for the first time. This allows us to use on average 6.6 loans per borrower for our interest rate prediction.

Table 1, Panel A provides summary statistics for both samples. The average annual interest rate is just above 14% for both samples and secured loans have on average lower interest rate than unsecured loans by about 70 to 90 basis points (i.e., by about 5% to 6% of the average loan interest rate).[12] About 40% of collateralized loans are secured with real estate ("Immovable"), 26% to 30% are secured with liquid movable assets such as bonds, securities, and deposits ("Liquid Movable"), and about 30% to 34% are secured with more firm-specific movable assets such as inventories, equipment, vehicles, accounts receivable that have typically smaller more illiquid secondary markets ("Illiquid Movable"). The average collateral value to the loan amount is between 2.5 to 2.7 in the both samples. The average loan amount is between USD 130k to USD 147k, with secured loans being on average larger (between USD 250k and USD 222k) relative to unsecured loans (between USD 102k and USD 99k). Loan maturity is rather short, with an average between 13 and 15 months, a median of 6 months, and over 95% of loans having maturities shorter than five years. Secured loans have on average longer maturities (between 19 and 24 months) relative to unsecured

---

Citibank (Foreign), Banco Ganadero, Banco Solidario, Banco do Brazil (Foreign), and Banco de la Nacion Argentina (Foreign). Foreign-owned banks operating in Bolivia have similar rights and responsibilities as domestically-owned institutions.

[11] We also estimated the model on this smaller subsample of 561 loans and found qualitatively and quantitatively similar results.

[12] Small interest rate discounts between secured and unsecured loans are driven by borrower heterogeneity, as riskier borrowers which pay higher premiums are also more likely to be asked to pledge collateral. Interest rate comparisons between secured and unsecured loans in the literature yield mixed results, with many studies finding no discounts or even higher interest rate on secured loans, even in regression analyses with borrower controls, due to inability to fully account for unobserved borrower heterogeneity (see for example Benmelech and Bergman 2009 and Berger, Frame and Ioannidou 2016).

loans (around 11 months). Between 50% to 55% of loans are installment loans, while the rest are single-payment loans. About 4% of loans to new borrowers and 12% of all loans are classified as having potential repayment problems ("Bad Credit Rating"). For both samples, about 65% of borrowers are corporations, while the rest are mainly sole proprietorships or partnerships. The largest sectors are wholesale and retail (25% of firms), manufacturing (18% of firms), and construction (13% of firms). Between 12% to 26% of loans are granted to "Defaulting Borrowers" with ex post repayment problems, i.e., borrowers who had at least one non-performing loan during the 18 months after receiving their first loan. This is also our definition of a "Defaulting Borrower" throughout the paper.

In Panel B of Table 1 we summarize monthly bank balance sheet information on household deposits – an important piece of data that we will use in our identification strategy later on. Deposits from households are distinguished into savings and demand deposits with a mean of 62 and 60 million USD, respectively. On average, deposits account for 73% of banks' liabilities, and the average annualized interest rate on savings deposits is 7 percentage points.

As illustrated in Figure 1, the number of banks that are lending to new borrowers varies significantly across regions, with more banks present in urban areas. For example in La Paz, the country's capital, all 12 banks originated loans to new borrowers, while in more rural areas such as Potosi only 3 banks originated loans to new borrowers. Each bank is active across different regions. For example, during the sample period, Banco Nacional De Bolivia and Banco De Credito De Bolivia established new lending relationships in almost all regions, while Banco Do Brasil only granted loans to new borrowers in La Paz. This gives us heterogeneity in borrowers' choice sets of banks depending on their location. In particular, we define a lending market as the region-quarter combination where and when each borrower is making its choice of preferred lender and loan, and all banks actively lending in each market as each borrower's potential choice set. In total, we have 105 region-quarter markets in the sample.

Table 1: Summary Statistics of Commercial Loans

Variable	N. Obs	Mean	St. Dev.	N. Obs	Mean	St. Dev.
Panel A: Loan Level	**New Borrowers**			**Borrowers Active since 6 Months**		
Interest Rate	1,650	14.29	2.62	9,400	14.33	2.32
Secured	519	13.80	2.40	2,185	13.66	2.53
Unsecured	1,131	14.51	2.68	7,215	14.53	2.22
Collateralized	1,650	0.33	0.46	9,400	0.23	0.42
Immovable	519	0.41	0.49	2,185	0.39	0.49
Liquid Movable	519	0.30	0.46	2,185	0.26	0.44
Illiquid Movable	519	0.29	0.46	2,185	0.35	0.48
Value-to-Loan Ratio	519	2.66	4.42	2,185	2.49	6.04
Amount	1,650	146.58	461.12	9,400	129.94	426.76
Maturity	1,650	15.49	21.95	9,400	12.63	18.05
Installment Loan	1,650	0.55	0.50	9,400	0.50	0.50
Bad Credit Rating	1,650	0.04	0.19	9,400	0.12	0.32
Corporation	1,650	0.65	0.48	9,400	0.65	0.48
Defaulting Borrower	1,650	0.12	0.32	9,400	0.26	0.44
Panel B: Bank Level						
Saving Deposit	619	62.17	51.78			
Demand Deposit	619	60.10	46.05			
Deposits to Liabilities	619	0.73	0.12			
Saving Deposit Interest Rate	619	6.99	3.32			
Panel C: Loss Rates						
Loss Given Default	283	0.35	0.46			
Loss from Defaulting Borrower	299	0.05	0.18			

Note: This table summarizes information from three datasets we use. Panel A's unit of observation is a new borrower's first loan or a loan granted to borrowers who entered the credit registry since no more than 6 months. Interest Rate is the annual percentage rate, which is divided into two subgroups: interest rate for secured loans (Secured) and unsecured loans (Unsecured). Collateral is a dummy variable taking the value of one if a loan is secured and zero if it is unsecured. Immovable is a dummy variable taking the value of one if the collateral is immovable (real estate) and zero otherwise. Movable Illiquid (Movable Liquid) is a dummy variable taking the value of one if the collateral is movable but illiquid (movable and liquid), for example, inventory, equipment, vehicle, accounts receivable (for example, bank deposits, bonds, securities), and zero otherwise. Value-to-Loan Ratio is the ratio of collateral value to the loan amount for secured loans only. The loan Maturity is in months, and loan Amount is in 1,000 USD. Installment is a dummy variable taking the value of one if this is an installment loan and zero if it is a single payment loan. Bad Credit Rating is a dummy variable taking the value of one if the loan has any overdue payments or is in default and zero otherwise. Corporation is a dummy variable taking the value of one if the borrower is a corporation and zero if it is a sole proprietorship or partnership. Defaulting Borrower is a dummy variable taking the value of one for loans that are granted to borrowers who had at least one non-performing loan within the sample period and zero otherwise. Panel B's unit of observation is a bank-month level balance sheet entry. Saving Deposit, Demand Deposit are in millions of USD. Saving Deposit Interest Rate is the annual percentage rate. Panel C's unit of observation is a defaulted loan or a loan granted to a defaulting borrower. Loss Given Default is the loss rate of defaulted loans. Loss from Defaulting Borrower is the loss rate from borrowers who had at least one non-performing loan during the sample period after receiving their first loan.
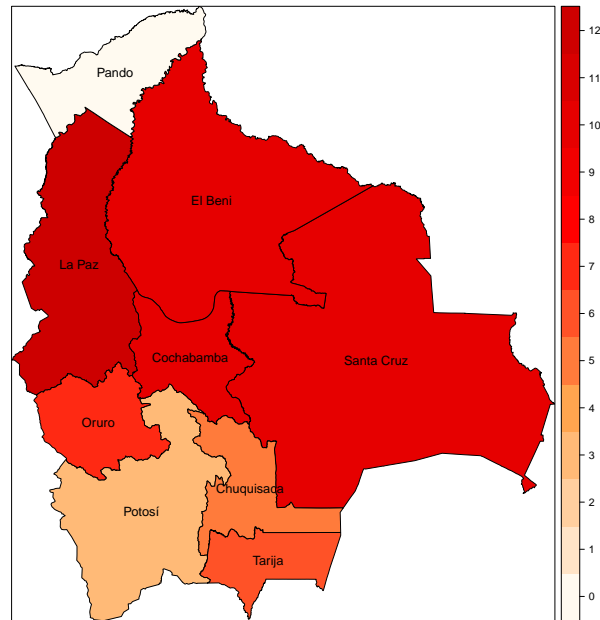
Figure 1: Number of Banks Establishing Lending Relationships with New Borrowers across Regions

Note: This figure shows the regions where banks granted loans to new borrowers during 1999 to 2003. The banks are Banco Nacional De Bolivia S. A., Banco Mercantil S. A., Banco De Credito De Bolivia S. A., Banco De La Nacion Argentina S. A., Banco Do Brasil S. A., Banco Industrial S. A., Citibank N.A. Sucursal Bolivia, Banco Santa Cruz S. A., Banco Union S. A., Banco Economico S. A., Banco Solidario S. A., Banco Ganadero S. A.. The regions are Chuquisaca, La Paz, Cochabamba, Oruro, Potosi, Tarija, Santa Cruz and El Beni, and foreign.

Among the loans granted to new borrowers within the first 18 months, nearly one-third of loans (519) are secured. Borrowers compare potential loan offers not only with respect to the bank, but also with respect to whether they have to pledge collateral or not. The data suggest that a certain level of discretion exists. For example, Figure 2 reports the distributions of the propensity score for taking a secured loan for borrowers that take up a secured or an unsecured loan.[13] The two distributions' overlap in the middle, which indicates that a wide range of borrowers are almost equally likely to choose secured or unsecured contracts.

Value-to-loan ratios vary significantly with the type of collateral pledged. As can be observed in Figure 3, collateral values for loans secured with immovable assets are often three to four times larger than the loan amount, possibly reflecting the indivisible nature of such assets. Consistent with the more divisible nature of movable assets, a larger number of loans secured with movable assets have value-to-loan ratios equal to one, particularly when secured with movable assets that are more "generic" and liquid in nature. For example, value-to-loan ratios for loans secured with deposits and other financial securities (liquid movable collateral) are clustered around one. Loans secured with other movable assets such inventories, equipment, vehicles, and accounts receivable (illiquid movable collateral) have instead somewhat higher value-to-loan ratios, consistent with lower expected recovery rates on such assets. Such assets are typically more firm-specific with smaller and less liquid secondary markets (Williamson 1988, Shleifer and Vishny 1992) and

---

[13]The propensity score is estimated using the bank identity, loan amount and maturity categories, borrower's legal structure, industry, and whether the loan is the borrower's first loan in the registry. In Section 4.1.2 we discuss the propensity score matching in detail.
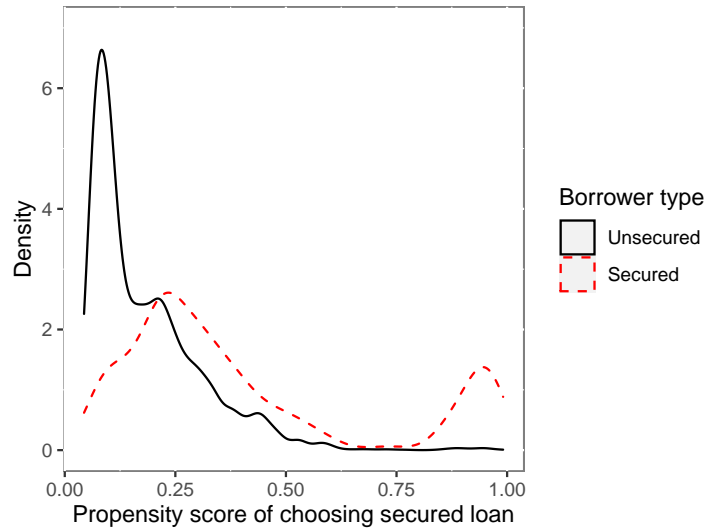
Figure 2: Propensity Score of Choosing A Secured Loan

Note: This figure shows the distributions of the propensity score of choosing a secured loan as opposed to an unsecured loan for borrowers that accepted a secured loan (secured borrower) or an unsecured loan (unsecured borrower). The solid line represents unsecured borrowers, and the dashed line represents secured borrowers. There is a wide range over which the two distributions overlap: A borrower with a propensity score in the overlapping region can become either a secured or an unsecured borrower.
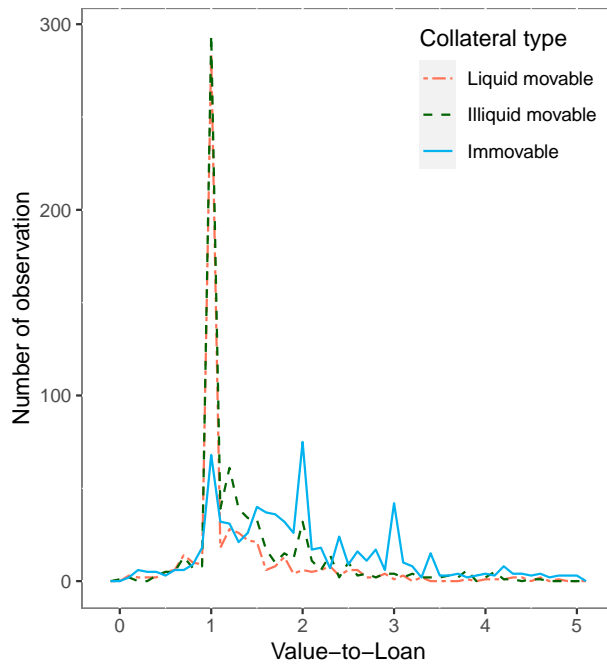
Figure 3: Collateral to Loan Ratio by Types

Note: This figure illustrates the distribution of collateral to loan value for immovable collateral, liquid movable collateral, and illiquid movable collateral. The collateral to loan ratio is truncated at 5, which means the collateral value is 5 times of the loan amount. For liquid movable, illiquid movable, and immovable collateral type, there are 3.8%, 3.9%, 14.5% of loans with Value-to-Loan ratio above 5 respectively.

are more susceptible to managerial tunnelling (Aghion and Bolton 1992, Hart and Moore 1994, 1998). The extant empirical literature provides supportive evidence of this, as several studies find that asset specificity reduces significantly the liquidation values of pledged assets (Benmelech, Garmaise and Moskowitz 2005, Benmelech and Bergman 2008, 2009). Using internal bank data, Degryse, Ioannidou, Liberti and Sturgess (2020) find that bank expected liquidation values on movable collateral carry on average a 30% discount relative to immovable collateral (i.e., the bank expects that on average 30% of the value of movable assets will be lost in liquidation, in sharp contrast to immovable assets which are found to carry almost no liquidation discounts).

In the empirical analysis, we account for this collateral "pecking order" by assigning a 100% expected recovery rate on defaulting loans secured with immovable collateral[14], a 90% expected recovery rate on loans secured with liquid movable collateral, and a 70% recovery rate on loans secured with illiquid movable collateral. We thus effectively assume that immovable collateral is fully pledgeable (as in Hart and Moore 1994, 1998), while movable collateral is only partially pledgeable.[15] We approximate banks' expected recovery rates on defaulted unsecured loans using the average recovery rates on defaulted unsecured loans to similar borrowers in the registry (i.e., borrowers in the same industry and with the same credit rating).[16] To avoid right censoring, we focus exclusively on loans that reach maturity before the end of our sample, and estimate the recovery rate on defaulted unsecured loans as 1 minus the write-off amount at maturity divided by the contractual loan amount. For these calculations, we only focus on loans that have been persistently classified as non-performing or in default for at least 6 months.

As shown in Table 1 Panel C, the average loss given default rate is 0.35 and therefore the average recovery rate in default is 0.65. This variable is calculated based on information that banks report ex-post, but matches closely their ex-ante expectation, and is in line with estimates in the literature.[17] Similarly, we define the loss rate of defaulting borrowers (i.e., those having at least one non-performing loan within the sample period) as the borrower's total amount of write-offs divided by the borrower's total amount of loans granted. This variable is mechanically smaller than the loss rate given default, as we are simply increasing the size of the denominator from the previous formula by taking into account the borrower's total amount of loans granted. As can be observed in Table 1, the average loss rate of an unsecured loan granted to a

---

[14]Reflecting both the high expected recovery rates on immovable assets and the high value-to-assets, arising possibly from the indivisible nature of immovable assets.

[15]In robustness checks we also assign 100% recovery rates on loans secured with deposits. Results (available upon request) are both qualitatively and quantitatively similar to those presented in the paper.

[16]Note that we cannot rely on the same data to derive banks' average recovery rates on secured loans, as recovery time for collateralized loans is considerably longer. For this reason we rely on literature evidence for recover rates on secured loans, and on our own data for unsecured loans.

[17]The literature suggests that bank loan recovery rates range from 60% to 90%. Several factors such as loan and borrower characteristics as well as macroeconomic conditions affect the recovery rates. Asarnow and Edwards (1995) use 831 commercial and industrial loans and 89 structured loans made by Citibank over 24 years and find an average recovery of 65% for commercial and industrial loans and 87% for heavily collateralized structured loans. Acharya, Bharath and Srinivasan (2007) report recovery rates of 81.12% for bank loans in the United States for the period from 1982 to 1999. Khieu, Mullineaux and Yi (2012) find the average recovery rate is 84.14% for North American loans in default in the period 1987 to 2007. Davydenko and Franks (2008) provide information on small firms that defaulted on their bank debt in France, Germany, and the United Kingdom in the years 1996 to 2003. The bank recovery rates are sharply different with median recovery rates of 92% in the United Kingdom, 67% in Germany, and 56% in France.

defaulting borrower is 0.05. We need this variable to match our definition of defaulting borrower in the structural model where the unit of observation is at the firm-bank level. Accordingly, if on the one hand our defaulting borrower variable is on average actually higher than the default probability over an individual loan, on the other hand this is balanced by the loss rate from defaulting borrower that is on average lower than the loss given default over an individual loan.

