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Collateral and asymmetric information in lending markets☆

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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.

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, 1987a), 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

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[1] Other important theoretical contributions include Besanko and Thakor (1987b) and Chan and Kanatas (1985) on ex ante frictions, Igawa and Kanatas (1990), Boot et al. (1991), Aghion and Bolton (1997), Holmstrom and Tirole (1997) on moral hazard, Banerjee and Newman (1993), Cooley et al. (2004) on imperfect contract enforcement, and

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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 et al., 2005; Benmelech and Bergman, 2009), while exogenous drops in collateral values lead to higher loan rates, tighter credit limits and lower monitoring intensity (Cerqueiro et al., 2016). The associated changes in credit supply are found to have a significant impact on firm outcomes, such as investment (Chaney et al., 2012; Gan, 2007) and entrepreneurship (Schmalz et al., 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 identify the joint role of both demand and supply channels.

We fill this gap in the empirical literature 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 quantify the role of credit demand and credit supply within the collateral channel, accounting for their interaction. 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 collateral 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 between 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 et al., 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 securitization. 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 et al., 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 the loan interest rate on default as additional evidence of moral haz-

Townsend (1979), Williamson (1986), Boyd and Smith (1994) on costly state verification.

ard. It is key from a policy perspective to separately identify the ex ante and ex post channels. While regulators can address adverse selection promoting information sharing tools, such as credit scoring, policymakers have no greater incentive than lenders to curb the welfare cost of moral hazard (Einav and Finkelstein, 2011).

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 et al. (2011b). 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. We validate the accuracy of our prediction exercise with in-sample and out-of-sample tests, using both the Bolivian data and a similar external dataset from a large European bank, which includes accepted and declined loan offers. 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 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, a median 4.4% decrease in expected borrowers' demand, defined as the combination of bank choice probabilities and predicted loan size, and a median

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

[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).

5.0% decrease 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. As expected, we find that loans with lower expected recovery rate and loans to borrowers with bad credit rating are more likely to be rationed.

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.

Related Literature. 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 et al. (2011b), 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 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. Our model allows for the mechanisms described by both sets of theories, as banks can use collateral as a screening device by offering both secured and unsecured loans, but can also ration borrowers based on their observable risk by offering only secured loans, only unsecured, or none.

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 et al., 2005), asset redeployability of airline fleets (Benmelech and Bergman, 2008; 2009), regulatory changes affecting creditor seniority (Cerqueiro et al., 2016; 2020), 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 et al., 2012; Gan, 2007), entrepreneurship (Adelino et al., 2015; Corradin and Popov, 2015; Kerr et al., 2015; Schmalz et al., 2017), and employment (Ersahin and Irani, 2018). 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 et al., 2009; Einav et al., 2012). Our modeling approach is closest to Crawford et al. (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

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

[5] Relatedly, Berger et al. (2011a) take advantage of the adoption of an information-enhancing loan underwriting technology, showing that after its introduction lower collateral incidence is consistent with the ex ante channel.

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 et al., 2017; Honka et al., 2017), corporate loans (Crawford et al., 2018), mortgages (Benetton, 2021; Robles-Garcia, 2020), insurance (Koijen and Yogo, 2016), and investors' demand for assets (Koijen and Yogo, 2019).

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 Bolivian 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 et al., 2003) and the vast majority of firms in the registry did not have audited financial statements (Sirtaine et al., 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, and to validate our price prediction exercise as described in Section 4.1.[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 Bolivia, half of which are foreign owned.[10] There are several types of commercial credit contracts in the data, including credit cards, overdrafts in the current account, credit lines, term loans (either installment or single payment), and mortgage loans. As in Berger et al. (2011b) 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). During our sample period, banks in Bolivia were under the Basel I capital requirements, with no differences in capital requirements, risk weights, or other regulatory incentives between secured and unsecured loans for banks. The same requirements apply to both domestic and foreign banks. 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 32,369 loan originations (i.e., loans originated sometime during the sample period) to 2676 unique firms, including new loans granted to new or existing customers.

In order to reduce 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 also helps reduce information asymmetries between banks, as these borrowers are new clients to all banks. This leads to a sample of 561 new borrowers that we track for

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, 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.

the first 18 months since their initial loan origination, resulting in 1650 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] Analyzing only a firm's first 18 months mitigates the concern that our results might be influenced by a company's asset accumulation over time, a dynamic dimension that we cannot model due to lack of data on firms' assets. 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 9400 loan originations to 1421 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 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 Fig. 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.[13]

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, Fig. 2 reports the distributions of the propensity score for taking a secured loan for borrowers that take up a secured or an unsecured loan.[14] 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 Fig. 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. Consis-

[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 et al. 2016).

[13] In the estimation sample we have 1650 observations, while in the price prediction sample we have 9400 observations. This means that on average we have 16 observations per market for the estimation sample, and 90 observations per market in the price prediction sample. Note however that due to the price prediction, when estimating the demand model we are imputing contracts that are not present in the sample, which leads to a total of 16,852 observations, corresponding to around 160 observations per market.

[14] 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.

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	1650	14.29	2.62	9400	14.33	2.32
Secured	519	13.80	2.40	2185	13.66	2.53
Unsecured	1131	14.51	2.68	7215	14.53	2.22
Collateralized	1650	0.31	0.46	9400	0.23	0.42
Immovable	519	0.41	0.49	2185	0.39	0.49
Liquid Movable	519	0.30	0.46	2185	0.26	0.44
Illiquid Movable	519	0.29	0.46	2185	0.35	0.48
Value-to-Loan Ratio	519	2.66	4.42	2185	2.49	6.04
Amount	1650	146.58	461.12	9400	129.94	426.76
Maturity	1650	15.49	21.95	9400	12.63	18.05
Installment Loan	1650	0.55	0.50	9400	0.50	0.50
Bad Credit Rating	1650	0.04	0.19	9400	0.12	0.32
Corporation	1650	0.65	0.48	9400	0.65	0.48
Defaulting Borrower	1650	0.12	0.32	9400	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			
Secured	134	0.29	0.45			
Unsecured	149	0.41	0.48			
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 1000 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.

tent 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 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 et al., 2005; Benmelech and Bergman, 2008; 2009). Using internal bank data, Degryse et al. (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,[15] 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

[15] 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.