It remains an open question whether borrowers in our sample use all of their pledgeable assets for the secured loans they take or whether they have any remaining assets that could be pledged if they wanted to take any extra collateralized credit. This is an important piece of information for our counterfactual analyses because when we simulate a drop in collateral value we do not give borrowers the option of pledging additional assets to increase their debt capacity. We justify this assumption with descriptive evidence consistent with borrowers being "collateral constrained". We find that 31% of borrowers whose first loan is unsecured, obtain a new unsecured loan within 3 months. We find instead that just 19% of borrowers whose first loan is secured obtain a new secured loan within 3 months. Among this 19%, only 4% use a different collateral type compared to the one used for the first loan, while the remaining 96% use the same collateral type (we focus on a 3-months horizon as firms might be acquiring new assets over time, eventually expanding their potential set of pledgeable assets). Focusing on the full 18 months, on average each month 46% of borrowers have more than one outstanding loan, but only 13% of borrowers have more than one secured loan outstanding. We interpret this as suggestive evidence that firms are collateral constrained, hence almost always using the maximum value of their pledgeable assets to take credit. This allows us to rule out the option of firms to pledge new assets when their pleaded assets drop in value.

3 The Model

3.1 Demand and Default Model

Our modeling approach generalizes that of Crawford, Pavanini and Schivardi (2018). We assume that new borrowers seek credit for an exogenously given amount and maturity combination,[18] and shop around banks that actively lend in their region-quarter looking for the most profitable option. We allow firms to choose not only their preferred bank, but also whether they want to pledge collateral or not, conditional on a bank offering them the option of both a secured and an unsecured loan. Unfortunately, we do not observe firms not taking loans, so we are unable to model borrowers' choice of an outside option. Specifically, we let borrower $i = 1, .., I$ in market $m = 1, .., M$, defined as a region-quarter combination, take a loan of type $k = \mathcal{S}, \mathcal{U}$, where $\mathcal{S}$ stands for secured and $\mathcal{U}$ for unsecured, from bank $j = 1, .., J_m$ based on the following indirect utility function, which determines the borrower's loan demand (D):

---

[18]We will allow firms to choose their preferred loan amount in the counterfactual exercises, as discussed in Section 4.3. However, allowing for endogenous firms' choice of amount and maturity at this stage would substantially complicate the model, as it would require us to assume a set of potential amount and maturity options available to the borrower that we do not observe in the data. Moreover, it would imply that banks could use amount and maturity as additional screening and competitive devices, on top of interest rates and collateral requirements. However, given the non-exclusive nature of these loan contracts, it is less likely that banks would use the loan amount as a screening device, as borrowers can linearize the price schedule by taking multiple loans from various banks. Modeling these margins is challenging and we leave it for future research.

$$U_{ijkm}^D = \alpha_{\mathcal{P}i}^D P_{ijkm} + \alpha_{\mathcal{C}i}^D C_{ijkm} + \alpha_{\mathcal{Z}}^D Z_{ijm} + X_{jm}' \alpha_{\mathcal{X}}^D + \nu_{ijkm}^D, \tag{1}$$

where P_{ijkm} is the interest rate offered by bank j to borrower i, C_{ijkm} is a dummy indicating whether the loan is secured $\mathcal{S}$ or unsecured $\mathcal{U}$, Z_{ijm} is a dummy indicating whether at the time of loan origination borrower i has any outstanding lending relationship with bank j, as a proxy for switching costs or inertia, X_{jm} are bank-market characteristics, and ν_{ijkm}^D are Type 1 Extreme Value distributed shocks. We let $\alpha_{\mathcal{P}i}^D, \alpha_{\mathcal{C}i}^D$ be borrowers' normally distributed heterogeneous preferences for interest rate and collateral, which will depend on the relationship dummy Z_{ijm}, as borrowers with an existing relationship may have different price and collateral sensitivities, and borrowers' private information $\varepsilon_{\mathcal{P}i}^D, \varepsilon_{\mathcal{C}i}^D$ (unobserved by banks and the econometrician) as follows:

$$\alpha_{\mathcal{P}i}^D = \overline{\alpha}_{\mathcal{P}}^D + \alpha_{\mathcal{P}\mathcal{Z}}^D Z_{ijm} + \varepsilon_{\mathcal{P}i}^D \quad , \quad \alpha_{\mathcal{C}i}^D = \overline{\alpha}_{\mathcal{C}}^D + \alpha_{\mathcal{C}\mathcal{Z}}^D Z_{ijm} + \varepsilon_{\mathcal{C}i}^D. \tag{2}$$

Following the descriptive evidence reported in Section 2, we assume that when choosing a secured loan a firm has no discretion over the type and amount of collateral to pledge, as this is entirely determined by the lender. We model a situation in which the firm presents its pledgeable assets to the lender and requires the maximum amount of credit that the lender is willing to grant using those assets as collateral. Hence, we rule out any signaling that the firm might engage in by choosing a specific type and amount of collateral to pledge. We do so to keep the model tractable, and because we do not have data on other potential pledgeable assets that each firm might have. Similarly to loan demand, we model borrowers' default (F) as being determined by the following indirect utility function:

$$U_{ijkm}^F = \overline{\alpha}^F + \alpha_{\mathcal{P}i}^F P_{ijkm} + \alpha_{\mathcal{C}i}^F C_{ijkm} + \alpha_{\mathcal{Z}}^F Z_{ijm} + X_{jm}' \alpha_{\mathcal{X}}^F + Y_i' \alpha_{\mathcal{Y}}^F + \varepsilon_i^F, \tag{3}$$

where ε_i^F represents the borrower's private information component, unobserved by banks and the econometrician, that affects their likelihood of repayment. Y_i are instead borrowers' observed characteristics.[19] We let price and collateral coefficients in the default model to depend on the relationship dummy Z_{ijm} as:

$$\alpha_{\mathcal{P}i}^F = \overline{\alpha}_{\mathcal{P}}^F + \alpha_{\mathcal{P}\mathcal{Z}}^F Z_{ijm} \quad , \quad \alpha_{\mathcal{C}i}^F = \overline{\alpha}_{\mathcal{C}}^F + \alpha_{\mathcal{C}\mathcal{Z}}^F Z_{ijm}. \tag{4}$$

In the spirit of the empirical literature on testing for the presence of asymmetric information (Chiappori and Salanié 2000, Einav, Jenkins and Levin 2012), we let $\varepsilon_{\mathcal{P}i}^D, \varepsilon_{\mathcal{C}i}^D, \varepsilon_i^F$ be distributed according to the following multivariate normal distribution:

$$\begin{pmatrix} \varepsilon_{\mathcal{P}i}^D \\ \varepsilon_{\mathcal{C}i}^D \\ \varepsilon_i^F \end{pmatrix} = \left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{\mathcal{P}}^2 & \rho_{\mathcal{P}\mathcal{C}}\sigma_{\mathcal{P}}\sigma_{\mathcal{C}} & \rho_{\mathcal{P}F}\sigma_{\mathcal{P}} \\ \rho_{\mathcal{P}\mathcal{C}}\sigma_{\mathcal{P}}\sigma_{\mathcal{C}} & \sigma_{\mathcal{C}}^2 & \rho_{\mathcal{C}F}\sigma_{\mathcal{C}} \\ \rho_{\mathcal{P}F}\sigma_{\mathcal{P}} & \rho_{\mathcal{C}F}\sigma_{\mathcal{C}} & 1 \end{pmatrix} \right). \tag{5}$$

The demand and default model allows us to disentangle the adverse selection and moral hazard channels. The adverse selection channel is identified through the covariance matrix of unobservables, which captures the relations of unobserved default risk and firms' unobservable preference for interest rate and collateral in

---

[19]Note that we cannot include Y_i in equation (2) because it would be constant across all alternatives.

loan demand. The moral hazard channel is identified through the direct impact of interest rate and collateral on default, given that the selection channel has been accounted through unobservables.

We interpret a positive correlation between unobservables determining price sensitivity and default $\rho_{\mathcal{P}F} > 0$ as evidence of adverse selection, as riskier borrowers have lower price sensitivity (as $\overline{\alpha}_{\mathcal{P}}^D < 0$) and therefore are more likely to take credit. We interpret a negative correlation between unobservables determining collateral sensitivity and default $\rho_{\mathcal{C}F} < 0$ as evidence that collateral mitigates adverse selection by inducing separation of borrowers of different risk, as riskier borrowers have higher disutility from pledging collateral. Moreover, we would expect $\rho_{\mathcal{P}C} < 0$, which implies that borrowers with higher disutility from price (i.e., safe borrowers if $\rho_{\mathcal{P}F} > 0$) are also those with lower disutility from pledging collateral (i.e., safe borrowers if $\rho_{\mathcal{C}F} < 0$). Finding that $\rho_{\mathcal{P}C} < 0$ is also evidence that collateral combined with interest rate can serve as a signaling or screening device, because it implies that a price sensitive borrower is more likely to be collateral tolerant. Consequently, safer firms find it more favorable than risky ones to pledge collateral for lower interest rate, and banks can offer a lower interest rate for collateralized loans as the pool of borrowers that self selects into those will be more creditworthy. This would be evidence consistent with the ex ante private information hypothesis that motivates collateral as a signaling device to mitigate adverse selection.

Our model captures moral hazard through two distinct channels. The first is through $\alpha_{\mathcal{P}i}^F$. Finding that $\alpha_{\mathcal{P}i}^F > 0$ implies that, conditional on selection, a higher interest rate increases the likelihood that a borrower will default, which provides evidence of moral hazard. The coefficient $\alpha_{\mathcal{P}i}^F$ can identify the moral hazard channel distinctly from the adverse selection channel, which is captured by the correlations between unobservables, leaving the remaining relationship between loan interest rates and default to capture the ex post moral hazard channel. The second is through $\alpha_{\mathcal{C}i}^F$. Finding that $\alpha_{\mathcal{C}i}^F < 0$ implies that, after controlling for selection, borrowers pledging collateral are less likely to default, as they have more at stake. This coefficient allows to evaluate whether collateral is effective in mitigating ex post incentive problems. We let both of these effects to depend on whether there is a pre-existing borrower-lender relationship, as the extent of moral hazard and the effectiveness of collateral can vary with the information set that the lender has about the borrower.

In our demand and default frameworks we decided to include collateral as a binary variable C_{ijkm}, instead of having a continuous variable measuring collateral value, for the following two reasons related to model tractability. First, a continuous collateral value in the demand model would have a constant value across lenders' alternatives for secured loans within a borrower's choice set, which would not provide extra identifying variation to estimate $\alpha_{\mathcal{C}i}^D$. Second, the unobserved heterogeneity of the demand random coefficient for collateral $\alpha_{\mathcal{C}i}^D$ is already capturing the heterogeneous valuation for collateral across borrowers. However, one limitation of this approach is that in our counterfactual simulations a drop in collateral value will not have a direct effect on borrowers' default rate, but will be instead affected indirectly through a change in the equilibrium interest rate.

3.2 Supply

We let banks use the interest rate on secured $\mathcal{S}$ and unsecured $\mathcal{U}$ loans both as a competitive and as a screening device. In particular, we assume that banks compete Bertrand-Nash on interest rates for each

individual borrower. We also let banks screen through rationing, that is by offering to each borrower either both contract types, only one of them, or neither, depending on the expected profits from each option. In the data, there is significant heterogeneity across borrowers one whether they are offered a loan as well as the types of loans they are offered (i.e., secured or unsecured), mostly varying across banks and firms' industries. As discussed in more detail in Section 4, we rely on propensity score matching to determine whether each borrower is offered by each bank both types of loans, only one type, or neither.[20] This implies that banks will be using rationing to screen borrowers based on their observables, and pricing to screen them over their unobservables. To be more specific, we allow each bank j to set its interest rates on secured $\mathcal{S}$ and unsecured $\mathcal{U}$ loans to maximize its expected profit from a relationship with borrower i as follows:

$$\Pi_{ijm} = \sum_{k \in \{\mathcal{S}, \mathcal{U}\}} \mathbb{1}_{ijkm} \Pi_{ijkm}, \tag{6}$$

where $\mathbb{1}_{ijkm}$ indicates the availability of type k loan. Banks can offer both loans, one of them or neither to any borrower. The bank's expected profit from secured and unsecured loans is defined as:

$$\begin{aligned} \Pi_{ijkm} &= [(1 + T_{ijm} P_{ijkm}) - MC_{ijkm}] Q_{ijkm} (1 - F_{ijkm}) + [R_{ijkm} - MC_{ijkm}] Q_{ijkm} F_{ijkm} \\ &= [(1 + T_{ijm} P_{ijkm}) (1 - F_{ijkm}) - MC_{ijkm} + R_{ijkm} F_{ijkm}] Q_{ijkm}, \end{aligned} \tag{7}$$

where T_{ijm} is the term of the loan (in years) determined by the firm demand, P_{ijkm} is the interest rate offered by bank j to borrower i for loan type k, and F_{ijkm} is the expected default probability of the borrower under each loan type. MC_{ijkm} is the marginal cost of the lending relationship with firm i, including cost of capital as well as administrative and screening costs, which can vary across banks, markets and loan type. Q_{ijkm} is the expected demand defined as the probability of demand times the size of the loan:

$$Q_{ijkm} = \Pr^{D}_{ijkm} LS_{ijkm}, \tag{8}$$

where $\Pr^{D}_{ijkm}$ is the probability of demand and LS_{ijkm} is the loan size.[21] R_{ijkm} is the bank's expected loan recovery rate in default. We assume that:

$$\begin{aligned} R_{ij\mathcal{S}m} &= \min \left\{ CV_{ijm} \omega_{ij\mathcal{S}m}, \left(1 + T_{ijm} P_{ij\mathcal{S}m}\right) \right\}, \tag{9} \\ R_{ij\mathcal{U}m} &= \omega_{ij\mathcal{U}m} \left(1 + T_{ijm} P_{ij\mathcal{S}m}\right), \tag{10} \end{aligned}$$

where CV_{ijm} is the collateral value to loan amount ratio if the firm would post collateral, and $\omega_{ij\mathcal{S}m}$ is the expected recovery rate for defaulting borrowers on secured loans, with $\omega_{ij\mathcal{S}m} = 1$ for immovable assets, $\omega_{ij\mathcal{S}m} = .9$ for liquid movable assets, and $\omega_{ij\mathcal{S}m} = .7$ for illiquid movable assets. The expected recovery rate for secured loans depends on the collateral value, but cannot exceed each borrower's total repayment obligation. The expected recovery rate for unsecured loans $\omega_{ij\mathcal{U}m}$ is calculated using the loss rate reported

---

[20] Alternatively, we could assume that all banks offer both secured and unsecured loans to all borrowers. This might however be an inaccurate representation of borrowers' choice sets, which could lead to biased estimates of price and collateral preferences.

[21] These two variables are defined in more detail in Section 4.2 and Section 4.3, respectively.

in Table 1, by taking 1 minus the average loss rate of unsecured loans to defaulting borrowers in the same industry and with the same credit rating. If a bank offers both a secured and an unsecured loan to a borrower, taking the first order conditions of the bank's profit with respect to each interest rate delivers the following equilibrium pricing equation:

$$
\begin{aligned}
1 + T_{ijm}P_{ijkm} \ = \ & \frac{MC_{ijkm}}{1 - F_{ijkm} - \frac{Q_{ijkm}}{Q_{ijkm,P_k}}F_{ijkm,P_k}} \\
& - \frac{T_{ijm}\left(1 - F_{ijkm}\right)\frac{Q_{ijkm}}{Q_{ijkm,P_k}} + R_{ijkm}\left(F_{ijkm} + \frac{Q_{ijkm}}{Q_{ijkm,P_k}}F_{ijkm,P_k}\right)}{1 - F_{ijkm} - \frac{Q_{ijkm}}{Q_{ijkm,P_k}}F_{ijkm,P_k}} \\
& + \frac{\left[\left(1 + T_{ijm}P_{ij-km}\right)\left(1 - F_{ij-km}\right) - MC_{ij-km}\right]Q_{ij-km,P_k}}{1 - F_{ijkm} - \frac{Q_{ijkm}}{Q_{ijkm,P_k}}F_{ijkm,P_k}}.
\end{aligned}
\tag{11}
$$

There are two types of loans, secured and unsecured, i.e., $k \in \{\mathcal{S},\mathcal{U}\}$ and $-k$ is the other loan type. $Q_{ijkm,P_\mathcal{S}}$ and $Q_{ijkm,P_\mathcal{U}}$ are the derivatives of demand with respect to secured and unsecured interest rates, $F_{ijkm,P_\mathcal{S}}$, $F_{ijkm,P_\mathcal{U}}$ are the derivatives of default with respect to secured and unsecured interest rates, and $-\frac{Q_{ijkm}}{Q_{ijkm,P_k}}$ is bank j's markup on a loan of type k to firm i. The first term on the right hand side of the equation shows how the *effective marginal costs* influence interest rates, whereas the second term describes the effect of the *effective markup*. We refer to Crawford, Pavanini and Schivardi (2018) for a detailed discussion on how these two terms, and in particular their denominator, capture the interaction of adverse selection and imperfect competition in their effect on loan pricing. We focus instead on two main novel aspects of our pricing first order condition.

The first novelty is that, in the second term on the right hand side of the pricing equation, the value of the collateral directly affects the recovery rate, and hence the interest rate offered. Intuitively, this implies that the higher is the collateral value (and the bank's expected recovery rate), the lower will be the interest rate, due to the negative sign in front of the second term on the right hand side of the equation. This makes economic sense, as more collateral (or better expected recovery rate) implies less risk and more profit for the lender in case of default. This effect, however, depends on the sign and magnitude of the term in the parenthesis that R_{ijkm} multiplies, which can be interpreted as follows. The more likely is the firm to default (larger F_{ijkm}), the larger is going to be the price reduction driven by the recovery rate, as the bank now gives more importance to the value of the collateral pledged. However, the stronger is the bank's markup $\frac{Q_{ijkm}}{Q_{ijkm,P_k}}$, which is negative, the smaller is going to be the price reduction driven by the recovery rate, as the bank exercises its market power.

The second new point is that the two interest rates on secured and unsecured loans in each bank-borrower combination are jointly determined and affect each other, as the two types of loans are in direct competition for the same borrowers. This competition effect is captured by the last term on the right hand side of equation (11). It shows that a higher profit for a secured (unsecured) loan is positively associated with the interest rate for the unsecured (secured) loan offered by the same bank to the same borrower. In other words, banks are multi-product firms and internalize their profits from the secured (unsecured) loans when setting the interest rate for the unsecured (secured) loan to borrower i. Our counterfactual on the collateral channel, where we shock the value of the collateral and hence the value of the recovery rate R_{ijkm}, will therefore rely on

the mechanisms highlighted by this first order condition to propagate to the supply response of banks, and consequently to their expected profits, and to borrowers' demand and default.

4 Econometric Model

4.1 Prediction of Contract Availability and Interest Rates

In order to construct the full choice set of each borrower we need to predict all loan contracts available to a borrower and their corresponding interest rates. We make a set of assumptions to determine borrowers' contract availability. First, we include a bank in a borrower's choice set if that bank granted at least one loan in the region-quarter combination where-when the borrower is taking her loan. Second, if a bank has never granted a loan with a similar amount, duration, or type (secured or unsecured) to a similar borrower, we assume that the bank and/or contract type is not part of the borrower's choice set. This means that we do not assume that all firms are offered both secured and unsecured loans by all banks, but we allow instead banks to screen borrowers also offering them only one contract type or neither. This assumption is justified not only from an economic perspective, as in our data it seems very unlikely that all banks offer all contract types to all borrowers, but also from an econometric perspective, as it aims at correctly specifying borrowers' choice sets. Once we determine each borrower's available choice set, we predict the interest rates of contracts not observed in the data following a three steps procedure.

First, we use an OLS regression model with a large set of fixed effects to predict the average interest rate across all loans that each borrower is offered by all banks it borrowed from in each market. Crucially, using multiple loans for each borrower, we are able to recover borrower-specific fixed effects that capture both hard and soft information common to all banks that is used for pricing. Second, as the first step does not give us a separate prediction for secured and unsecured loans' interest rates, we use propensity score matching to pair borrowers that are equally likely to take a secured loan from a given bank, and then assign the secured rate of a firm that took a collateralized loan in the data to its matched counterpart that took instead an uncollateralized loan, and vice-versa. A drawback of our data is that we do not observe what assets could be pledged as collateral for borrowers that only take unsecured loans. For this reason, we use this same propensity score matching to assign the collateral value and type of collateral of secured borrowers to their matched unsecured ones.[22] Last, we combine these two methods to give the most credible prediction of loan interest rates for secured and unsecured loans for each borrower-bank combination. In what follows, we describe these steps in detail and assess the prediction accuracy of our approach. Note that we only need to predict interest rates to estimate our demand model, whereas we will use actual interest rates to estimate our default model.

4.1.1 Fixed Effects Model

In the first step we predict the average interest rate I_{ijm} across secured and unsecured loans of firm i from bank j in market m as follow:

---

[22]The lack of data on borrowers' assets prevents us from allowing for a richer choice set of secured contracts offered to borrowers, including for each borrower-bank combination a set of offered secured contracts with different interest rates for each type of collateral.

$$I_{ijm} = \overline{\beta} + \beta_{\mathcal{A}}A_i + \beta_{\mathcal{M}}M_i + \gamma_{jm} + \lambda_i + \epsilon_{ijm}, \tag{12}$$

where A_i indicates borrower i's loan amount category, and M_i indicates i's maturity category. Both variables are categorized by quantiles.[23] γ_{jm} are bank-market fixed effects, λ_i are borrower fixed effects, and ϵ_{ijm} are prediction errors. By including multiple loans granted to the same borrower, we gain the possibility of identifying borrowers' fixed effects, which are likely to capture, at least to some extent, how the soft and hard information that banks acquire at origination (unobserved by the econometrician) maps into interest rates. Using the estimated coefficients $\widetilde{\beta}, \widetilde{\gamma}_{jm}, \widetilde{\lambda}_i$ we can predict I_{ijm} for all banks j that are available in market m.

Table 2 shows the results for predicting the average interest rate. In the first column, we report adjusted R-square from estimating equation (12). The model's adjusted R-square is 0.85, indicating that the explanatory variables explain a large fraction of the variation of the average loan interest rate in the data. To evaluate the accuracy of this model, in the second column of Table 2 we report estimation results of a default model where the dependent variable is a dummy equal to one if a borrower has any non-performing loans within our sample period and the residuals from equation (12) along with all other explanatory variables are included as explanatory variables, except for the borrower-fixed effects, which cannot be included in the default model because the dependent variable has no within borrower variation.[24] Crucially, we find that residuals are not statistically nor economically significant, which suggests that our prediction error is not related to borrowers' default and hence represents noise in banks' pricing strategy. In contrast, the third and fourth columns repeat the exercise without borrower fixed effects in equation (12). In this case the adjusted R-squared is reduced markedly to 0.63 and the price residuals now have a positive and statistically significant effect on borrowers' default, highlighting that a pricing prediction without borrower fixed effects would miss an important component of price variation used for screening. The comparison between the first two and last two columns of Table 2 provides evidence that loan features, borrower's observable characteristics, and the interaction of bank, time and market unobserved heterogeneity is not enough to fully explain variation in interest rates, but instead borrowers' soft information, observed by banks but not by the econometrician, plays an important role in pricing risk.

This approach does not yet take into account the different interest rates that a bank offers to the same borrower for a secured or an unsecured loan, mostly for reasons of statistical power, as we do not have enough observations to identify firm-secured loan and firm-unsecured loan fixed effects. The predicted average interest rate from equation (12) can thus be thought as the weighted average of interest rate between secured and unsecured loans that bank j has granted to borrower i, where the weight is given by the likelihood that i will take a secured or an unsecured loan. In the next sub-section, we use propensity score matching to separately predict interest rates for collateralized and uncollateralized loans for each borrower-bank combination.

---

[23]The four loan amount categories are 600\$ to 15,000\$, 15,001\$ to 40,000\$, 40,001\$ to 100,000\$, and over 100,000\$. The four maturity categories are 1 to 2.9 months, 3 to 5.9 months, 6 to 12 months, and over 12 months.

[24]This implies that there is no variation in the default dependent variable across loans within a borrower, therefore we cannot include borrower fixed effects.

Table 2: Price Prediction for Average Interest Rate

	Borrower FE		No Borrower FE	
	Observed Price	**Default**	**Observed Price**	**Default**
Price Residual		−0.002		0.04***
		(0.01)		(0.003)
Loan Controls	Yes	Yes	Yes	Yes
Borrower Controls	No	Yes	Yes	Yes
Bank-Market FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	No	No	No
Observations	9,400	9,400	9,400	9,400
Adjusted R^2	0.85	0.19	0.63	0.21

Note: This table shows the price prediction for average cost. The first column shows the OLS regression result for equation (12). The dependent variable is observed interest rate. Loan controls include fixed effects for loan amount and maturity categories, and a dummy for installment loan. Borrower controls include dummies for bad credit rating, corporation, and industry. The second column is to show the price prediction does not miss determinants for default. The price residual means the residuals from equation (12). The dependent variable is the indictor for Non-performing. The third and fourth column repeat the exercise with no borrower fixed effects in the model *p<0.1; **p<0.05; ***p<0.01. More details on this regression are reported in Table A.4.

4.1.2 Propensity Score Matching

In the second step we use propensity score matching (PSM) to determine for each firm-bank relationship in each market the probability that the firm will select a secured loan. This probability will be then used to derive from the predicted average interest rate $\widehat{I}_{ijm}$ the predicted loan interest rates for secured and unsecured loans $\widehat{P}_{ij\mathcal{S}m}, \widehat{P}_{ij\mathcal{U}m}$. The matching process works as follows. First, following the criteria suggested by Caliendo and Kopeinig (2008), we select as variables for the PSM the bank identity, the loan amount category, the loan maturity category, the borrower's industry, the borrower-bank relationship dummy Z_{ijm}, and the borrower's legal structure (i.e., a dummy variable indicating whether the borrower is a corporation). Second, based on these variables, we use a logistic model to determine the propensity score PSC_{ijm} of borrower i in market m taking a secured loan from bank j. Third, we match each firm i that took a secured (unsecured) loan from bank j with another firm with the same propensity score PSC_{ijm} that has instead taken an unsecured (secured) loan from bank j, and assign to each other the secured (unsecured) interest rate $\tau_{ij\mathcal{S}m}$ ($\tau_{ij\mathcal{U}m}$) for the loan we do not observe in the data. When there are more than one match for the same combination of PSC_{ijm} we use random assignment. As a result, for each firm we obtain the interest rate for secured and unsecured loans offered by all banks that are actively lending in the market. Appendix A.1 provides detailed information on the optimal matching algorithm and the selection of the variables.

We restrict the potential matches to be loan contracts provided by the same bank with the same matching variables, which implies that for some borrower type-bank combinations we may not find any secured or

unsecured match, and hence assume that either the secured or the unsecured loan is not offered to that borrower. This implies that we are allowing banks to use also this margin of contract availability, on top of interest rates, to screen borrowers and manage credit risk. Therefore, the predicted loan contracts are those provided by banks that are actively lending in a region-quarter combination, and those that are offered to borrowers with similar characteristics in the sample. When both secured and unsecured loans are available and the matching is done, we define the interest rate difference $\mathcal{D}_{ijm}$ as the difference between the matched unsecured interest rate $\tau_{ij\mathcal{U}m}$ and the matched secured interest rate $\tau_{ij\mathcal{S}m}$:

$$\mathcal{D}_{ijm} = \tau_{ij\mathcal{U}m} - \tau_{ij\mathcal{S}m}. \tag{13}$$

In the next step, we use both this interest rate difference $\mathcal{D}_{ijm}$ and the propensity score PSC_{ijm} to derive the predicted interest rates $\widehat{P}_{ij\mathcal{S}m}, \widehat{P}_{ij\mathcal{U}m}$. The reason why we do not use the matched $\tau_{ij\mathcal{U}m}, \tau_{ij\mathcal{S}m}$ as predicted interest rates is that $\widehat{I}_{ijm}$ captures much more heterogeneity across borrowers because of the firm-specific fixed effects, and as a result a combination of the two steps is what provides an accurate prediction as shown in Section 4.1.4.

4.1.3 Interest Rate of Secured and Unsecured Loans

In the last step we predict the interest rate of secured and unsecured loans by adjusting the predicted average interest rate $\widehat{I}_{ijm}$ depending on the propensity score. Intuitively, if most of the loans used to predict $\widehat{I}_{ijm}$ are secured, then $\widehat{I}_{ijm}$ will be a good predictor for $\widehat{P}_{ij\mathcal{S}m}$, but a bad predictor for $\widehat{P}_{ij\mathcal{U}m}$. The opposite occurs if most of the loans used to predict $\widehat{I}_{ijm}$ are unsecured. The propensity score, which determines the probability that the borrower takes a secured loan offer, can similarly be interpreted as the probability that the loans used to predict $\widehat{I}_{ijm}$ are secured. Therefore, for a given average interest rate $\widehat{I}_{ijm}$ and price difference $\mathcal{D}_{ijm}$, the interest rates for secured and unsecured loans are defined as follows:

$$\widehat{P}_{ij\mathcal{S}m} = \widehat{I}_{ijm} - (1 - PSC_{ijm})\mathcal{D}_{ijm}, \tag{14}$$

$$\widehat{P}_{ij\mathcal{U}m} = \widehat{I}_{ijm} + PSC_{ijm}\mathcal{D}_{ijm}. \tag{15}$$

Taking a secured loan as an example, this means that if a borrower is very likely to choose a secured loan ($PSC_{ijm} \approx 1$), then also most of the loans used to predict $\widehat{I}_{ijm}$ should be secured ones, and therefore it is reasonable to have that $\widehat{P}_{ij\mathcal{S}m} \approx \widehat{I}_{ijm}$. If on the other hand a borrower is very unlikely to choose a secured loan ($PSC_{ijm} \approx 0$), then most of the loans used to predict $\widehat{I}_{ijm}$ should be unsecured ones, which implies that $\widehat{I}_{ijm} \approx \tau_{ij\mathcal{U}m}$, and therefore it is reasonable to have that $\widehat{P}_{ij\mathcal{S}m} \approx \widehat{I}_{ijm} - \tau_{ij\mathcal{U}m} + \tau_{ij\mathcal{S}m} \approx \tau_{ij\mathcal{S}m}$.

A similar argument applies for the case of the unsecured loan interest rate. If bank j only provides one contract to borrower i, then the average interest rate is just the price of the available contract, and the other contract is not available. Hence:

$$\widehat{P}_{ij\mathcal{S}m} = \widehat{I}_{ijm} \quad \text{if only secured loan is available;}$$

$$\widehat{P}_{ij\mathcal{U}m} = \widehat{I}_{ijm} \quad \text{if only unsecured loan is available.}$$

If bank j provides neither contract to borrower i, then no contract is available to that firm from bank j.

4.1.4 Prediction Results

Based on our choice set assumptions and matching procedure, we predict the set of available contracts for each borrower at the time of her first loan's origination. From the benchmark case in which all banks were to offer both types of loans to each borrower, our assumptions and matching end up keeping 51% of those contracts as actually available to the borrowers. Among the unavailable contracts, in 69% of the cases they are not available because the bank is not actively lending in the borrower's market, and in 31% of the cases because the bank does not offer the amount and maturity combination required by the borrower to borrowers with characteristics. The median *secured borrower* (i.e., a borrower that chose a secured loan in the data) has 5 secured and 7 unsecured loans available, while the median *unsecured borrower* (i.e., a borrower that chose an unsecured loan in the data) has 5 secured and 8 unsecured loans available. Among the available contracts, in 10% of the cases the bank only provides a secured loan to a borrower, in 37% of the cases only an unsecured one, and in 53% of the cases it offers both types of loans. Our propensity score matching allows for different contract availability between secured and unsecured borrowers, which implies that banks can screen borrowers both with contract terms and contract availability. More detailed information on the contract availability is presented in Appendix A.2.

We also assess the accuracy of our prediction approach by investigating whether the predicted contract assignment reasonably matches key theoretical predictions and prior literature. In particular, in Table 3 we study how the average loan and borrower characteristics vary depending on whether the borrower has been offered both types of contracts, or only secured or unsecured loans. We find that larger firms (proxied by the loan amount and the corporation dummy) and firms without a bad credit score are more likely to be offered both types of contracts. Borrowers with a bad credit score are instead more likely to be offered only a secured loan. Borrowers demanding loans with the longer maturities are also more likely to be offered only a secured contract, while those demanding the shorter maturities are more likely to be offered only an unsecured loan. There does not seem to be a significant difference in the type of contracts offered across borrowers operating in different sectors. Borrowers offered both contracts are those that on average are charged the lowest interest rate, while those offered only a secured loan are charged the highest.

Table 3: Loan and Borrower Characteristics for Different Contract Types

	Both	Only Unsecured	Only Secured
Loan Amount	128,221	122,494	165,775
Maturity	11.30	10.49	14.67
Corporation	0.67	0.66	0.65
Bad Credit Rating	0.13	0.13	0.14
Interest Rates	13.47	13.87	13.91
Manufacturing	0.30	0.28	0.24
Construction	0.09	0.08	0.08
Wholesale and Retail Trade	0.28	0.26	0.29
Real Estate Activities	0.04	0.04	0.03
Social Services	0.01	0.02	0.02
Other Activities	0.27	0.33	0.33
Observations	39,778	28,379	7,976

Note: This table summarizes average characteristics of borrowers and of loans that were offered by all available banks. A bank may offer both secured and unsecured contracts to a borrower (Both), only an unsecured loan (Only Unsecured), or only a secured loan (Only Secured). Amount is the loan amount in USD. Maturity is in months. Corporation is a dummy variable taking the value of one if the borrower is a corporation and zero if it is a sole proprietorship or partnership. Bad Credit Rating is a dummy variable taking the value of one if the loan has any overdue payments or is in default and zero otherwise. Interest Rate is the annual percentage rate. Manufacturing, Construction, Wholesale and Retail Trade, Real Estate Activities, Social Services, Other Activities are dummy variables indicating borrowers' industry.

These results are consistent with banks using contract availability to screen borrowers based on observable risk, offering only secured loans to observably riskier borrowers, and using pricing to screen unobservable risk, offering both types of contracts to borrowers that are not observably risky. Consistent with this interpretation, looking at default rates of borrowers conditional on their contract choices, we find that borrowers that were offered both contracts and choose an unsecured loan are the ones with the highest incidence of default (12%), whereas those that were offered both contracts and choose a secured loan have the lowest likelihood of default (7%), and those offered only one type are somewhere in between (12% for unsecured and 11% for secured).[25] These can be interpreted as preliminary evidence consistent with both the ex-ante and ex-post theories of collateral. Our structural model will allow us to separately quantify the effect of both of these theories.

Last, in order to assess the accuracy of our price prediction, we compare the actual and predicted interest rates for the contracts that we observe in the data. Figure 4 shows the distribution of observed and predicted interest rates. Although the predicted prices have a higher standard deviation, the two distributions have a very large overlap, lending strong support to our predicted exercise.