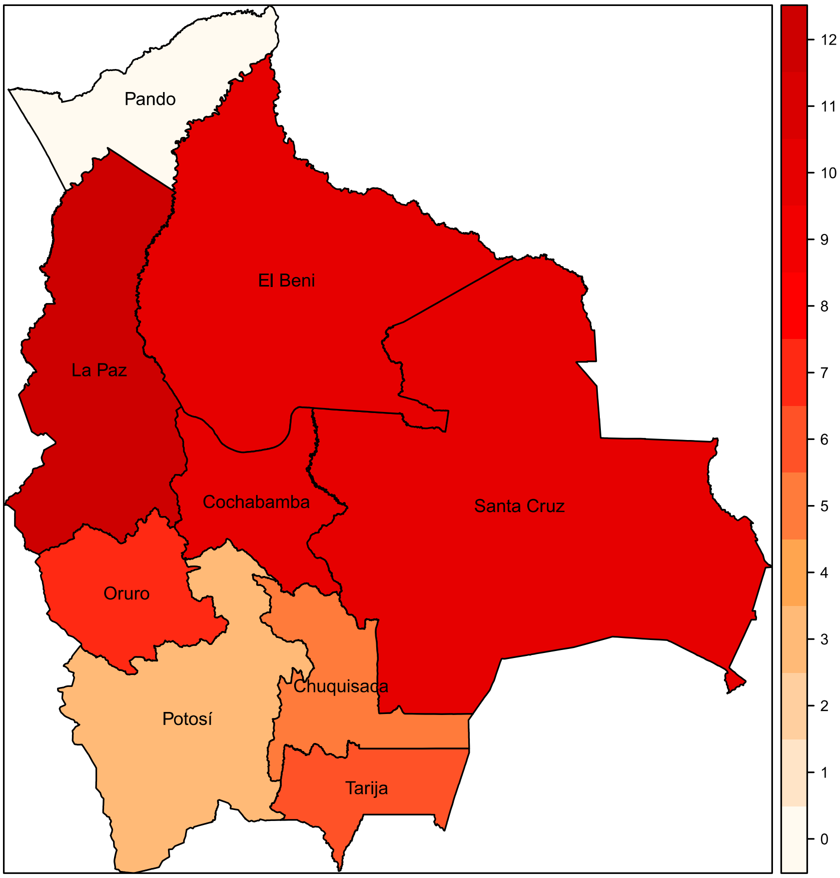


Fig. 1. Number of Banks Establishing Lending Relationships with New Borrowers across Regions. *Note:* This figure shows the regions where banks granted loans to new borrowers during 1999 to 2003. The banks are Banco Nacional De Bolivia S. A., Banco Mercantil S. A., Banco De Credito De Bolivia S. A., 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.

is only partially pledgeable.[16] 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).[17] 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.[18] 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

[16] 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.

[17] 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.

[18] 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 et al. (2007) report recovery rates of 81.12% for bank loans in the United States for the period from 1982 to 1999. Khieu et al. (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.

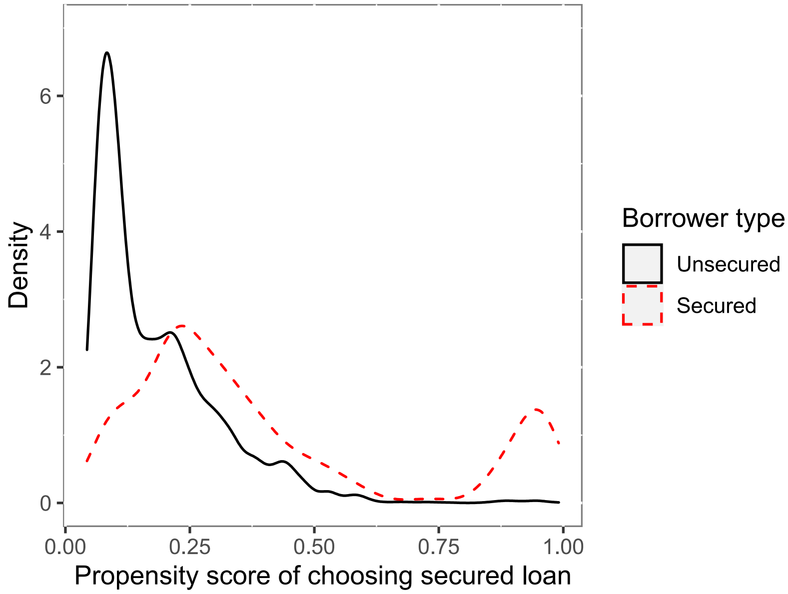


Fig. 2. Propensity Score of Choosing A Secured Loan. *Note:* This figure shows the distributions of the propensity score of choosing a secured loan as opposed to an unsecured loan for borrowers that accepted a secured loan (secured borrower) or an unsecured loan (unsecured borrower). The solid line represents 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.

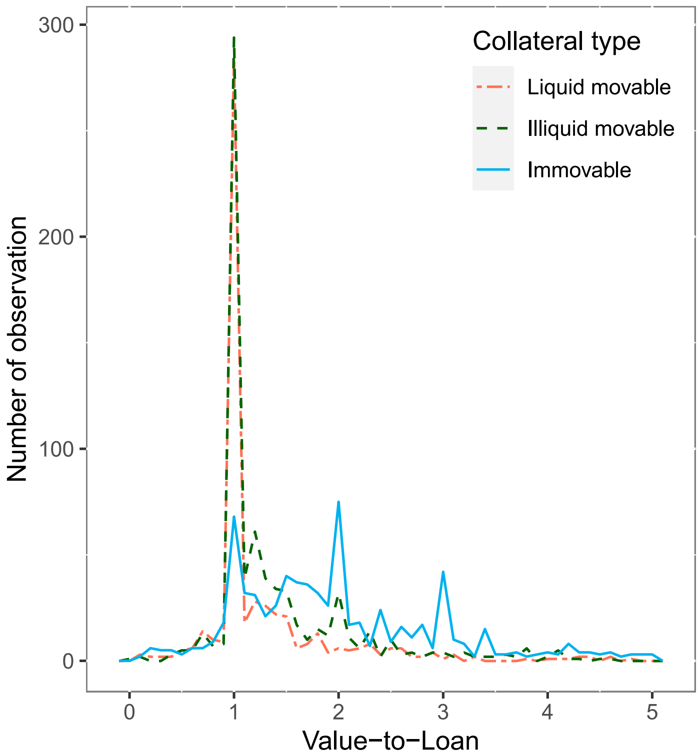


Fig. 3. Collateral to Loan Ratio by Types. *Note:* This figure illustrates the distribution of collateral to loan value for immovable collateral, liquid movable collateral, and illiquid movable collateral. The collateral to loan ratio is truncated at 5, which means the collateral value is 5 times of 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.

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 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 et al. (2018). We assume that new borrowers seek credit for an exogenously given amount and maturity combination,[19] 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.[20] Specifically, we let borrower $i = 1, \ldots, I$ in market $m = 1, \ldots, M$, 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 $j = 1, \ldots, J_m$ based on the following indirect utility function, which determines the borrower's loan demand (D):

$$U^D_{ijkm} = \alpha^D_{\mathcal{P}i} P_{ijkm} + \alpha^D_{\mathcal{C}i} C_{ijkm} + \alpha^D_{\mathcal{Z}} Z_{ijm} + X'_{jm}\alpha^D_{\mathcal{X}} + \nu^D_{ijkm}, \quad (1)$$

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^D_{ijkm} are Type 1 Extreme Value distributed shocks. We let $\alpha^D_{\mathcal{P}i}, \alpha^D_{\mathcal{C}i}$ 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 $\varepsilon^D_{\mathcal{P}i}, \varepsilon^D_{\mathcal{C}i}$ (unobserved by banks and the econometrician) as follows:

$$\alpha^D_{\mathcal{P}i} = \overline{\alpha}^D_{\mathcal{P}} + \alpha^D_{\mathcal{P}\mathcal{Z}} Z_{ijm} + \varepsilon^D_{\mathcal{P}i}, \alpha^D_{\mathcal{C}i} = \overline{\alpha}^D_{\mathcal{C}} + \alpha^D_{\mathcal{C}\mathcal{Z}} Z_{ijm} + \varepsilon^D_{\mathcal{C}i}. \quad (2)$$

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:

$$\begin{aligned} U^F_{ijkm} = \quad & \overline{\alpha}^F + \alpha^F_{\mathcal{P}i} P_{ijkm} + \alpha^F_{\mathcal{C}i} C_{ijkm} + \alpha^F_{\mathcal{Z}} Z_{ijm} \\ & + X'_{jm}\alpha^F_{\mathcal{X}} + Y'_i \alpha^F_{\mathcal{Y}} + \varepsilon^F_i, \end{aligned} \quad (3)$$

where ε^F_i 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,[21] including firm type, credit rating, and fixed effects for industry, region, and

[19] 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.

[20] As described in Section 4.3, we compensate this lack of outside option data by modeling firms' choice of loan size. This implies that in the counterfactual scenarios firms can potentially adjust their loan size to zero, which is equivalent to choosing the outside option of not borrowing.

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

loan amount granted (as proxy for firm size). We include in the default indirect utility the dummy C_{ijkm} for secured loan rather than the ratio of collateral value to loan size. This is because, as reported in Fig. 3, the vast majority of loans have a value to loan of exactly 1, and those that do not are indivisible real estate assets, over which the lender only has a claim up to the loan value. We let price and collateral coefficients in the default model to depend on the relationship dummy Z_{ijm} as:

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

In the spirit of the empirical literature on testing for the presence of asymmetric information (Chiappori and Salanié, 2000; Einav et al., 2012), we let $\varepsilon^D_{\mathcal{P}i}, \varepsilon^D_{\mathcal{C}i}, \varepsilon^F_i$ be distributed according to the following multivariate normal distribution:

$$\begin{pmatrix} \varepsilon^D_{\mathcal{P}i} \\ \varepsilon^D_{\mathcal{C}i} \\ \varepsilon^F_i \end{pmatrix} = \left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{\mathcal{P}} & \rho_{\mathcal{P}\mathcal{C}}\sigma_{\mathcal{P}}\sigma_{\mathcal{C}} & \rho_{\mathcal{P}\mathcal{F}}\sigma_{\mathcal{P}} \\ \rho_{\mathcal{P}\mathcal{C}}\sigma_{\mathcal{P}}\sigma_{\mathcal{C}} & \sigma^2_{\mathcal{C}} & \rho_{\mathcal{C}\mathcal{F}}\sigma_{\mathcal{C}} \\ \rho_{\mathcal{P}\mathcal{F}}\sigma_{\mathcal{P}} & \rho_{\mathcal{C}\mathcal{F}}\sigma_{\mathcal{C}} & 1 \end{pmatrix} \right). \tag{5}$$