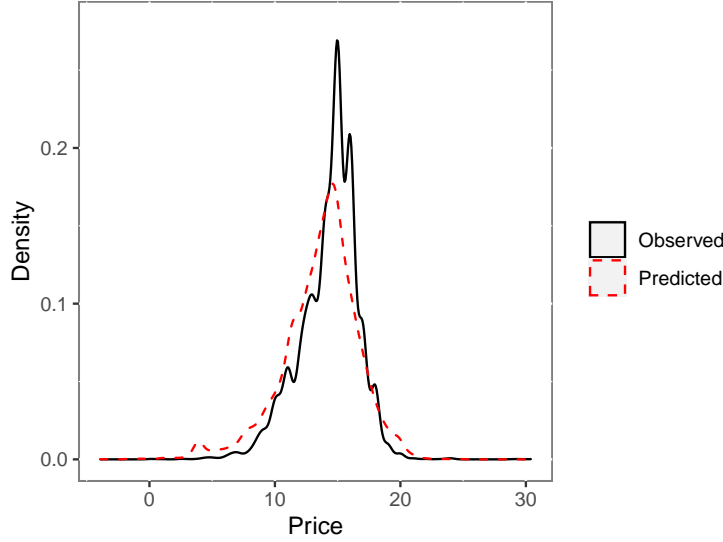[25]We thank David De Meza for suggesting us this test.

Figure 4: Price Prediction Accuracy

Note: This figure shows the distributions of observed prices (black solid line) and predicted prices (red dashed line). The total number of observation is 9,400.

4.2 Demand and Default

We estimate the model by simulated maximum likelihood, using a mixed logit for the demand model and a probit for the default model. Starting from the former, we define the probability that borrower $i = 1, .., I$ in market $m = 1, .., M$ takes a type $k = \mathcal{S}, \mathcal{U}$ loan from bank $j = 1, .., J_m$ as follows:

$$
\begin{aligned}
\Pr^D_{ijkm} &= \int \int \frac{\exp\left(\alpha^D_{\mathcal{P}i} P_{ijkm} + \alpha^D_{\mathcal{C}i} C_{ijkm} + \alpha^D_{\mathcal{Z}} Z_{ijm} + X'_{jm}\alpha^D_{\mathcal{X}}\right)}{\sum_{j=i}^{J_m} \sum_{\ell=\mathcal{S}}^{\mathcal{U}} \mathbb{1}_{ij\ell m} \exp\left(\alpha^D_{\mathcal{P}i} P_{ij\ell m} + \alpha^D_{\mathcal{C}i} C_{ij\ell m} + \alpha^D_{\mathcal{Z}} Z_{ijm} + X'_{jm}\alpha^D_{\mathcal{X}}\right)} f(\varepsilon^D_{\mathcal{P}i}, \varepsilon^D_{\mathcal{C}i}) d\varepsilon^D_{\mathcal{P}i} d\varepsilon^D_{\mathcal{C}i} \\
&\approx \frac{1}{S} \sum_{s=1}^{S} \underbrace{\frac{\exp\left(\alpha^D_{\mathcal{P}is} P_{ijm} + \alpha^D_{\mathcal{C}is} C_{ijm} + \alpha^D_{\mathcal{Z}} Z_{ijm} + X'_{jm}\alpha^D_{\mathcal{X}}\right)}{\sum_{j=i}^{J_m} \sum_{\ell=\mathcal{S}}^{\mathcal{U}} \mathbb{1}_{ij\ell m} \exp\left(\alpha^D_{\mathcal{P}is} P_{ij\ell m} + \alpha^D_{\mathcal{C}is} C_{ij\ell m} + \alpha^D_{\mathcal{Z}} Z_{ijm} + X'_{jm}\alpha^D_{\mathcal{X}}\right)}}_{\Pr^D_{isjkm}},
\end{aligned}
\tag{16}
$$

where $\mathbb{1}_{ij\ell m}$ indicates the availability of type ℓ loan, and we approximate the integral in the first row using Monte Carlo simulations with $S = 100$ Halton draws, and index each draw by s. The simulation draws enter the random coefficients on interest rate and collateral as in equation (2):

$$
\begin{aligned}
\alpha^D_{\mathcal{P}is} &= \overline{\alpha}^D_{\mathcal{P}} + \alpha^D_{\mathcal{P}\mathcal{Z}} Z_{ijm} + \varepsilon^D_{\mathcal{P}is}, \\
\alpha^D_{\mathcal{C}is} &= \overline{\alpha}^D_{\mathcal{C}} + \alpha^D_{\mathcal{C}\mathcal{Z}} Z_{ijm} + \varepsilon^D_{\mathcal{C}is},
\end{aligned}
$$

where, following the conditional distribution of the multivariate normal:

$$\varepsilon_{\mathcal{P}is}^{D} = \sigma_{\mathcal{P}}\zeta_{\mathcal{P}is}^{D},$$

$$\varepsilon_{\mathcal{C}is}^{D} = \frac{\sigma_{\mathcal{C}}}{\sigma_{\mathcal{P}}}\rho_{\mathcal{PC}}\varepsilon_{\mathcal{P}is}^{D} + \sqrt{(1-\rho_{\mathcal{PC}}^{2})\sigma_{\mathcal{C}}^{2}}\zeta_{\mathcal{C}is}^{D} = \sigma_{\mathcal{C}}\rho_{\mathcal{PC}}\zeta_{\mathcal{P}is}^{D} + \sqrt{(1-\rho_{\mathcal{PC}}^{2})}\sigma_{\mathcal{C}}\zeta_{\mathcal{C}is}^{D}, \tag{17}$$

with $\zeta_{\mathcal{P}is}^{D}, \zeta_{\mathcal{C}is}^{D} \sim N(0,1)$. Conditional on taking a specific loan from the most preferred bank, which is determined by $\varepsilon_{\mathcal{P}i}^{D}$ and $\varepsilon_{\mathcal{C}i}^{D}$, we model each borrower's default probability, that is the probability that the utility from defaulting is positive, as:

$$\Pr_{ijkm}^{F} = \int \int \Phi_{\varepsilon_{i}^{F}|\varepsilon_{\mathcal{P}i}^{D},\varepsilon_{\mathcal{C}i}^{D}} \left(\frac{\overline{\alpha}^{F} + \alpha_{\mathcal{P}i}^{F}P_{ijkm} + \alpha_{\mathcal{C}i}^{F}C_{ijkm} + \alpha_{\mathcal{Z}}^{F}Z_{ijm} + X_{jm}'\alpha_{\mathcal{X}}^{F} + Y_{i}'\alpha_{\mathcal{Y}}^{F} + \widetilde{\mu}_{Fi}}{\widetilde{\sigma}_{F}} \right) f(\varepsilon_{\mathcal{P}i}^{D}, \varepsilon_{\mathcal{C}i}^{D})d\varepsilon_{\mathcal{P}i}^{D}d\varepsilon_{\mathcal{C}i}^{D}$$

$$\approx \frac{1}{S}\sum_{s=1}^{S} \underbrace{\Phi_{\varepsilon_{i}^{F}|\varepsilon_{\mathcal{P}i}^{D},\varepsilon_{\mathcal{C}i}^{D}} \left(\frac{\overline{\alpha}^{F} + \alpha_{\mathcal{P}i}^{F}P_{ijkm} + \alpha_{\mathcal{C}i}^{F}C_{ijkm} + \alpha_{\mathcal{Z}}^{F}Z_{ijm} + X_{jm}'\alpha_{\mathcal{X}}^{F} + Y_{i}'\alpha_{\mathcal{Y}}^{F} + \widetilde{\mu}_{Fis}}{\widetilde{\sigma}_{F}} \right)}_{\Pr_{isjkm}^{F}},$$
$$\tag{18}$$

where $\varepsilon_{i}^{F}|\varepsilon_{\mathcal{P}i}^{D}, \varepsilon_{\mathcal{C}i}^{D} \sim N(\widetilde{\mu}_{Fi}, \widetilde{\sigma}_{F})$. Following the conditional distribution of the multivariate normal, we have that:

$$\widetilde{\mu}_{Fis} = (A_{F}'B_{F}^{-1}C_{F})',$$

$$\widetilde{\sigma}_{F} = 1 - A_{F}'B_{F}^{-1}A_{F}, \tag{19}$$

with:

$$A_{F} = \begin{pmatrix} \rho_{\mathcal{PF}}\sigma_{\mathcal{P}} \\ \rho_{\mathcal{CF}}\sigma_{\mathcal{C}} \end{pmatrix}, \quad B_{F} = \begin{pmatrix} \sigma_{\mathcal{P}}^{2} & \rho_{\mathcal{PC}}\sigma_{\mathcal{P}}\sigma_{\mathcal{C}} \\ \rho_{\mathcal{PC}}\sigma_{\mathcal{P}}\sigma_{\mathcal{C}} & \sigma_{\mathcal{C}}^{2} \end{pmatrix}, \quad C_{F} = \begin{pmatrix} \varepsilon_{\mathcal{P}is}^{D} \\ \varepsilon_{\mathcal{C}is}^{D} \end{pmatrix}. \tag{20}$$

Solving the matrix multiplication we get:

$$\widetilde{\mu}_{Fis} = \frac{\rho_{\mathcal{PF}} - \rho_{\mathcal{CF}}\rho_{\mathcal{PC}}}{\sigma_{\mathcal{P}}(1-\rho_{\mathcal{PC}}^{2})}\varepsilon_{\mathcal{P}is}^{D} + \frac{\rho_{\mathcal{CF}} - \rho_{\mathcal{PF}}\rho_{\mathcal{PC}}}{\sigma_{\mathcal{C}}(1-\rho_{\mathcal{PC}}^{2})}\varepsilon_{\mathcal{C}is}^{D}$$

$$= \frac{\rho_{\mathcal{PF}} - \rho_{\mathcal{CF}}\rho_{\mathcal{PC}}}{1-\rho_{\mathcal{PC}}^{2}}\zeta_{\mathcal{P}is}^{D} + \frac{\rho_{\mathcal{CF}} - \rho_{\mathcal{PF}}\rho_{\mathcal{PC}}}{1-\rho_{\mathcal{PC}}^{2}}\left(\rho_{\mathcal{PC}}\zeta_{\mathcal{P}is}^{D} + \sqrt{(1-\rho_{\mathcal{PC}}^{2})}\zeta_{\mathcal{C}is}^{D} \right), \tag{21}$$

$$\widetilde{\sigma}_{F} = 1 - \frac{\rho_{\mathcal{PF}}^{2} + \rho_{\mathcal{CF}}^{2} - 2\rho_{\mathcal{PF}}\rho_{\mathcal{CF}}\rho_{\mathcal{PC}}}{1-\rho_{\mathcal{PC}}^{2}}. \tag{22}$$

We use these probabilities to estimate all the parameters $\theta = \{\alpha^{D}, \alpha^{F}, \Sigma\}$ jointly by maximum simulated likelihood, where $\alpha^{D} = \{\overline{\alpha}_{\mathcal{P}}^{D}, \overline{\alpha}_{\mathcal{C}}^{D}, \alpha_{\mathcal{PZ}}^{D}, \alpha_{\mathcal{CZ}}^{D}, \alpha_{\mathcal{X}}^{D}, \alpha_{\mathcal{Z}}^{D}\}$, $\alpha^{F} = \{\overline{\alpha}^{F}, \overline{\alpha}_{\mathcal{P}}^{F}, \overline{\alpha}_{\mathcal{C}}^{F}, \alpha_{\mathcal{PZ}}^{F}, \alpha_{\mathcal{CZ}}^{F}, \alpha_{\mathcal{X}}^{F}, \alpha_{\mathcal{Z}}^{F}, \alpha_{\mathcal{Y}}^{F}\}$, and $\Sigma = \{\sigma_{\mathcal{P}}, \sigma_{\mathcal{C}}, \rho_{\mathcal{PC}}, \rho_{\mathcal{PF}}, \rho_{\mathcal{CF}}\}$. We use the following log likelihood function:

$$\mathcal{L}(\theta) = \sum_{i}\log\left\{ \frac{1}{S}\sum_{s=1}^{S}\left[\prod_{m}\left(\prod_{j}\prod_{k}\mathbb{1}_{ijkm}\left(\Pr_{isjkm}^{D}\right)^{d_{ijkm}} \right) \left(\left(\Pr_{isjkm}^{F}\right)^{f_{ijkm}}\left(1 - \Pr_{isjkm}^{F}\right)^{1-f_{ijkm}} \right) \right] \right\}, \tag{23}$$

where d_{ijkm} takes the value of one if the borrower chooses a bank-loan combination j with loan type k, and zero otherwise, and f_{ijkm} takes the value of one if the borrower defaults, and zero otherwise. The product over the m dimension for the demand probability captures the fact that most borrowers take multiple loans within our sample period at different points in time, so in this case m identifies different quarters at which they borrow.

4.3 Loan Amount

In the demand model we assume that loan amount and maturity are exogenously determined, depending on firms' financing needs. If the exogenous amount assumption can be justified for the demand estimation, it can become problematic when simulating counterfactual scenarios, especially because we do not allow borrowers to choose the outside option of not taking a loan, which would make aggregate credit demand invariant across scenarios. To overcome this limitation, we model separately the loan size LS_{ijkm} (i.e., total amount granted) that firm i borrows from bank j in market m when choosing contract k as follow:

$$\log(LS_{ijkm}) = \overline{\zeta} + \zeta_{\mathcal{P}i}P_{ijkm} + \zeta_{\mathcal{C}i}C_{ijkm} + \zeta_{\mathcal{Z}}Z_{ijm} + X'_{jm}\zeta_{\mathcal{X}} + Y'_i\zeta_{\mathcal{Y}} + v_{ijkm}, \tag{24}$$

where:

$$\zeta_{\mathcal{P}i} = \overline{\zeta}_{\mathcal{P}} + \zeta_{\mathcal{P}\mathcal{Z}}Z_{ijm},$$
$$\zeta_{\mathcal{C}i} = \overline{\zeta}_{\mathcal{C}} + \zeta_{\mathcal{C}\mathcal{Z}}Z_{ijm},$$

P_{ijkm} is the interest rate, C_{ijkm} is the collateral dummy, and Z_{ijm}, X_{jm}, Y_i include the same variables as in demand and default utility except for the loan amount categories. v_{ijkm} is an IID normally distributed error term. This model will allow us to have variation in credit demand in the counterfactual scenarios, as it will enter banks' profit functions.[26]

4.4 Identification

Since we do not know the precise actuarial model that banks use to determine the interest rate for each borrower, a natural concern is that the loan interest rate, both predicted (used in the demand model) and observed (used in the default model), may be endogenously related to unobservables that influence borrowers' demand and default. A similar identification concern applies to the collateral dummy in the demand and default models. If this is the case, our estimates of the price and collateral sensitivities in both the demand and the default models are likely to be biased. To address this potential endogeneity concern, we use the control function approach suggested by Train (2009), motivated by the fact that both demand and default are nonlinear models.[27] This method consists of two steps. In the first stage, we regress the predicted and actual interest rates on the same set of observables that we use in the demand and default models, plus a set of

---

[26]An alternative approach is to incorporate the optimal loan size into the structural framework with discrete-continuous choice model (Benetton 2019), and estimate the discrete and continuous component of demand jointly. This however requires stronger functional form assumptions for borrowers' indirect utility, and relies on observing data on borrowers' income, unavailable to us.

[27]We implement this approach also in the loan amount model, using the same instruments as in the demand model.

instrumental variables. In the second stage, we include the residuals from each pricing regression as control variables in the demand and default models to control for any unobserved factors correlated with prices, thus allowing the identifying variation left over in prices to be orthogonal to demand and default unobservables. The same approach is used for the collateral dummy, using a linear probability model in the first stage.

We use two different instruments for interest rates and collateral requirements, in both the demand and the default models, as they need to satisfy different exclusion restrictions. For loan interest rates we use as instrument the interest rates on households' savings deposits, as a proxy for banks' funding costs. This instrument fulfills the exclusion restriction because household deposit markets represent a different segment of banking activity compared to corporate loans, therefore any change in its conditions is uncorrelated with unobserved determinants of firms' choice of bank and of their likelihood to default. For collateral requirements, we use as instrument the quarterly share of non-performing loans in banks' outstanding loans, originated in previous quarters and in other geographic markets. The different time and geographic dimension of the instrument assures that the exclusion restriction is satisfied, but also guarantees the relevance of the instrument, because non-performing loans in the current bank's portfolio are likely to affect the likelihood of offering a secured contract to a new borrower. Columns (1) and (2) in Table 4 present the first-stage results for observed and predicted loan interest rates, showing that these instruments are relevant and with coefficients of the expected sign. Columns (3) and (4) present the first-stage results for observed and predicted collateral requirements, with positive and significant coefficients for the instrument as expected.

A concern about a potential violation of the exclusion restriction in the pricing model may arise due to the following reason. The market discipline literature in banking shows that banks' funding costs reflect their riskiness, as subordinated debt holders (i.e., large depositors and other subordinated bond holders) demand a premium for lending to riskier banks (Flannery and Sorescu 1996, Martinez Peria and Schmukler 2001). A related literature on the credit side which argues that bank-firm matching is not random, as firms tend to select healthier banks and multiple banks to avoid shocks in credit supply (Detragiache, Garella and Guiso 2000, Ippolito, Peydró, Polo and Sette 2016). This evidence suggests that bank risk jointly determines banks' funding sources and costs, as well as firms' choice of banks, which would invalidate the exogeneity of our instrument. We address this concern by focussing only on small household deposits, which are covered by deposit insurance and implicit government guarantees, and are therefore not sensitive to banks' level of risk (Egan, Hortaçsu and Matvos 2017).

The use of predicted prices in the demand model can also give rise to measurement error. Our instruments help address this potential source of bias. As borrowers are also likely to be predicting some of the prices that banks in their choice sets might be offering them, these approach allows us to better approximate of the potential prices that firms actually consider in their borrowing decision.

Table 4: First Stage Results

	Price		Collateral	
	Observed	Predicted	Observed	Predicted
Savings Deposit Interest Rate	0.36***	0.16***		
	(0.01)	(0.01)		
Share of Non-Performing Loans			1.04***	0.11***
			(0.08)	(0.03)
Loan Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	8,938	103,137	9,190	105,883
Adjusted R^2	0.45	0.10	0.25	0.06

Note: This table shows the first stage results for prices and collateral using the first 18 months of each borrower in the original sample. In the first column, the dependent variable is the price we observe in the sample. In the second column, the dependent variable is the predicted price. Similarly, the third column is the collateral dummy observed in the sample, while the fourth column is the collateral dummy resulting from our prediction model. The instrumental variable is the interest rate of household saving deposits for interest rates, and the share of non-performing loans in banks' outstanding loans for collateral. Loan Controls include dummy variables for Installment, Corporation, Bad Credit Rating, amount and maturity categories. The number of observation for prices is less than the total number of predicted and observed contracts due to some missing values of the instrumental variables. There is no missing value in the sample used for estimation. $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

5 Results

We use data on each borrower's choice of loans within her first 18 months to estimate the demand, loan amount, and default models. Table 5 presents the estimation results of our structural model. The first column refers to the demand equation, the second column reports regression results for the loan amount model, and the third column refers to the default equation. The bottom panel shows the covariance matrix of the unobservables. The demand and the default equations are estimated using maximum simulated likelihood.

In the demand equation, we control for bank-fixed effects and the impact of a pre-existing borrower-lender lending relationship (within the 18 months that we consider) on borrowers' current choice, by including a dummy variable taking value of one if there exists already a firm-bank relationship at the time of the loan origination, and zero otherwise. We also allow the random coefficients on prices and collateral to depend both on whether the borrower has a pre-existing lending relationship with the bank, and on un-

observed heterogeneity in the form of borrowers' private information.[28] The mean utilities from interest rate and collateral for borrowers without an outstanding relationship in the demand model are reported in the first column of Table 5, corresponding to coefficients of the Price and Collateral variables, while the standard deviations are in the Covariance matrix below. We find that on average borrowers get disutility from higher interest rates and from pledging collateral, and the disutility is greater when the borrower has a prior relationship with the bank. Firms that have already been granted a loan are in fact likely to be safer borrowers, who are more price sensitive, as documented by the positive correlation between price sensitivity and borrowers' unobserved riskiness $\rho_{\mathcal{P}F}$ in the bottom panel of Table 5. There is also significant unobserved heterogeneity in overall borrowers' preferences. The mean own price and collateral elasticities suggest that a 10% increase in interest rate reduces the own probability of demand by 3.2%, and requiring collateral reduces the own probability of demand by 45.9%. The second column shows that a higher interest rate has also a negative impact on the loan amount they demand: one percentage point increase in interest rate decreases the loan amount demanded by 21.9%. Therefore, in our counterfactuals we allow demand to adjust to price changes through both the extensive margin (demand probability) and the intensive margin (loan amount). Combining the two margins, a 10% increase in interest rates reduces loan demand by 32.7%. The borrow-lender relationship dummy ("Relationship FE") has a positive and significant effect on demand, suggesting that borrowers are likely to stay with their current lender.

In the default equation, we include fixed effects for bank, relationship, loan amount, maturity, region, and the borrower's industry. We find that the loan interest rate has a positive and significant effect on default, while collateral has a negative and significant effect. The results suggest that on average a 10% increase in the interest rate increases the probability of default by 16.7%, while posting collateral decreases the probability of default by 27.6%. Consistent with Stiglitz and Weiss (1981), the price effect implies that, conditional on selection, a higher interest rates makes borrowers less likely to repay their loan. The collateral result instead is consistent with collateral mitigating the ex post incentive problem. When borrowers pledge collateral they are more likely to repay, given that they have more at stake in the loan. Consistent with the ex post theories of collateral, this result indicates that collateral is a very effective tool in mitigating moral hazard and other ex post frictions that facilitate or encourage defaults. This conclusion on the role of collateral however does not apply for borrowers having an existing relationship with a lender, as for those collateral is associated with higher default probability. This is consistent with the relationship bank having learnt the creditworthiness of the borrower, and hence requiring to pledge collateral to risky firms with higher default probability.

The bottom panel of Table 5 shows the covariance matrix for unobservable shocks. The positive and significant correlation between price sensitivity and borrowers' unobserved riskiness $\rho_{\mathcal{P}F}$ suggests that firms with high unobservable default risk are less price sensitive and more likely to take credit, which we interpret as evidence of adverse selection. On the other hand, the negative and significant correlation between collateral sensitivity and borrowers' unobserved riskiness $\rho_{\mathcal{C}F}$ suggests that riskier firms are less likely to demand credit if collateral is required, which we interpret as evidence that collateral can mitigate adverse selection

---

[28]Since we have no information on borrowers that do not demand a bank loan, we cannot control for loan and borrower characteristics, as these are constant across borrowers' options in their choice set and their effect on demand would therefore not be identified. We have experimented interacting price and collateral with the borrowers' variables we have (legal status and rating), but found no statistically significant effect.

and induce separation of borrowers of different risk. Moreover, the negative correlation between price and collateral sensitivities $\rho_{\mathcal{PC}}$ implies that firms with higher disutility from interest rate have instead lower disutility from collateral. This implies that borrowers with higher unobservable risk are more price tolerant as well as collateral sensitive, suggesting that safe borrowers prefer a secured loan with lower interest rate, while risky borrowers prefer an unsecured loan with higher interest rate.

Figure 5 gives a graphical interpretation of these results. Figure 5a reports the joint distribution of the heterogeneous price and collateral coefficients $(\varepsilon_{\mathcal{P}i}^{D}, \varepsilon_{\mathcal{C}i}^{D})$, obtained by subtracting the two mean utilities from total price and collateral coefficients. The two random coefficients are negatively correlated as indicated by the red dashed line. Figure 5b shows the relationship between borrowers' preferences for price and collateral and their unobserved riskiness levels. As conditional on taking a specific loan the unobserved risk ε_i^F is normally distributed with idiosyncratic mean $\tilde{\mu}_{Fi}$, we use as measure of unobserved risk the estimate of this mean as of equation (21), which is distributed with mean 0.00 and standard deviation 0.01. A standard deviation increase in our measure of unobserved risk $\tilde{\mu}_{Fi}$ increases the probability of default by 2% on average.

Figure 5b demonstrates that it is possible for banks to screen borrowers using collateral. Riskier (safer) borrowers are in red (green). As can be observed in the figure, the riskier a borrower is, the further away it locates from the center towards the top-left corner. That is, riskier borrowers have lower price disutility and higher collateral disutility. The opposite holds for safer borrowers, which are closer to the bottom-right corner, as they have lower collateral disutility and higher price disutility. Notice that the collateral coefficient to price coefficient ratio corresponds to the borrower's marginal rate of substitution of collateral for price $MRS_{\mathcal{C},\mathcal{P}}$. As illustrated in the figure, riskier borrowers have higher $MRS_{\mathcal{C},\mathcal{P}}$, as assumed by the theoretical literature that motivates collateral as a screening device of unobserved borrower risk. Therefore, by setting the interest rates on secured and unsecured contracts, banks can make the interest rate benefit of choosing a secured loan compared to choosing an unsecured loan high enough for safe borrowers but too low for risky borrowers, inducing a separating equilibrium. Hence, safe borrowers will be more likely to choose a secured loan with low interest rate, while risky borrowers will be more likely to choose an unsecured loan with a high interest rate, just as Figure 5b shows.

These results confirm the existence of both ex ante and ex post asymmetric information frictions and show that collateral can reduce both kinds of frictions. Furthermore, they provide empirical evidence that risky borrowers have a higher marginal rate of substitution of collateral for price, a fundamental assumption in the ex ante theories of collateral (Bester 1985, Chan and Thakor 1987), which to the best of our knowledge has never been verified before. Overall, our results show that by exploiting the variation in borrowers' preferences, lenders can use interest rate and collateral to affect borrowers' choices, implement screening, reduce credit rationing, and increase social welfare.

Table 5: Structural Estimation Results

	Demand	Log Amount	Default
Price	−0.43***	−0.22***	0.93***
	(0.01)	(0.01)	(0.01)
Price × Relationship	−1.15***	0.03	0.22***
	(0.00)	(0.03)	(0.01)
Collateral	−0.50***	0.44***	−0.11***
	(0.01)	(0.12)	(0.01)
Collateral × Relationship	−0.19***	0.28*	0.44***
	(0.01)	(0.14)	(0.02)
Installment		−0.06	−0.26***
		(0.10)	(0.01)
Corporation		0.30***	0.04***
		(0.07)	(0.01)
Bad Credit Rating		0.78***	0.96***
		(0.18)	(0.04)
Bank FE	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes
Amount FE	No	No	Yes
Maturity FE	No	Yes	Yes
Industry FE	No	Yes	Yes
Region FE	No	Yes	Yes
Price residual	Yes	Yes	Yes
Collateral residual	Yes	Yes	Yes
Observations	16,852	1,650	1,650

	$\sigma_{\mathcal{P}} = 1.75^{***}$		
	(0.01)		
Covariance matrix	$\rho_{\mathcal{PC}} = -0.60^{***}$	$\sigma_{\mathcal{C}} = 0.36^{***}$	
	(0.00)	(0.01)	
	$\rho_{\mathcal{PF}} = 0.10^{***}$	$\rho_{\mathcal{CF}} = -0.42^{***}$	$\sigma_F = 1$
	(0.01)	(0.01)	

Note: This table presents the estimates of the structural model. The first column is for demand and the third column is for default, all of which are estimated using maximum simulated likelihood. The second column is for loan amount estimated using a two-step regression with the control function approach, where the dependent variable of the second step is the logarithm of loan amount. There are two random coefficients in demand, price and collateral, with mean coefficient reported in the first column of results, and with standard deviation coefficients reported in the Covariance matrix panel. In the demand part, the variable Price stands for predicted price, while in the default part, Price stands for observed price. Price and Price residual are normalized at the 95th percentile of predicted price (i.e., 18 percentage points per year) in the demand and default models. *p<0.1; **p<0.05; ***p<0.01.
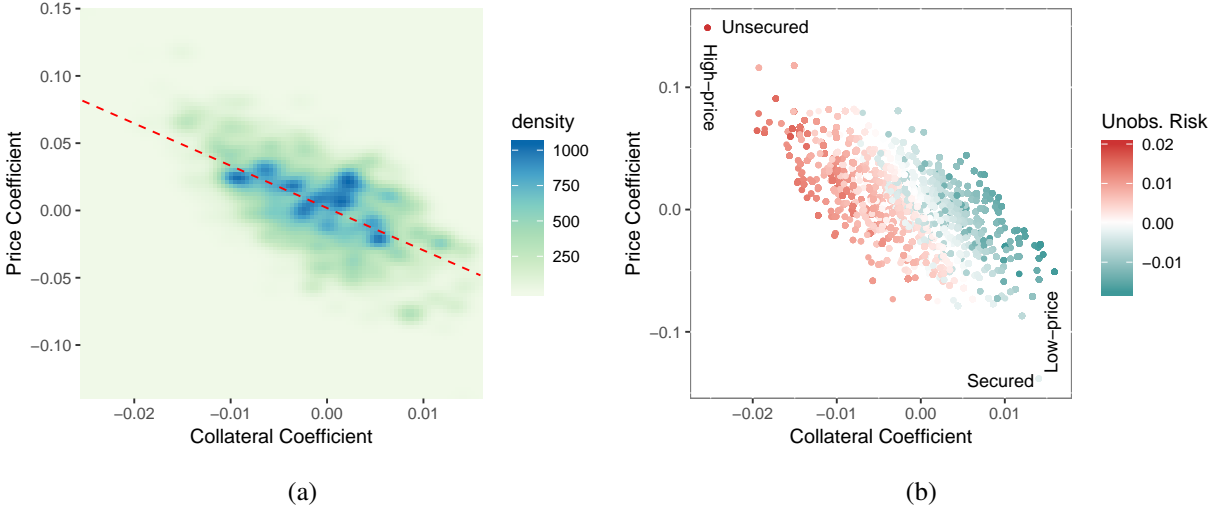
Figure 5: Random Coefficients of Price and Collateral

Note: These figures plot model estimated heterogeneity in price and collateral coefficients for all loans. Subfigure (a) plots the joint density of the random price and collateral coefficients. The red dashed line is the linear model fitted line which captures the correlation between the heterogeneous price and collateral coefficients. Subfigure (b) plots each observation explicitly. *Unobs. Risk* is the estimated unobserved risk. High unobserved risk firms are in red and low unobserved risk firms are in green.

5.1 Model Fit

To evaluate the model's goodness of fit, we use the estimates of the demand, loan amount, and default models to calculate predicted credit demand $\widehat{Q}_{ij\mathcal{S}m}$, $\widehat{Q}_{ij\mathcal{U}m}$, default probabilities $\widehat{F}_{ij\mathcal{S}m}$, $\widehat{F}_{ij\mathcal{U}m}$, and their derivatives with respect to interest rates and contrast these to the same equilibrium outcomes observed in the data. Credit demand is defined as demand probability times the loan amount. Results are reported in Table 6. The first rows of the first four sections ("Actual") reports the interest rates, demand, default, and profits, obtained from the actual data, where interest rates are predicted as described in Section 4.1, while the second row ("Baseline") shows the same equilibrium outcomes as predicted by our structural model in the baseline scenario. For each variable, we report the mean, median and standard deviation.[29] As can be observed in Table 6, the model predicted equilibrium is very close to the observed outcomes. This is also illustrated in the distribution of actual and model fit outcomes in Figure A.2.

The last two rows of Table 6 report banks' marginal costs and profit margins, variables usually unobserved in the data, backed out from our model's first-order conditions as of equation (11).[30] To make marginal costs comparable to loan prices, we normalize the model-implied marginal cost $\widehat{MC}_{ijkm}$ by subtracting 1 (the principal) and then dividing by the loan maturity T_{ijkm}. These marginal costs capture the overall cost of lending an extra dollar for one year, including among other things funding, screening, and

---

[29]We exclude from these descriptive statistics a few cases of loans with negative expected profits (4.9% and 4.3% of observations respectively for Actual variables and Baseline variables). In fact, given that our model does not allow for borrower rejection, in a few cases of unprofitable borrowers, the equilibrium price is pushed to a very high level in order to minimize the borrower's demand probability and loan amount, which in turn leads to a negative expected profit based on equation (7).

[30]We report in Appendix A.3 the formulas for marginal costs.

monitoring costs. We can then calculate how profitable an extra dollar lent is, by looking at the difference between the interest rate and the marginal cost. A large spread suggests that the bank can extract high margins from lending. In Figure 6 we also relate the normalized marginal costs to observed banks' financing costs to examine whether the estimated marginal costs capture the decreasing interest rates in Bolivia over the sample period. The grey line shows the median of marginal costs for each year-quarter combination of the sample period, and the red line displays the median of originating banks' funding costs, represented by the interest rates on savings deposits. The estimated marginal costs have a similar magnitude and decrease over time, in line with the steady drop in banks' funding costs as reported in their balance sheets, confirming the reliability of our marginal costs' estimates.

Table 6: Descriptives of Model Fit

	N. Obs	Mean	Median	Std. Dev
Actual Interest Rate	14,338	13.37	13.76	3.37
Baseline Interest Rate	14,313	13.12	13.55	3.68
Actual Default	14,338	0.09	0.08	0.09
Baseline Default	14,313	0.09	0.08	0.09
Actual Demand	14,338	7,644	0.00	24,242
Baseline Demand	14,313	8,720	0.00	27,133
Actual Profit	14,338	507	0.00	2,878
Baseline Profit	14,313	524	0.00	3,048
Marginal Cost	14,313	8.02	8.33	3.52
Profit Margin	14,313	5.34	5.16	1.40

Note: This table summarizes the model fit results. For each variable we report both descriptive statistics from the data (Actual) and the model predicted equilibrium in the baseline scenario (Baseline). Interest Rate is in percentage points, Default is a probability, Demand is the product of demand probability and loan amount in USD. Profit is in USD. Marginal Cost is the annualized cost of lending in percentage points. Profit Margin is the spread between the interest rate and the marginal cost.
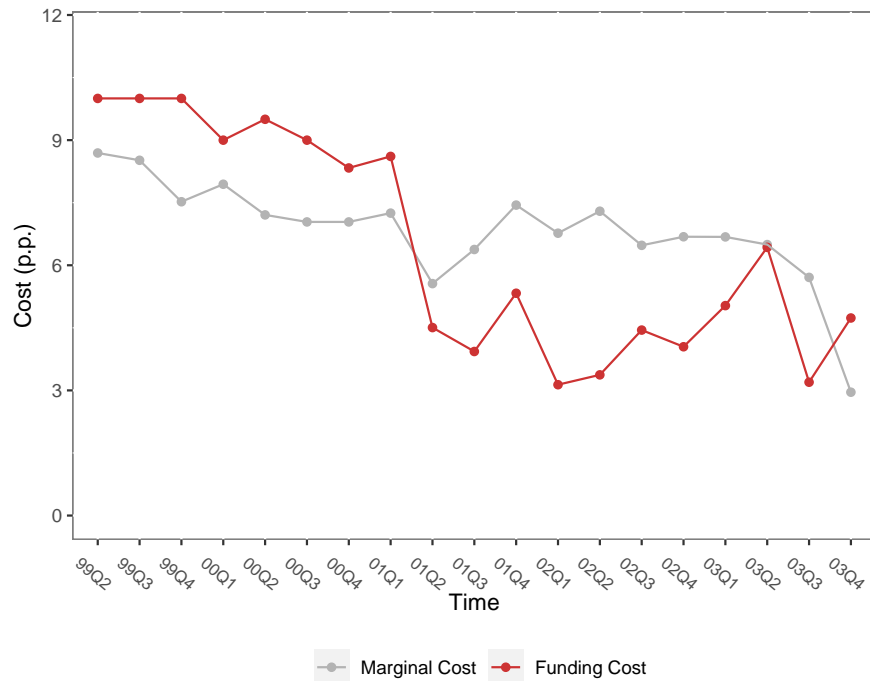
Figure 6: Model-Implied Marginal Costs and Banks' Funding Costs

Note: This figure compares model-implied marginal costs and banks' funding costs over time. The grey line shows the median of normalized marginal costs (in percentage points for each lending dollar) in each quarter, while the red line illustrates the median of banks' saving deposit interest rates in that quarter (in percentage points), which represents banks' funding costs.