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 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 $\rho_{\mathcal{P}\mathcal{F}} > 0$ as evidence of adverse selection, as riskier borrowers have lower price sensitivity (as $\overline{\alpha}^D_{\mathcal{P}} < 0$) and therefore are more likely to take credit. We interpret a negative correlation between unobservables determining collateral sensitivity and default $\rho_{\mathcal{C}\mathcal{F}} < 0$ 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 $\rho_{\mathcal{P}\mathcal{C}} < 0$, which implies that borrowers with higher disutility from price (i.e., safe borrowers if $\rho_{\mathcal{P}\mathcal{F}} > 0$) are also those with lower disutility from pledging collateral (i.e., safe borrowers if $\rho_{\mathcal{C}\mathcal{F}} < 0$). Finding that $\rho_{\mathcal{P}\mathcal{C}} < 0$ 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 $\alpha^F_{\mathcal{P}i}$. Finding that $\alpha^F_{\mathcal{P}i} > 0$ 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 $\alpha^F_{\mathcal{P}i}$ 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 $\alpha^F_{\mathcal{C}i}$. Finding that $\alpha^F_{\mathcal{C}i} < 0$ 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 $\alpha^D_{\mathcal{C}i}$. Second, the unobserved heterogeneity of the demand random coefficient for collateral $\alpha^D_{\mathcal{C}i}$ 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.[22] 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

[22] 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.

i as follows:

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

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:

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

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:

$$Q_{ijkm} = \Pr^{D}_{ijkm} LS_{ijkm}, \quad (8)$$

where $\Pr^{D}_{ijkm}$ is the probability of demand and LS_{ijkm} is the loan size.[23] R_{ijkm} is the bank's expected loan recovery rate in default. We assume that:

$$R_{ij\mathcal{S}m} = \min\left\{CV_{ijm}\omega_{ij\mathcal{S}m}, \left(1 + T_{ijm}P_{ij\mathcal{S}m}\right)\right\}, \quad (9)$$

$$R_{ij\mathcal{U}m} = \omega_{ij\mathcal{U}m}\left(1 + T_{ijm}P_{ij\mathcal{S}m}\right), \quad (10)$$

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 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:

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

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 et al. (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 Eq. (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.

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

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.[24] 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.

[24] 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.

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:

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

where A_i indicates borrower i's loan amount category, and M_i indicates i's maturity category. Both variables are categorized by quantiles.[25] γ_{jm} are bank-market fixed effects, λ_i are borrower fixed effects, and ϵ_{ijm} are prediction errors. The use of bank-market fixed effects allows us to control, among other things, for systematic differences across banks in their reliance on soft information when setting interest rates. 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-squared from estimating Eq. (12). The model's adjusted R-squared is 0.85, indicating that the explanatory variables explain a large fraction of the variation of the average loan interest rate in the data.[26] 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 Eq. (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.[27] Crucially, we find that the coefficient from regressing borrower's default on price residuals is not statistically nor economically significant, which suggests that our prediction error is not related to borrowers' default. Moreover, by examining each borrower's internal credit ratings across banks, we find no evidence that the unexplained variation in pricing can be explained by systematic variation in banks' assessment of borrower risk (due, e.g., to systematic differences in soft information across banks, not captured by our controls).

In contrast, the third and fourth columns repeat the exercise without borrower fixed effects in Eq. (12). In this case the adjusted R-squared is reduced markedly to 0.63

[25] 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.

[26] An R-squared of 0.85 compares quite favorably with the existing literature. For example, Crawford et al. (2018), the paper closet to ours, finds an R-squared of at most 0.72. In Degryse and Ongena (2005) the R-squared for loans over € 50,000 is 0.67. In other papers, the R-squared on price regressions are even lower (see, among others, Petersen and Rajan (1994) and Cerqueiro et al. (2011)).

[27] 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	9400	9400	9400	9400
Adjusted R^2	0.85	0.19	0.63	0.21

Note: This table shows the price prediction for average interest rate. The first column shows the OLS regression result for Eq. (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 Eq. (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 of the Appendix.

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 and hard information, observed by banks but not by the econometrician, plays an important role in banks' loan pricing.

The first step 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 Eq. (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.

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 and accuracy assessment

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 similar 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.

To assess the accuracy of our prediction approach we begin by investigating whether the predicted contract assignment reasonably matches key theoretical predictions and prior literature. In further tests below, we also study the overlap of interest rates on actual and predicted contracts both in and out of sample. 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.[28]

Another potential determinant of contract offering is banks' information acquisition. We conjecture that as a firm-bank relationship evolves, lenders are able to learn about borrowers' creditworthiness, and adjust their contract offering accordingly. Within each firm-bank relationship, comparing the first loan offer to the subsequent ones, we find that the probability of being offered only a secured loan decreases by 9 percentage points, while the probability of being offered only an unsecured one increases by 6 percentage points. The probability of being offered both contracts does not vary significantly over the relationship. These results are consistent with banks having greater uncertainty over firms' creditworthiness at the beginning of the relationship, therefore offering only a secured contract, but as this uncertainty is reduced over time they tend to offer more unsecured loans.

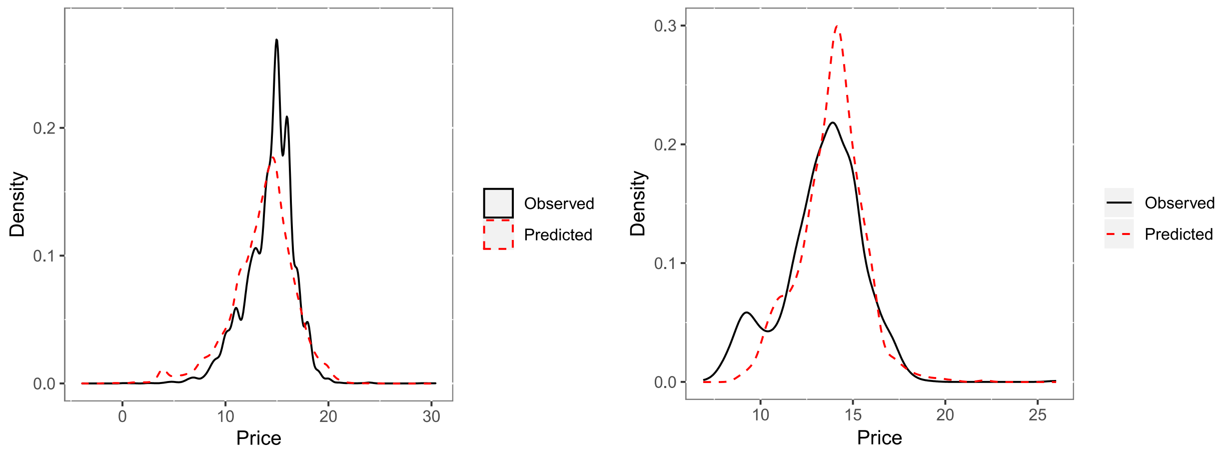
These results are consistent with banks using contract availability to screen borrowers based on observable risk, offering only secured loans to observably riskier borrowers, and using pricing to screen unobservable risk, offering both types of contracts to borrowers that are not observably risky. Consistent with this interpretation, looking at default rates of borrowers conditional on their contract choices,

[28] We also find that 6.7% of firms in our price prediction sample do not receive a secured offer from any bank at least once, which is a likely estimate of the number of firms that do not have assets to pledge. This estimate is quite similar to the range of values reported in the 2018–2020 EBRD-EIB-WBG Enterprise Survey, which reports that in countries with similar development indexes as Bolivia between 1.5% and 7.5% of firms did not apply for a loan because collateral requirements were too high.

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	7976

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.



(a) In Sample

(b) Out of Sample

Fig. 4. Price Prediction Accuracy. *Note:* This figure shows the distributions of observed prices (solid line) and predicted prices (dashed line). Subfigure (a) plots the in-sample prediction. The total number of observation is 9,400. Subfigure (b) plots the out-of-sample prediction. The total number of observation is 854.

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).[29] 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.

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(a) 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. We further examine the performance of our prediction with an out-of-sample test. As explained in Section 2, we use for price prediction only loans to borrowers who entered the credit register no more than 6 months before the beginning of our sample period (March 1999). We do however have information on 1048 loans to 353 of those same borrowers granted between January 1998 and March 1999 that we can use for an out of sample test. Applying the same price prediction procedure on this test sample, we find that 81.5% of the observed loans are predicted to be available, which confirms the good performance of our approach. Furthermore, Fig. 4(b) shows the distribution of observed and predicted interest rates for the loans predicted

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

to be available in the test sample. Predicted prices have a similar distributional pattern as observed prices albeit a smaller standard deviation compared to observed prices. The out-of-sample R squared is 0.15, which compared to the in-sample R squared of 0.27 still lends strong support to our price prediction method.

In a second out-of-sample exercise, we also assess the predictive quality of our approach using a sample of loans to small and medium size enterprises from one of the top five commercial banks in the Netherlands. This proprietary dataset from Mosk (2018) is unique in that it includes detailed loan contract and borrower information on both accepted and rejected loan offers. Results, reported in Table A.5 of the Appendix, confirm the insights from Table 2 for this sample. Further analysis similar in spirit to Fig. 4 shows that our approach, which uses only data of accepted offers, predicts reasonably well also the interest rates on offers that were declined. In particular, Figure A.2 in the Appendix compares the predicted interest rates on declined offers with the actual interest rates on declined offers and shows a very high overlap. As explained in the Appendix, this analysis is based only on the first-stage of our prediction procedure as this data are only available for one bank, and not for the entire banking sector as in our sample.

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 $i = 1, \dots, I$ in market $m = 1, \dots, M$ takes a type $k = \mathcal{S}, \mathcal{U}$ loan from bank $j = 1, \dots, J_m$ as follows:

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

where $\mathbb{1}_{i\jmath\ell m}$ 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 Eq. (2):

$$\alpha^D_{\mathcal{P}is} = \overline{\alpha}^D_{\mathcal{P}} + \alpha^D_{\mathcal{PZ}} Z_{ijm} + \varepsilon^D_{\mathcal{P}is},$$
$$\alpha^D_{\mathcal{C}is} = \overline{\alpha}^D_{\mathcal{C}} + \alpha^D_{\mathcal{CZ}} Z_{ijm} + \varepsilon^D_{\mathcal{C}is},$$

where, following the conditional distribution of the multivariate normal:

$$\varepsilon^D_{\mathcal{P}is} = \sigma_{\mathcal{P}} \zeta^D_{\mathcal{P}is},$$
$$\begin{aligned}
\varepsilon^D_{\mathcal{C}is} &= \frac{\sigma_{\mathcal{C}}}{\sigma_{\mathcal{P}}} \rho_{\mathcal{PC}} \varepsilon^D_{\mathcal{P}is} + \sqrt{(1-\rho^2_{\mathcal{PC}})\sigma^2_{\mathcal{C}}}\,\zeta^D_{\mathcal{C}is} \\
&= \sigma_{\mathcal{C}} \rho_{\mathcal{PC}} \zeta^D_{\mathcal{P}is} + \sqrt{(1-\rho^2_{\mathcal{PC}})}\,\sigma_{\mathcal{C}} \zeta^D_{\mathcal{C}is},
\end{aligned} \tag{17}$$