Regression results in Table 7 further show that secured loans have higher marginal costs and lower profit margins. Our estimates indicate that the marginal cost of lending one dollar with collateral is 4.5 percentage points higher than that of unsecured loans, equivalent to 57% of the average marginal cost (column 1). Consequently, the banks' profit margin on secured loans is on average 5 percentage points lower than that of unsecured loans, equivalent to 91% of the average profit margin (column 3). Results in columns (2) and (4) further indicate that using collateral as a screening device is costly. We find that offering both types of contracts to a firm (Both) yields higher marginal costs and lower profit margins for banks.

Table 7: Determinants of Marginal Cost and Profit Margin

	Marginal Cost		Profit Margin	
	(1)	(2)	(3)	(4)
Collateral	4.45***	3.82**	−4.98***	−4.33***
	(1.53)	(1.58)	(1.54)	(1.58)
Both		2.88		−2.96*
		(1.76)		(1.76)
Loan Controls	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	16,852	16,852	16,852	16,852
Adjusted R^2	0.03	0.03	0.03	0.03

Note: This table shows the OLS regression results of model implied marginal costs and of the profit margins on different loan and firm characteristics. The dependent variable in Columns (1) to (2) are the normalized marginal costs, and in Columns (3) to (4) are the profit margin, i.e., the difference between interest rates and marginal costs. *Collateral* is an indicator which equals one for a secured loan and zero for an unsecured one. *Both* equals one if a loan belongs to a pair of secured and unsecured loans that are offered by one bank to the same borrower. *Loan Controls* include variables for Amount, Maturity, Installment, Bad Credit Rating, Relationship. *Borrower Controls* include variables for Corporation, Industry. *p<0.1; **p<0.05; ***p<0.01.

6   Counterfactuals

We conduct two counterfactual policy experiments to quantify the credit demand and supply responses to a shock to collateral value, and to understand the effectiveness of banks' screening strategies within the collateral channel. Using the estimates of our demand and default models, together with our supply-side framework, we quantify the changes in lenders' expected profits and interest rates, and in borrowers' demand and default, when the collateral value CV_{ijm} drops by 40%. This is similar to the magnitude of various collateral value shocks documented in the literature, such as the burst of the Japanese assets price bubble that caused a 50% drop in land prices in Japan between 1991 and 1993 (Gan 2007), the nearly 30% drop of the Case-Shiller 20-City Composite Home Price Index in the U.S. during the 2007-2009 financial crisis, and the rise in average repo haircut on seven categories of structured debt from zero in August 2007 to 45% in December 2008 (Gorton 2010).

We consider two alternative scenarios. First, we hold constant the set of available contracts at the baseline level, and let banks respond to the shock only adjusting interest rates. Second, we allow banks to accommodate the drop in collateral value via both pricing and rationing. We define a loan contract as being rationed if it is not offered by a bank to a specific borrower, and we assume this happens when the

expected profit of that loan based on equation (7) is negative. Assuming that banks' marginal costs of lending to each firm remain constant in the counterfactual scenarios, we find the new equilibrium in terms of interest rate P_{ijkm}, probability of default F_{ijkm}, expected demand Q_{ijkm}, banks' expected profit Π_{ijkm}, and number of loan contracts offered. The drop in collateral value gives rise to various effects through our model. First, it affects directly banks' expected profits from secured loans through the level of collateral, implying that banks will change their equilibrium interest rate, which will in turn affect demand and default. Also banks' expected profits from unsecured loans are affected, as some borrowers might now change their choice between a secured and an unsecured loan, which will in turn imply a change in equilibrium interest rates also for uncollateralized loans. This highlights how our model is able to capture spillover effects of the collateral channel from secured to unsecured loans, a novel result compared to the existing literature.

Table 8 summarizes the new equilibrium after the collateral value shock compared with the baseline model, for the case of banks responding either through pricing (top panel) or through pricing and rationing (bottom panel). In each panel we consider counterfactual outcomes for two samples, that is either all the loans offered to new borrowers in their first 18 months (All Loans), or only the first loan that new borrowers are offered (First Loan), as the latter will not be affected by inertia due to previous relationships. We begin describing banks' response to a collateral value shock only through pricing. We find that a 40% decrease in collateral value generates a median 2.4% and 1.3% increase in the interest rates of secured and unsecured loans, respectively. Overall, the median interest rate increase is 2.1%, namely 0.3 percentage points. The median increase in the probability of default is 1.5%. The expected demand and profit drop significantly, with a 4.4% and a 5.0% median decrease, respectively.[31] The results for the first loan are qualitatively the same, but magnitudes are larger. When we allow banks to respond to the collateral value shock also with rationing, we find that 39% of the baseline loan contracts are not available anymore in the counterfactual scenario, with a 42% and a 35% reduction in unsecured and secured loans offered respectively. However, rationing allows banks to significantly mitigate their price response to the collateral value shock, with a median increase in interest rates exclusively driven by secured contracts, and almost only for first loans. This small price effect leads to no change in default rates, and a considerably small median drop in borrowers' demand and banks' profits of around 1.2% and 1.9% for each outcome.

These results quantify the relevance of various components of the mechanism at play in our model, following up on the discussion at the end of Section 3.2. A shock to collateral value directly impacts lenders' profits through the recovery rate term. When banks can only adjust pricing, they respond to this shock increasing the interest rate on both secured and unsecured loans, as they can use both margins to make up for this potential profit loss. The heterogeneity in these price responses is driven by both the average borrowers' default rate (F_{ijkm}) and banks' markup terms, as can be seen in equation (11). As expected, borrowers respond to this by reducing their credit demand and increasing their likelihood of default, through the moral hazard channel $\alpha_{\mathcal{P}i}^{F}$. Another driver of the larger increase in interest rates for secured loans compared to unsecured ones is adverse selection, because safe borrowers are the most price sensitive ones, and the larger price increase might induce them to switch to unsecured loans, worsening the pool of borrowers choosing collateralized loans. In other words, the increase in interest rates for unsecured loans is also determined by

---

[31]These results are qualitatively in line with the findings in Cerqueiro, Ongena and Roszbach (2016), who investigate how a legal change in Sweden reduces the collateral value by 13% for outstanding loans, generating a 0.2 percentage points increase in interest rate, an 11% decrease in internal credit limit, and 12 percentage points more delinquent borrowers.

the riskiness of the marginal borrowers who switch away from secured loans.

Table 8: The Collateral Channel

	Available	Median Percentage Change			
	Contracts	Interest Rate	Default	Demand	Profit
A: Pricing					
All Loans					
Secured	7,277	2.35	3.09	-1.24	-5.10
Unsecured	9,575	1.27	0.71	0.00	-0.28
Total	16,852	2.05	1.51	-4.35	-4.97
First Loan					
Secured	2,333	3.97	5.35	-4.83	-10.47
Unsecured	2,649	0.93	1.17	-3.59	-4.75
Total	4,982	3.96	5.19	-7.15	-9.15
B: Pricing & Rationing					
All Loans					
Secured	4,743	0.00	0.00	0.00	-0.00
Unsecured	5,539	0.00	0.00	0.00	0.00
Total	10,282	0.00	-0.00	0.00	0.00
First Loan					
Secured	1,725	0.59	0.00	-2.48	-5.51
Unsecured	1,727	0.00	-0.02	0.00	0.00
Total	3,452	0.00	0.00	-1.17	-1.88

Note: This table summarizes the median percentage change in equilibrium price (*Interest Rate*), probability of default (*Default*), expected demand (*Demand*) and banks' expected profit (*Profit*) of loans after a 40% collateral value drop compared with the baseline model. Each row stands for secured loans, unsecured loans, and both. The top panel presents the scenario where the set of available contracts is fixed, whereas the bottom panel shows the rationing case, where loans with negative expected profits are not offered to borrowers. The percentage changes in interest rate (probability of default, or demand) are calculated by comparing the average interest rate (probability of default, or demand) across loan offers in each borrower's choice set, weighted by their demand probabilities in the counterfactual and in the baseline scenario. The percentage changes in profit are calculated by comparing the sum of the expected profit of loan offers in each borrower's choice set in the counterfactual and in the baseline scenario.

6.1   Effectiveness of Collateral as Screening Device

We provide additional evidence of the main mechanisms driving the results in our counterfactuals, by further investigating how collateral values and banks' supply strategies affect the effectiveness of collateral as a screening device. We estimate a simple regression model using our baseline and counterfactual results to understand the relationship between borrowers' likelihood of choosing a secured loan, given by the corresponding estimated demand probabilities, and their unobserved riskiness, defined as our estimate of $\widetilde{\mu}_{Fi}$

from equation (21). We take as unit of observation each bank-firm combination for which a lender offers both a secured and an unsecured loan, and use as dependent variable in an OLS regression the probability of choosing a secured loan from each bank, conditional on having chosen that specific bank. We estimate this model for our baseline case and for the two counterfactuals we run, and summarize the results in Table 9. We include the interest rate of secured loans, as well as fixed effects for bank, loan amount, loan maturity, industry, region, and year-quarter. The benefits of this exercises are twofold. First, we can summarize within a single regression model an important takeaway of our counterfactuals, that is how the effectiveness of collateral as a screening device changes across different scenarios. Second, we make direct use of our model-implied borrowers' unobserved riskiness, not explicitly employed in our previous policy experiments.

In the baseline model, that is the first column on Table 9, we find that the probability of choosing a secured loan is negatively related to borrowers' unobserved risk, which implies that safe borrowers are more likely to choose a secured loan. In particular, one standard deviation increase in a borrower's unobserved risk leads to a 0.5 percentage points decrease in her probability of choosing a secured loan. This is consistent with collateral mitigating adverse selection problems by inducing separation of borrowers of different risk. However, once we shock the collateral value and only let banks respond through pricing, the screening effect of collateral loses explanatory power, as can be seen from the coefficient of unobserved risk in the second column of Table 9. This reinforces the results reported in Table 8, as the drop in collateral value decreases lenders' expected profits from secured loans, which in turn decreases their incentive to differentiate between safe and risky borrowers using collateral. Moreover, from the borrowers' perspective, the collateral value shock increases significantly the interest rate on secured loans, which decreases safe borrowers' demand for secured loans.

On the other hand, when banks can respond to the shock in collateral value both through pricing and rationing, the screening effect of collateral is again negative and statistically significant, as reported in the third column of Table 9. These results suggest that rationing is a considerably more effective strategy to tackle the collateral channel relative to pricing, for the following reasons. As collateral values drop, most secured contracts become less profitable relative to unsecured ones, reducing the interest rate discount that banks give for pledging collateral, which eventually prevents collateral from being able to separate safe and risky borrowers. Rationing instead allows banks to not offer loan contracts with negative expected profits, which would otherwise be offered to borrowers most severely affected by the collateral value shock, and to keep offering both secured and unsecured loans to borrowers least affected by the shock, like those with immovable assets that had an initial value well above the requested loan amount. This implies that for those least affected borrowers collateral still serves as an effective screening device, as assets did not depreciate excessively, while the remaining borrowers are rationed. This result suggests that in times of crisis, when collateral values drop, rationing is an effective tool to preserve the screening role of collateral for the least affected borrowers, benefiting banks and non-rationed borrowers.

Table 9: Effectiveness of Collateral as a Screening Device

| | **Probability of Choosing Secured Loan** | | |
| | Baseline | Collateral Shock with Screening via | |
		Pricing	*Pricing & Rationing*
Unobserved Risk	−0.55**	−0.41	−0.37***
	(0.24)	(0.35)	(0.12)
Borrower Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	5,784	5,784	3,364
Adjusted R^2	0.03	0.05	0.10

Note: This table summarizes OLS regression results. The unit of observation is a borrower-bank combination, conditional on the bank offering both secured and unsecured loans to the borrower. Interest Rate is the interest rate of the secured loan. The dependent variable is the conditional probability of choosing the secured contract from the pair of contracts provided by the same bank. The explanatory variable *Unobserved Risk* is the simulated unobserved risk. The three columns correspond to baseline model, collateral channel with pricing response, and collateral channel with pricing and rationing response. We add a dummy variable to control for loan contracts with negative expected profit, and exclude contracts with extremely low demand probabilities (the median demand probability of these excluded contracts is 8.47e-11.) *p<0.1; **p<0.05; ***p<0.01.

7   Conclusions

In this paper we study the benefits and costs of collateral requirements in bank lending markets with asymmetric information. We develop a structural model of firms' credit demand for secured and unsecured loans, banks' contract offering and pricing, and firm default using detailed credit registry data on corporate loans and borrowers' performance from Bolivia, a country where asymmetric information problems in credit markets are pervasive. We make three important contributions to the literature.

First, by modeling borrowers' demand for secured and unsecured credit, we provide micro-founded evidence of the benefits of collateral pledging, estimating structural parameters that measure both the ex ante and ex post reduction in agency costs that collateral determines. We provide evidence supporting both the ex ante and ex post theories of collateral. Consistent with the ex ante theories, we find a negative and significant correlation between borrowers' sensitivity to collateral and their default unobservables, which suggests that borrowers with high default risk tend to have high disutility from pledging collateral, and are therefore less likely to demand a secured loan compared to safe borrowers. Furthermore, we provide empirical evidence that riskier borrowers have a higher marginal rate of substitution of collateral for price, a key assumption in the ex ante theories which, to the best of our knowledge, has never been verified before.

Consistent with the ex post theories, we find a negative and significant causal effect of collateral on default, suggesting that on average posting collateral decreases the probability of default by 27.6%.

Second, by modeling also lenders' supply of both collateralized and uncollateralized loans, we are able to separately quantify the role of credit demand and supply within the collateral channel, accounting for their interaction. We simulate the effects of a 40% drop in collateral value on credit supply, credit allocation, interest rates, and banks' expected profits. When banks respond to this shock only through pricing, we document for the median loan a 2.1% increase in interest rates, a 4.4% reduction in borrowers' expected demand, a 1.5% rise in default probabilities, and a 5.0% drop in banks' expected profits.

Third, we can study how the use of collateral and the propagation of collateral shocks depends differently on banks' pricing and rationing responses. When banks respond to the collateral value shock through both pricing and rationing, 39% of the loan contracts result as being unprofitable and are hence not offered to borrowers anymore. Allowing for rationing implies very small changes in interest rates, borrowers' default, expected demand and profits. Furthermore, we document that absent the shock to collateral value, collateral is an effective screening device, as it induces sorting of unobservably risky borrowers into secured contracts. The screening role of collateral is however negatively affected when we introduce the collateral channel, but it is preserved if banks are allowed to respond both via pricing and rationing, highlighting in particular the importance of the latter margin. Rationing allows in fact banks to reject borrowers whose assets were most severely affected by the shock, for whom collateral would not achieve an effective screening anymore, while still offering secured and unsecured loans to the least affected borrowers, for whom instead the screening role of collateral is still preserved.

Overall, our results indicate that collateral has a large impact on firms' access and terms of credit. Swings in collateral values have a large effect on the fraction of borrowers that are able to obtain credit, as well as on the amount and terms of credit, by altering banks' expected profitability and equilibrium loan interest rates. Our work opens the floor for various other potential directions of research. First, our approach could be extended to quantify not only how the severity of adverse selection, but also how the severity of moral hazard can influence the propagation of shocks to collateral values. This would have important implications for policymakers, who could then prioritize their interventions on the key friction. Second, the current analysis holds banks' marginal cost of funds constant. Additional counterfactual experiments could allow this to change, providing insights on the role monetary policy in the transmission of shocks to collateral values. Last, this framework could be used to investigate how policy interventions aimed at improving lenders' recovery rates could mitigate the negative effects of a shock to collateral value. We regard all of these as promising directions of future research.

References

Acharya, V. V., Bharath, S. T. and Srinivasan, A. (2007), 'Does industry-wide distress affect defaulted firms? evidence from creditor recoveries', *Journal of Financial Economics* **85**(3), 787–821.

Adams, W., Einav, L. and Levin, J. (2009), 'Liquidity constraints and imperfect information in subprime lending', *American Economic Review* **99**(1), 49–84.

Adelino, M., Schoar, A. and Severino, F. (2015), 'House prices, collateral, and self-employment', *Journal of Financial Economics* **117**(2), 288–306.

Aghion, P. and Bolton, P. (1992), 'An incomplete contracts approach to financial contracting', *Review of Economic Studies* **59**(3), 473–494.

Aghion, P. and Bolton, P. (1997), 'A theory of trickle-down growth and development', *Review of Economic Studies* **64**(2), 151–172.

Albuquerque, R. and Hopenhayn, H. A. (2004), 'Optimal lending contracts and firm dynamics', *Review of Economic Studies* **71**(2), 285–315.

Asarnow, E. and Edwards, D. (1995), 'Measuring loss on defaulted bank loans: A 24-year study', *Journal of Commercial Lending* **77**(7), 11–23.

Banerjee, A. and Newman, A. (1993), 'Occupational choice and the process of development', *Journal of Political Economy* **101**(2), 274–298.

Benetton, M. (2019), Leverage regulation and market structure: An empirical model of the U.K. mortgage market. Working Paper.

Benmelech, E. and Bergman, N. K. (2008), 'Liquidation values and the credibility of financial contract renegotiation: Evidence from U.S. airlines', *Quarterly Journal of Economics* **123**(4), 1635–1677.

Benmelech, E. and Bergman, N. K. (2009), 'Collateral pricing', *Journal of Financial Economics* **91**(3), 339–360.

Benmelech, E. and Bergman, N. K. (2011), 'Bankruptcy and the collateral channel', *Journal of Finance* **LXVI**(2), 337–378.

Benmelech, E., Garmaise, M. J. and Moskowitz, T. J. (2005), 'Do liquidation values affect financial contracts? evidence from commercial loan contracts and zoning regulation', *Quarterly Journal of Economics* **120**(3), 1121–1154.

Berger, A. N., Espinosa-Vega, M. A., Frame, W. S. and Miller, N. H. (2011), 'Why do borrowers pledge collateral? new empirical evidence on the role of asymmetric information', *Journal of Financial Intermediation* **20**(1), 55–70.

Berger, A. N., Frame, W. S. and Ioannidou, V. (2011), 'Tests of ex ante versus ex post theories of collateral using private and public information', *Journal of Financial Economics* **100**(1), 85–97.

Berger, A. N., Frame, W. S. and Ioannidou, V. (2016), 'Reexamining the empirical relation between loan risk and collateral: The roles of collateral liquidity and types', *Journal of Financial Intermediation* **26**, 28–46.

Berger, A. N. and Udell, G. F. (1990), 'Collateral, loan quality and bank risk', *Journal of Monetary Economics* **25**(1), 21–42.

Berger, A. N. and Udell, G. F. (1995), 'Relationship lending and lines of credit in small firm finance', *Journal of Business* **68**(3), 351–381.

Bernanke, B. (1983), 'Nonmonetary effects of the financial crisis in the propagation of the great depression', *American Economic Review* **73**(3), 257–276.

Bernanke, B. and Gertler, M. (1989), 'Agency costs, net worth, and business fluctuations', *American Economic Review* **79**(1), 14–31.

Besanko, D. and Thakor, A. V. (1987*a*), 'Collateral and rationing: Sorting equilibria in monopolistic and competitive credit markets', *International Economic Review* **28**(3), 671–689.

Besanko, D. and Thakor, A. V. (1987*b*), 'Competitive equilibrium in the credit market under asymmetric information', *Journal of Economic Theory* **42**(1), 167–182.

Bester, H. (1985), 'Screening vs. rationing in credit markets with imperfect information', *American Economic Review* **75**(4), 850–855.

Blackwell, D. W. and Winters, D. B. (1997), 'Banking relationships and the channel of monitoring on loan pricing', *Journal of Financial Research* **20**(2), 275–289.

Boot, A. W. A. and Thakor, A. V. (1994), 'Moral hazard and secured lending in an infinitely repeated credit market game', *International Economic Review* **35**(4), 899–920.

Boot, A. W. A., Thakor, A. V. and Udell, G. F. (1991), 'Secured lending and default risk: Equilibrium analysis, policy implications and empirical results', *Economic Journal* **101**(406), 458–472.

Boyd, J. H. and Smith, B. D. (1994), 'How good are standard debt contracts? stochastic versus nonstochastic monitoring in a costly state verification environment', *Journal of Business* **67**(4), 539–561.

Brick, I. E. and Palia, D. (2007), 'Evidence of jointness in the terms of relationship lending', *Journal of Financial Intermediation* **16**(3), 452–476.

Caliendo, M. and Kopeinig, S. (2008), 'Some practical guidance for the implementation of propensity score matching', *Journal of Economic Surveys* **22**(1), 31–72.

Cerqueiro, G., Ongena, S. and Roszbach, K. (2016), 'Collateralization, bank loan rates, and monitoring', *Journal of Finance* **LXXI**(3), 1295–1322.

Cerqueiro, G., Ongena, S. and Roszbach, K. (2019), Collateral damaged? priority structure, credit supply, and firm performance. forthcoming *Journal of Financial Intermediation*.

Chan, Y.-S. and Kanatas, G. (1985), 'Asymmetric valuations and the role of collateral in loan agreements', *Journal of Money, Credit and Banking* **17**(1), 84–95.

Chan, Y.-S. and Thakor, A. V. (1987), 'Collateral and competitive equilibria with moral hazard and private information', *Journal of Finance* **XLII**(2), 345–363.

Chaney, T., Sraer, D. and Thesmar, D. (2012), 'The collateral channel: How real estate shocks affect corporate investment', *American Economic Review* **102**(6), 2381–2409.

Chiappori, P. A. and Salanié, B. (2000), 'Testing for asymmetric information in insurance markets', *Journal of Political Economy* **108**(1), 56–78.

Cooley, T., Marimon, R. and Quadrini, V. (2004), 'Aggregate consequences of limited contract enforceability', *Journal of Political Economy* **112**(4), 817–847.

Corradin, S. and Popov, A. (2015), 'House prices, home equity borrowing, and entrepreneurship', *Review of Financial Studies* **28**(8), 2399–2428.

Crawford, G. S., Pavanini, N. and Schivardi, F. (2018), 'Asymmetric information and imperfect competition in lending markets', *American Economic Review* **108**(7), 1659–1701.

Davydenko, S. A. and Franks, J. R. (2008), 'Do bankruptcy codes matter? a study of defaults in France, Germany, and the U.K.', *Journal of Finance* **LXIII**(2), 565–608.

De Janvry, A., Sadoulet, E., McIntosh, C., Wydick, B., Luoto, J., Gordillo, G. and Schuetz, G. (2003), 'Credit bureaus and the rural microfinance sector: Peru, Guatemala, and Bolivia', *Collaborative Research Support Program. The University of California and The FAO Office for Latin America* .

Degryse, H., Ioannidou, V., Liberti, J. M. and Sturgess, J. (2020), 'How do laws and institutions affect recovery rates for collateral?', *The Review of Corporate Finance Studies* **9**(1), 1–43.

Degryse, H. and Van Cayseele, P. (2000), 'Relationship lending within a bank-based system: Evidence from european small business data', *Journal of Financial Intermediation* **9**, 90–109.

Detragiache, E., Garella, P. and Guiso, L. (2000), 'Multiple versus single banking relationships: Theory and evidence', *Journal of Finance* **LV**(3), 1133–1161.

Egan, M., Hortaçsu, A. and Matvos, G. (2017), 'Deposit competition and financial fragility: Evidence from the U.S. banking sector', *American Economic Review* **107**(1), 169–216.

Einav, L., Jenkins, M. and Levin, J. (2012), 'Contract pricing in consumer credit markets', *Econometrica* **80**(4), 1387–1432.

Ersahin, N. and Irani, R. M. (2018), Collateral shocks and corporate employment. Working Paper.

Flannery, M. J. and Sorescu, S. M. (1996), 'Evidence of bank market discipline in subordinated debenture yields: 1983-1991', *Journal of Finance* **LI**(4), 1347–1377.

Gale, D. and Hellwig, M. (1985), 'Incentive-compatible debt contracts: The one-period problem', *Review of Economic Studies* **52**(4), 647–663.

Gan, J. (2007), 'Collateral, debt capacity, and corporate investment: Evidence from a natural experiment', *Journal of Financial Economics* **85**(3), 709–734.

Godlewski, C. and Weill, L. (2011), 'Does collateral help mitigate adverse selection? a cross-country analysis', *Journal of Financial Services Research* **40**(1-2), 49–78.

Gorton, G. B. (2010), *Slapped by the invisible hand: The panic of 2007*, Oxford University Press.

Hart, O. and Moore, J. (1994), 'A theory of debt based on the inalienability of human capital', *Quarterly Journal of Economics* **109**(4), 841–879.

Hart, O. and Moore, J. (1998), 'Default and renegotiation: A dynamic model of debt', *Quarterly Journal of Economics* **113**(1), 1–41.

Ho, K. and Ishii, J. (2011), 'Location and competition in retail banking', *International Journal of Industrial Organization* **29**(5), 537–546.

Holmstrom, B. and Tirole, J. (1997), 'Financial intermediation, loanable funds, and the real sector', *Quarterly Journal of Economics* **122**(3), 663–691.

Honka, E., Hortaçsu, A. and Vitorino, M. A. (2017), 'Advertising, consumer awareness, and choice: Evidence from the U.S. banking industry', *RAND Journal of Economics* **48**(3), 611–646.

Ippolito, F., Peydró, J.-L., Polo, A. and Sette, E. (2016), 'Double bank runs and liquidity risk management', *Journal of Financial Economics* **122**(1), 135–154.

Jiménez, G. and Saurina, J. (2004), 'Collateral, type of lender and relationship banking as determinants of credit risk', *Journal of Banking and Finance* **28**(9), 2191–2212.

John, K., Lynch, A. and Puri, M. (2003), 'Credit ratings, collateral, and loan characteristics: Implications for yield', *Journal of Business* **76**(3), 371–409.

Karlan, D. and Zinman, J. (2009), 'Observing unobservables: Identifying information asymmetries with a consumer credit field experiment', *Econometrica* **77**(6), 1993–2008.

Kerr, S., Kerr, W. R. and Nanda, R. (2015), House money and entrepreneurship. Working Paper.

Khieu, H. D., Mullineaux, D. J. and Yi, H.-C. (2012), 'The determinants of bank loan recovery rates', *Journal of Banking and Finance* **36**(4), 923–933.

Kiyotaki, N. and Moore, J. (1997), 'Credit cycles', *Journal of Political Economy* **105**(2), 211–248.

Koijen, R. S. J. and Yogo, M. (2016), 'Shadow insurance', *Econometrica* **84**(3), 1265–1287.

Koijen, R. S. J. and Yogo, M. (2019), 'A demand system approach to asset pricing', *Journal of Political Economy* **127**(4), 1475–1515.

Luck, S. A. and Santos, J. A. C. (2019), The valuation of collateral in bank lending. Working Paper.

Machauer, A. and Weber, M. (1998), 'Bank behavior based on internal credit ratings of borrowers', *Journal of Banking and Finance* **22**(10-11), 1355–1383.

Martinez Peria, M. S. and Schmukler, S. L. (2001), 'Do depositors punish banks for bad behavior? market discipline, deposit insurance, and banking crises', *Journal of Finance* **LVI**(3), 1029–1051.

Mian, A. and Sufi, A. (2011), 'House prices, home equity-based borrowing, and the U.S. household leverage crisis', *American Economic Review* **101**(5), 2132–2156.

Mian, A. and Sufi, A. (2014), 'What explains the 2007-2009 drop in employment?', *Econometrica* **82**(6), 2197–2223.

Petersen, M. A. and Rajan, R. G. (1994), 'The benefits of lending relationships: Evidence from small business data', *Journal of Finance* **XLIX**(1), 3–37.

Robles-Garcia, C. (2019), Competition and incentives in mortgage markets: The role of brokers. Working Paper.

Schmalz, M., Sraer, D. A. and Thesmar, D. (2017), 'Housing collateral and entrepreneurship', *Journal of Finance* **LXII**(1), 99–132.

Shleifer, A. and Vishny, R. W. (1992), 'Liquidation values and debt capacity: A market equilibrium approach', *Journal of Finance* **XLVII**(4), 1343–1366.

Sirtaine, S., Skamnelos, I. and Frank, S. (2004), 'Bolivia: Challenges in the corporate and banking sectors', *World Bank, Washington, DC* .

Stiglitz, J. and Weiss, A. (1981), 'Credit rationing in markets with imperfect information', *American Economic Review* **71**(3), 393–410.

Townsend, R. M. (1979), 'Optimal contracts and competitive markets with costly state verification', *Journal of Economic Theory* **21**(2), 265–293.

Train, K. E. (2009), *Discrete Choice Methods with Simulation*, Cambridge University Press.

Williamson, O. E. (1988), 'Corporate finance and corporate governance', *Journal of Finance* **XLIII**(3), 567–591.

Williamson, S. D. (1986), 'Costly monitoring, financial intermediation, and equilibrium credit rationing', *Journal of Monetary Economics* **18**(2), 159–179.

A Internet Appendix

A.1 The Matching Algorithm

This section explains the process of determining the optimal matching algorithm. We first provide a simple example of matching, and then show how to determine the optimal matching algorithm, based on the performance of matching observed unsecured loans (untreated) to observed secured loans (treated).

A simple example for matching: Take the case in which we only observe four firms obtaining a loan of the same amount and maturity in the same region and quarter from two banks, Bank A and Bank B. Table A.1 summarizes the interest rates observed in the data (in bold) and those predicted by our matching exercise (in italics). Following the table, we observe Firm 1 taking a secured loan from Bank A at a rate of 14 p.p., Firms 2 and 3 taking an unsecured loan from Bank A at respectively 16 p.p. and 15p.p., and Firm 4 obtaining an unsecured loan from Bank B at a rate of 18 p.p.. If Firm 3 is the best match for Firm 1, then we can assign Firm 3's rate on the unsecured loan form Bank A to Firm 1's unobserved unsecured loan from Bank A. Similarly, if Firm 2 is the best match for Firm 4, then we can assign Firm 2's rate on the unsecured loan form Bank A to Firm 4's unobserved unsecured loan from Bank A. Given that Firm 1 is the only firm that received a secured loan from Bank A, its interest rate will be the best predictor for what the other three firms would have been offered for a secured loan from Bank A. Similarly, given that Firm 4 is the only firm that received an unsecured loan from Bank B, its interest rate will be the best predictor for what the other three firms would have been offered for an unsecured loan from Bank B. Last, given that no firm has been given a secured loan from Bank B, we assume that no firm has been offered a secured loan from Bank B.

Table A.1: An Example for Matching

	Interest Rates from Bank A		Interest Rates from Bank B	
	Secured	Unsecured	Secured	Unsecured
Firm 1	**14**	*15*	-	*18*
Firm 2	*14*	**16**	-	*18*
Firm 3	*14*	**15**	-	*18*
Firm 4	*14*	*16*	-	**18**

Selecting the variables for propensity score: Following Caliendo and Kopeinig (2008), we use two criteria to select the variables for our propensity score matching exercise. First, the variables must be statistically significant at predicting the propensity score. Second, the variables are chosen to maximize the rate of correct prediction. We start including only banks' identifiers, and progressively add variables only if they are statistically significant and can improve the number of correct predictions. We end up with the following set of variables: banks' identifiers, amount category, maturity category, first loan dummy, corporation dummy. The propensity score generated by these variables delivers 580 correct predictions out of 842 secured loans.

Choosing the algorithm: To ensure that after matching the covariates are as close as possible between matched secured and unsecured loans, we set the radius very close to zero such that the matched loans must share the same characteristics as the loan to be matched (i.e., exact matching). If there are more than one loan that have the same characteristics, we randomly choose one loan as the match. This gives us balanced

covariates after the matching. There are 168 secured loan could not be matched. Table A.2 summarizes the statistics before and after matching. Table A.3 presents the matching covariates before and after matching. Through matching, the differences between the covariates of secured and unsecured loans are completely removed, as the percentage of bias is zero for all covariates. This is also illustrated in Figure A.1 (a). Figure A.1 (b) shows the propensity score distribution of secured loans (Treated) and unsecured loans (Untreated). "Treated: Off Support" indicates the unmatched secured loans.

(a)   (b)
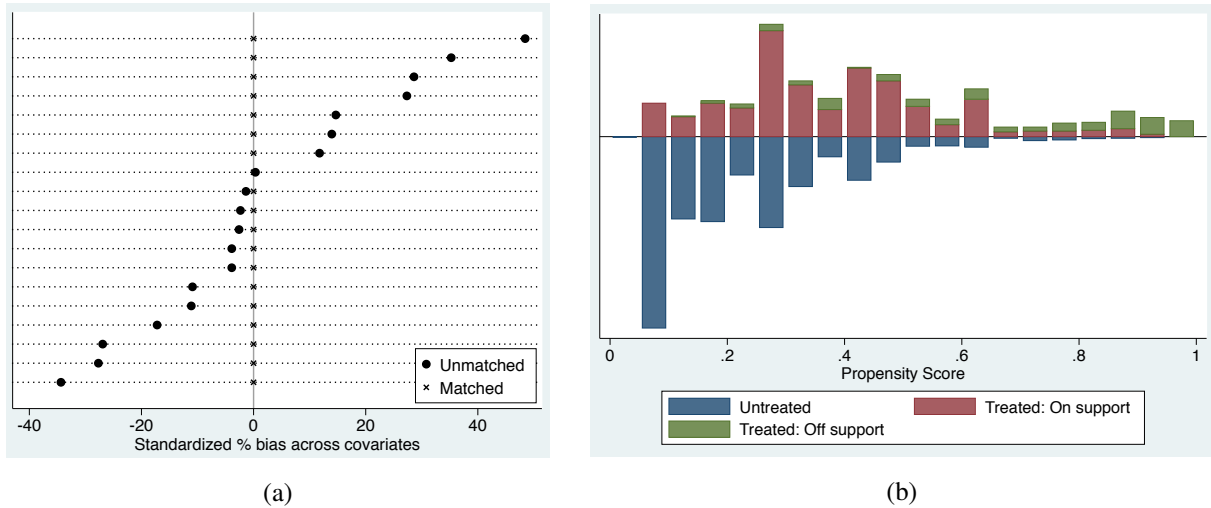
Figure A.1: Propensity Score Matching Performance

Table A.2: Matching Results I

Sample	Pseudo-R2	LR χ^2	$p > \chi^2$	Mean Bias	Med Bias	Rubin's B	Rubin's R
Unmatched	0.176	610.97	0.000	17.0	13.9	104.0*	1.79
Matched	-0.000	-0.00	1.000	0.0	0.0	0.0	1.00

Note: This table summarizes the statistics before (Unmatched) and after (Matched) matching. A rule of thumb for a good match is to have mean and median bias below 3% to 5%, Rubin's B below 25% and Rubin's R between 0.5 and 2.