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

$$\begin{aligned}
\Pr^F_{ijkm} &= \int\int \Phi_{\varepsilon^F_i|\varepsilon^D_{\mathcal{P}i},\varepsilon^D_{\mathcal{C}i}}\left(\frac{\overline{\alpha}^F + \alpha^F_{\mathcal{P}i} P_{ijkm} + \alpha^F_{\mathcal{C}i} C_{ijkm} + \alpha^F_{\mathcal{Z}} Z_{ijm} + X'_{jm}\alpha^F_{\mathcal{X}} + Y'_i\alpha^F_{\mathcal{Y}} + \widetilde{\mu}_{Fi}}{\widetilde{\sigma}_F}\right) \\
&\quad f(\varepsilon^D_{\mathcal{P}i}, \varepsilon^D_{\mathcal{C}i}) d\varepsilon^D_{\mathcal{P}i} d\varepsilon^D_{\mathcal{C}i} \\
&\approx \frac{1}{S}\sum_{s=1}^{S} \underbrace{\Phi_{\varepsilon^F_i|\varepsilon^D_{\mathcal{P}i},\varepsilon^D_{\mathcal{C}i}}\left(\frac{\overline{\alpha}^F + \alpha^F_{\mathcal{P}i} P_{ijkm} + \alpha^F_{\mathcal{C}i} C_{ijkm} + \alpha^F_{\mathcal{Z}} Z_{ijm} + X'_{jm}\alpha^F_{\mathcal{X}} + Y'_i\alpha^F_{\mathcal{Y}} + \widetilde{\mu}_{Fis}}{\widetilde{\sigma}_F}\right)}_{\Pr^F_{isjkm}},
\end{aligned} \tag{18}$$

where $\varepsilon^F_i|\varepsilon^D_{\mathcal{P}i}, \varepsilon^D_{\mathcal{C}i} \sim N(\widetilde{\mu}_{Fi}, \widetilde{\sigma}_F)$.[30] We use these probabilities to estimate all the parameters $\theta = \{\alpha^D, \alpha^F, \Sigma\}$ jointly by maximum simulated likelihood, where $\alpha^D = \{\overline{\alpha}^D_{\mathcal{P}}, \overline{\alpha}^D_{\mathcal{C}}, \alpha^D_{\mathcal{PZ}}, \alpha^D_{\mathcal{CZ}}, \alpha^D_{\mathcal{X}}, \alpha^D_{\mathcal{Z}}\}$, $\alpha^F = \{\overline{\alpha}^F, \overline{\alpha}^F_{\mathcal{P}}, \overline{\alpha}^F_{\mathcal{C}}, \alpha^F_{\mathcal{PZ}}, \alpha^F_{\mathcal{CZ}}, \alpha^F_{\mathcal{X}}, \alpha^F_{\mathcal{Z}}, \alpha^F_{\mathcal{Y}}\}$, and $\Sigma = \{\sigma_{\mathcal{P}}, \sigma_{\mathcal{C}}, \rho_{\mathcal{PC}}, \rho_{\mathcal{PF}}, \rho_{\mathcal{CF}}\}$. We use the following log likelihood function:

$$\begin{aligned}
\mathcal{L}(\theta) = \sum_i \log\Bigg\{\frac{1}{S}\sum_{s=1}^{S}\Bigg[\prod_m \Bigg(\prod_j\prod_k \mathbb{1}_{ijkm}\left(\Pr^D_{isjkm}\right)^{d_{ijkm}}\Bigg) \\
\times \left(\left(\Pr^F_{isjkm}\right)^{f_{ijkm}}\left(1-\Pr^F_{isjkm}\right)^{1-f_{ijkm}}\right)\Bigg]\Bigg\},
\end{aligned} \tag{19}$$

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 demanded 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:

$$\begin{aligned}
\log(LS_{ijkm}) = \overline{\zeta} + \zeta_{\mathcal{P}i} P_{ijkm} + \zeta_{\mathcal{C}i} C_{ijkm} + \zeta_{\mathcal{Z}} Z_{ijm} \\
+ X'_{jm}\zeta_{\mathcal{X}} + Y'_i\zeta_{\mathcal{Y}} + \upsilon_{ijkm},
\end{aligned} \tag{20}$$

where:

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

[30] We report in Appendix A.3 the formulas for this distribution.

$\zeta_{Ci} = \overline{\zeta}_C + \zeta_{CZ} Z_{ijm},$

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. υ_{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.[31] More specifically, when simulating a shock to collateral value, our model will allow banks to respond adjusting credit supply, which will determine equilibrium interest rates and in turn affect the demanded loan size via Eq. (20).

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.[32] 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 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.[33] 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 et al., 2000; Ippolito et al., 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 et al., 2017). Nevertheless, when estimating our model without instruments we obtain very similar results, suggesting that the extent of the potential endogeneity bias is rather limited.

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.

Lastly, the correlation coefficient that measures adverse selection is identified by the heterogeneous effect of interest rates on credit demand. Controlling for loan, bank and observable firm characteristics, we document that this heterogeneous credit demand response to changes in interest rates is driven by unobservable (to the bank) firm risk. A similar identification logic applies to the correlation coefficient between collateral and firm default risk, which measures the effect of collateral on mitigating adverse selec-

[31] An alternative approach is to incorporate the optimal loan size into the structural framework with discrete-continuous choice model (Benetton, 2021), 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.

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

[33] In the control function approach the residuals from the first stage capture the variation in prices that is not explained by observables and instrumental variables. These residuals are hence a proxy for any unobserved confounder that affects prices as well as demand and default. Including the residuals as a control variable in the second stage is equivalent to controling for the endogeneity of prices. The identification requires instrumental variables that are correlated with the endogenous variable (i.e., prices), but that do not directly affect demand and default conditional on prices, to avoid multicollinearity. More details on the control function approach are provided in Train (2009), Wooldridge (2015).

Table 4
First Stage Results.

	Price		Collateral	
	Observed	Predicted	Observed	Predicted
Savings Deposit Interest Rate	0.36*** (0.01)	0.16*** (0.01)		
Share of Non-Performing Loans			1.04*** (0.08)	0.11*** (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	8938	103,137	9190	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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

tion. The intuition underlining our identification is similar to that of a two-stage Heckman selection model, where default is estimated conditional on a specific choice of bank-interest rate-collateral combination. Hence, as we control for the correlation structure of the error term in firms' default and demand decisions, which captures the effect of adverse selection on default risk, the effect of moral hazard is instead identified by the effect of the remaining variation in interest rates on firms' default.

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 unobserved heterogeneity in the form of borrowers' private information.[34] 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%, which implies a price elasticity of 3.2.[35] 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.

[34] 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.