Table A.3: Matching Results II

Variable	Unmatched vs. Matched	Mean		%Reduction		t-Test	
		Treated	Control	%bias	|bias|	t	p>|t|
Bank 3	U	.09609	.10374	-2.6		-0.62	0.536
	M	.10815	.10815	0.0	100.0	0.00	1.000
Bank 5	U	.172	.12979	11.8		2.95	0.003
	M	.20444	.20444	0.0	100.0	0.00	1.000
Bank 7	U	.06524	.00246	35.2		10.94	0.000
	M	.01481	.01481	0.0	100.0	-0.00	1.000
Bank 8	U	.0427	.00246	27.3		8.39	0.000
	M	.01037	.01037	0.0	100.0	-0.00	1.000
Bank 9	U	.13879	.24336	-26.8		-6.28	0.000
	M	.16593	.16593	0.0	100.0	0.00	1.000
Bank 10	U	.0866	.04966	14.7		3.79	0.000
	M	.08741	.08741	0.0	100.0	-0.00	1.000
Bank 11	U	.09727	.15388	-17.1		-4.03	0.000
	M	.11704	.11704	0.0	100.0	0.00	1.000
Bank 14	U	.09253	.09145	0.4		0.09	0.927
	M	.0963	.0963	0.0	100.0	0.00	1.000
Bank 16	U	.03677	.03933	-1.3		-0.32	0.746
	M	.03259	.03259	0.0	100.0	0.00	1.000
Bank 17	U	.00119	.00295	-3.9		-0.87	0.382
	M	0	0	0.0	100.0	.	.
Bank 18	U	.07117	.03933	14.0		3.62	0.000
	M	.04148	.04148	0.0	100.0	0.00	1.000
Amount: 15,000$ to 30,000$	U	.20403	.24926	-10.8		-2.60	0.009
	M	.20148	.20148	0.0	100.0	-0.00	1.000
Amount: 30,000$ to 90,000$	U	.23369	.24385	-2.4		-0.58	0.562
	M	.22963	.22963	0.0	100.0	-0.00	1.000
Amount: 90,000$ to 12,000,000$	U	.33926	.21239	28.7		7.22	0.000
	M	.33926	.33926	0.0	100.0	0.00	1.000
Maturity: 3 to 6 months	U	.21352	.26008	-11.0		-2.64	0.008
	M	.21333	.21333	0.0	100.0	0.00	1.000
Maturity: 6 to 18 months	U	.16845	.2822	-27.5		-6.47	0.000
	M	.15407	.15407	0.0	100.0	-0.00	1.000
Maturity: 18 to 180 months	U	.40095	.18732	48.2		12.36	0.000
	M	.42222	.42222	0.0	100.0	-0.00	1.000
First Loan	U	.60142	.75959	-34.4		-8.65	0.000
	M	.62963	.62963	0.0	100.0	0.00	1.000
Corporation	U	.58363	.60226	-3.8		-0.93	0.354
	M	.62815	.62815	0.0	100.0	0.00	1.000

A.2 Prediction Results

Table A.4: Price Prediction for Average Interest Rate

	Borrower FE		No Borrower FE	
	Observed Price	**Default**	**Observed Price**	**Default**
Price Residual		−0.002		0.04***
		(0.01)		(0.003)
Amount: 15,000$ to 40,000$	−0.07*	0.002	−0.36***	0.002
	(0.04)	(0.01)	(0.04)	(0.01)
Amount: 40,000$ to 100,000$	−0.05	0.01	−0.79***	0.01
	(0.04)	(0.01)	(0.05)	(0.01)
Amount: over 100,000$	−0.07	0.002	−1.26***	0.002
	(0.05)	(0.01)	(0.05)	(0.01)
Maturity: 3 to 6 months	−0.25***	0.001	−0.47***	0.001
	(0.03)	(0.01)	(0.05)	(0.01)
Maturity: 6 to 12 months	−0.19***	−0.04***	−0.63***	−0.04***
	(0.04)	(0.02)	(0.05)	(0.01)
Maturity: over 12 months	−0.07*	−0.04**	−0.41***	−0.04**
	(0.04)	(0.02)	(0.07)	(0.02)
Installment		0.06***	0.46***	0.06***
		(0.01)	(0.05)	(0.01)
Bad Credit Rating		0.20***	0.45***	0.20***
		(0.01)	(0.05)	(0.01)
Corporation		0.05***	−0.40***	0.05***
		(0.01)	(0.04)	(0.01)
Constant	17.33***	−0.07	14.58***	−0.07
	(1.31)	(0.23)	(0.82)	(0.22)
Bank-Market FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	No	No	No
Industry FE	No	Yes	Yes	Yes
Observations	9,400	9,400	9,400	9,400
R^2	0.88	0.25	0.66	0.27
Adjusted R^2	0.85	0.19	0.63	0.21

Note: This table shows the price prediction for average cost. The first column shows the OLS regression result for equation (12). The dependent variable is observed interest rate. Loan amount and maturity categorized by their quantiles. The first category of loan amount (600$ to 15,000$) and maturity (0 to 3 months) are omitted. The second column is to show the price prediction does not miss determinants for default. The price residual means the residuals from equation (12). The dependent variable is the indictor for Non-performing. The third and fourth column repeat the exercise with no borrower fixed effects in the model $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Contract Availability: Table A.5 shows the number of secured and unsecured loan contracts that are predicted to be available to secured and unsecured borrowers, where secured borrowers are those that chose a collateralized loan in the data, and unsecured borrowers are those who chose an unsecured loan. Our sample includes 9,400 loan contracts (2,185 secured and 7,215 unsecured), 561 new borrowers, and 12 banks. The maximum number of potential contracts is therefore $9,400 \times 2 \times 12 = 225,600$. For secured and unsecured contracts, the first column shows the total number of contracts to be predicted, the second column the number of contracts predicted to be available, and the last column the share of contracts predicted to be available contracts among all potential contracts. Our matching exercises predicts that secured borrowers are more likely to be offered a secured loan than unsecured borrowers (44% vs 42%), while unsecured borrowers are more likely to be offered an unsecured loan than secured borrowers (58% vs 56%).

Table A.5: Summary of Price Prediction by Propensity Score Matching

	Secured Loans			Unsecured Loans		
	Total	Available	% Available	Total	Available	% Available
Secured borrowers	26,220	11,417	44	26,220	14,394	55
Unsecured borrowers	86,580	36,337	42	86,580	53,763	62
All borrowers	112,800	47,754	42	112,800	68,157	60

Note: This table summarizes the number of secured and unsecured loans that are available for borrowers. The first column is the total number of potential contracts to be predicted (Total), the second column is the number of contracts predicted to be available (Available), and the last column is the percentage of contracts predicted to be available (% Available).

Table A.6 shows the availability of the pair of contracts offered by banks to firms. Our matching method allows for the possibility that a bank provides only secured or only unsecured loans to each firm. It also allows banks not to offer any contract to some borrowers, either because the bank is not active in the borrower's market (in 69% of the cases), or because the bank does not offer the type of loan required by the borrower in terms of amount and maturity to borrowers with similar characteristics (in 31% of the cases). Our propensity score matching allows for different contract availability between secured and unsecured borrowers, which means that banks can screen differently secured and unsecured borrowers not only with contract terms, but also with contract availability.

Table A.6: Contract Availability of Secured and Unsecured Contracts

	Both	Only Secured	Only Unsecured	Neither
Secured borrowers	9,061	2,356	5,333	9,470
Unsecured borrowers	30,717	5,620	23,046	27,197
All borrowers	39,778	7,976	28,379	36,667

Note: This table shows the availability of the two contracts offered by a bank to a borrower. Both means bank borrower offers both secured and unsecured loans. Only Secured (Only Unsecured) means a bank offers only secured (unsecured) loan to a borrower. Neither means a bank offers neither contracts to a borrower. The numbers in the table are the number of bank-firm pair that belongs to the four categories.

A.3 Formulas for Marginal Costs

Based on equation (11), we solve the first order conditions to back out the marginal costs for secured and unsecured loans, which are the following:

$$\widehat{MC}_{ij\mathcal{S}m} = \frac{1}{\widehat{Q}_{ij\mathcal{S}m,P_{\mathcal{U}}}\widehat{Q}_{ij\mathcal{U}m,P_{\mathcal{S}}} - \widehat{Q}_{ij\mathcal{S}m,P_{\mathcal{S}}}\widehat{Q}_{ij\mathcal{U}m,P_{\mathcal{U}}}}(B\widehat{Q}_{ij\mathcal{U}m,P_{\mathcal{S}}} - A\widehat{Q}_{ij\mathcal{U}m,P_{\mathcal{U}}}), \tag{25}$$

$$\widehat{MC}_{ij\mathcal{U}m} = \frac{1}{\widehat{Q}_{ij\mathcal{S}m,P_{\mathcal{U}}}\widehat{Q}_{ij\mathcal{U}m,P_{\mathcal{S}}} - \widehat{Q}_{ij\mathcal{S}m,P_{\mathcal{S}}}\widehat{Q}_{ij\mathcal{U}m,P_{\mathcal{U}}}}(A\widehat{Q}_{ij\mathcal{S}m,P_{\mathcal{U}}} - B\widehat{Q}_{ij\mathcal{S}m,P_{\mathcal{S}}}), \tag{26}$$

where:

$$
\begin{aligned}
A &= \left[(1 + T_{ijm}\widetilde{P}_{ij\mathcal{S}m})(1 - \widehat{F}_{ij\mathcal{S}m}) + \widehat{R}_{ij\mathcal{S}m}\widehat{F}_{ij\mathcal{S}m}\right]\widehat{Q}_{ij\mathcal{S}m,P_{\mathcal{S}}} \\
&+ \left[T_{ijm}(1 - \widehat{F}_{ij\mathcal{S}m}) - (1 + T_{ijm}\widetilde{P}_{ij\mathcal{S}m})\widehat{F}_{ij\mathcal{S}m,P_{\mathcal{S}}} + \widehat{R}_{ij\mathcal{S}m}\widehat{F}_{ij\mathcal{S}m,P_{\mathcal{S}}}\right] \\
&+ \left[(1 + T_{ijm}\widetilde{P}_{ij\mathcal{U}m})(1 - \widehat{F}_{ij\mathcal{U}m}) + \widehat{R}_{ij\mathcal{U}m}\widehat{F}_{ij\mathcal{U}m}\right]\widehat{Q}_{ij\mathcal{U}m,P_{\mathcal{S}}}, \tag{27} \\
B &= \left[(1 + T_{ijm}\widetilde{P}_{ij\mathcal{U}m})(1 - \widehat{F}_{ij\mathcal{U}m}) + \widehat{R}_{ij\mathcal{U}m}\widehat{F}_{ij\mathcal{U}m}\right]\widehat{Q}_{ij\mathcal{U}m,P_{\mathcal{U}}} \\
&+ \left[T_{ijm}(1 - \widehat{F}_{ij\mathcal{U}m}) - (1 + T_{ijm}\widetilde{P}_{ij\mathcal{U}m})\widehat{F}_{ij\mathcal{U}m,P_{\mathcal{U}}} + \widehat{R}_{ij\mathcal{U}m}\widehat{F}_{ij\mathcal{U}m,P_{\mathcal{U}}}\right] \\
&+ \left[(1 + T_{ijm}\widetilde{P}_{ij\mathcal{S}m})(1 - \widehat{F}_{ij\mathcal{S}m}) + \widehat{R}_{ij\mathcal{S}m}\widehat{F}_{ij\mathcal{U}m}\right]\widehat{Q}_{ij\mathcal{S}m,P_{\mathcal{U}}}. \tag{28}
\end{aligned}
$$

If only one type $k \in \{\mathcal{S},\mathcal{U}\}$ is offered, then the marginal costs implied by our model estimates are:

$$
\begin{aligned}
\widehat{MC}_{ijkm} &= (1 + T_{ijm}\widetilde{P}_{ijkm})\left(1 - \widehat{F}_{ijkm} - \widehat{F}_{ijkm,P_k}\frac{\widehat{Q}_{ijkm}}{\widehat{Q}_{ijkm,P_k}}\right) \\
&+ T_{ijm}(1 - \widehat{F}_{ijkm})\frac{\widehat{Q}_{ijkm}}{\widehat{Q}_{ijkm,P_k}} + \widehat{R}_{ijkm}\left(\widehat{F}_{ijkm} + \frac{\widehat{Q}_{ijkm}}{\widehat{Q}_{ijkm,P_k}}\widehat{F}_{ijkm,P_k}\right), \tag{29}
\end{aligned}
$$

where the recovery rates $\widehat{R}_{ij\mathcal{S}m}$ and $\widehat{R}_{ij\mathcal{U}m}$ are defined in equations (9) and (10). Note that these depend on the collateral value CV_{ijm}, which is observable for secured borrowers, but not for unsecured borrowers. Hence, for each unsecured borrower, we take the collateral value of their respective matched secured borrower found using propensity score matching.

A.4 Figures Model Fit

(a) Equilibrium Price

(b) Probability of Default
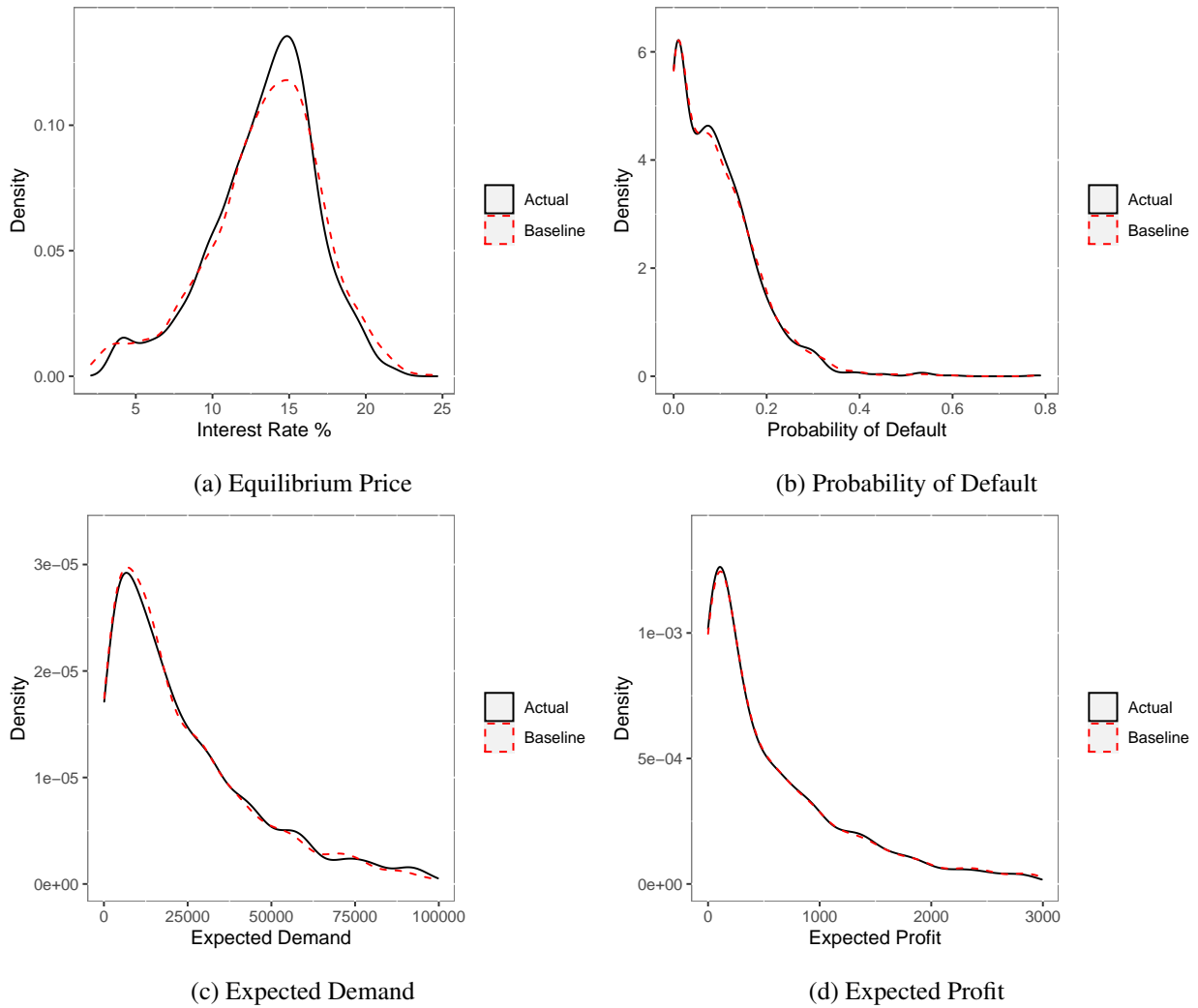
(c) Expected Demand

(d) Expected Profit

Figure A.2: Model Fit

Note: This figure shows the distribution of interest rate, demand, default, and profit for not rejected contracts. Expected demand is trimmed at 100,000$, which represents 92% of all contracts. Expected profit is trimmed at 1000$, which represents 70% of all contracts.