[35] These elasticities are quite close in magnitude to the results of other structural demand models of corporate loans (Crawford et al., 2018) and mortgages (Benetton, 2021; Robles-Garcia, 2020; Buchak et al., 2020).

Table 5
Structural Estimation Results.

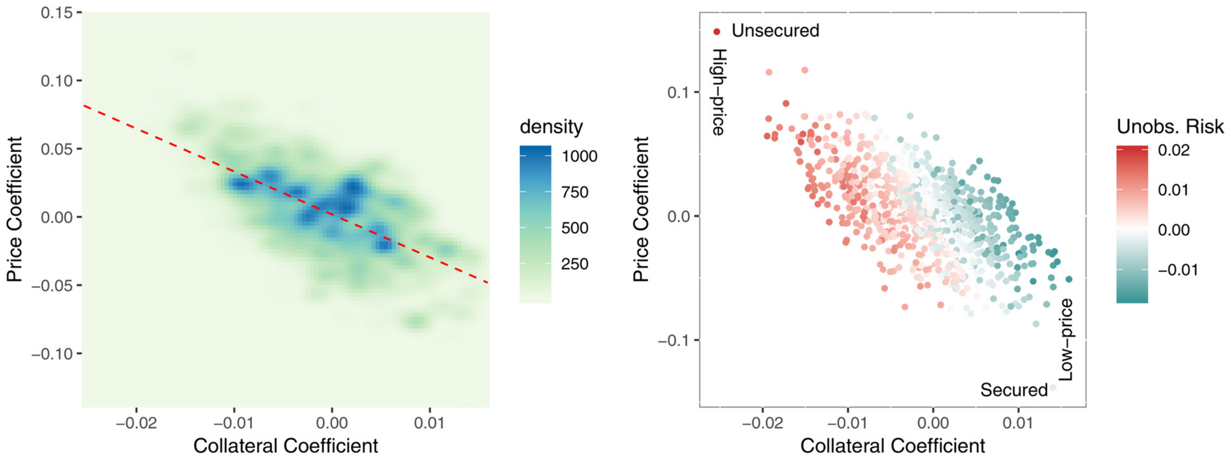
	Demand	Loan Size	Default
Price	-0.43^{***}	-0.22^{***}	0.93^{***}
	(0.01)	(0.01)	(0.01)
Price × Relationship	-1.15^{***}	0.03	0.22^{***}
	(0.00)	(0.03)	(0.01)
Collateral	-0.50^{***}	0.44^{***}	-0.11^{***}
	(0.01)	(0.12)	(0.01)
Collateral × Relationship	-0.19^{***}	0.28^{*}	0.44^{***}
	(0.01)	(0.14)	(0.02)
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	1650	1650
	$\sigma_{\mathcal{P}} = 1.75^{***}$		
	(0.01)		
Covariance matrix	$\rho_{\mathcal{PC}} = -0.60^{***}$	$\sigma_{\mathcal{C}} = 0.36^{***}$	
	(0.00)	(0.01)	
	$\rho_{\mathcal{P}F} = 0.10^{***}$	$\rho_{\mathcal{C}F} = -0.42^{***}$	$\sigma_F = 1$
	(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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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 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 $(\varepsilon^D_{\mathcal{P}i}, \varepsilon^D_{\mathcal{C}i})$, 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



(a) (b)

Fig. 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 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

dashed line. Fig. 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 (A.3) in the Appendix, 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 Fig. 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.

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.[36] 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

[36] 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 Eq. (7).

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	7644	0.00	24,242
Baseline Demand	14,313	8720	0.00	27,133
Actual Profit	14,338	507	0.00	2878
Baseline Profit	14,313	524	0.00	3048
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.

of actual and model fit outcomes in Figure A.3 in the Appendix.

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 Eq. (11).[37] 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 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 Fig. 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.

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. Higher marginal costs for secured loans are consistent with collateralized contracts requiring extra monitoring and screening effort by the lender, which are directed towards not only the borrower itself, as for the case of unsecured loans, but also towards the assets pledged.

6. Counterfactuals

We conduct two sets of counterfactual exercises using the estimates of our structural framework. First, we simulate three scenarios to quantify the importance of secured lending, adverse selection, and moral hazard. Second, we conduct two 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. 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}, loan size LS_{ijkm}, expected demand Q_{ijkm} (calculated as the average loan size weighted by the probability of demand), banks' expected profit Π_{ijkm}, and number of loan contracts offered.

6.1. Secured lending, adverse selection, and moral hazard

In the first counterfactual scenario we ban secured lending by excluding all secured loan offers from banks. This allows us to quantify the benefit of using collateral to improve access to credit and banks' profits. In the second scenario we eliminate adverse selection, setting the correlation between unobserved risk and credit demand to zero. In the third scenario we eliminate moral hazard, simulating a setting where interest rates and collateral requirements have no direct impact on borrowers' default. These last two counterfactuals help us understand how asymmetric information affect credit supply and demand, and the relative importance of adverse selection and moral

[37] We report in Appendix A.4 the formulas for marginal costs.

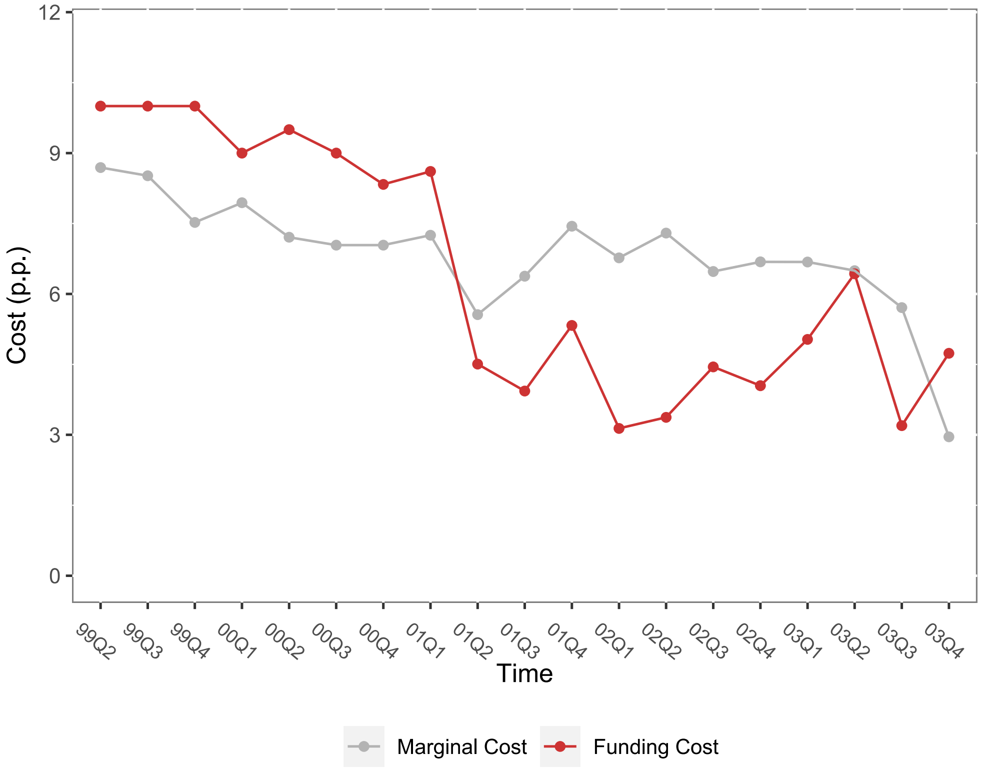


Fig. 6. Model-Implied Marginal Costs and Banks' Funding Costs. *Note:* This figure compares model-implied marginal costs and banks' funding costs over time. The grey line shows the median of normalized marginal costs (in percentage points for each lending dollar) in each quarter, while the red line illustrates the median of banks' saving deposit interest rates in that quarter (in percentage points), which represents banks' funding costs. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

hazard. Table 8 summarizes the new counterfactual equilibrium relative to the baseline model for all the loans offered to new borrowers in their first 18 months.

Panel A in Table 8 reports the scenario without secured lending, where secured contracts are not available anymore. This forces potential secured borrowers to choose unsecured loans, which tend to have higher interest rates than secured loans. As a result, we find that the median interest rate of unsecured loans drops by 1.26%. The reason for this drop is that borrowers choosing secured loans are on average more price sensitive and less risky, as reported in Section 5, so lenders need to reduce rates to attract them to their unsecured loans and make them borrow a profitable amount. As a consequence, the median default

Table 8
Secured Lending, Adverse Selection, and Moral Hazard.

	Available	Median Percentage Change				
	Contracts	Interest Rate	Default	Loan Size	Demand	Profit
(A) No Secured Loans						
Secured	0	NA	NA	NA	−100	−100
Unsecured	9575	−1.26	−1.57	1.24	62.74	52.71
Total	9575	−0.00	−0.00	−25.50	−16.65	−17.96
(B) No Adverse Selection						
Secured	7277	0.41	1.17	−0.40	−1.65	−0.73
Unsecured	9575	−0.41	−0.44	0.23	1.25	0.53
Total	16,852	−0.04	0.07	−0.11	−0.11	−0.06
(C) No Moral Hazard						
Secured	7277	0.29	−66.68	−0.45	−2.47	0.00
Unsecured	9575	−1.42	−78.21	1.45	3.49	35.39
Total	16,852	−0.41	−75.27	0.00	−0.00	17.65

Note: This table summarizes the median percentage change in equilibrium price (*Interest Rate*), probability of default (*Default*), loan size (*Loan Size*) expected demand (*Demand*) and banks' expected profit (*Profit*) of loans in three counterfactual scenarios compared with the baseline model. Each row stands for secured loans, unsecured loans, and both. Panel A, B, and C present the scenarios without secured lending, adverse selection, and moral hazard, respectively. 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 loan size is calculated by comparing the average loan size across offers in each borrower's choice set. 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.

probability for unsecured loans drops by 1.57%, because of the decreased moral hazard risk for lower interest rate and the better quality of the new pool of unsecured borrowers. Overall, the interest rate and probability of default in the no secured lending scenario are almost unaffected compared with the baseline case. The decreased interest rate also increases the demand for unsecured loans: the median size of unsecured loans increases by 1.24%, and the expected demand of unsecured loans increases by 62.74%. However, the total effect of banning secured lending on loan size and expected demand is negative, because secured loans tend to be larger, and the increased demand for unsecured loans cannot fully offset the decreased demand for secured loans. Overall, the median credit demand decreases by 16.65% and banks' profits decrease by 17.96%, meaning that collateral can increase borrowers' credit accessibility and banks' profitability.

Panel B in Table 8 reports the counterfactual outcomes when there is no adverse selection, modeled by setting the correlation coefficients $\rho_{\mathcal{PC}}, \rho_{\mathcal{PF}}, \rho_{\mathcal{CF}}$ to zero. We find that the median interest rate increases for secured loans and decreases for unsecured loans, in both cases by around 0.41%, consistent with the reduced role of collateral as a screening device. In fact, if in the baseline model secured loans were chosen by price sensitive low risk borrowers, while unsecured loans were chosen by price insensitive high risk borrowers, in this new scenario the correlation between price sensitivity and risk is set to zero. As a result, the price difference between the two types of loans reduces, and collateral is less effective at screening. Relatedly, we find that for secured (unsecured) loans the probability of default increases (decreases), loan size decreases (increases), the expected demand decreases (increases), and banks' profit decreases (increases).

Panel C in Table 8 reports the new equilibrium outcomes when there is no moral hazard. In this case, loan interest rates have no direct impact on the probability of default ($\alpha^F_{\mathcal{P}i} = 0$) and collateral plays no role as a discipline device ($\alpha^F_{\mathcal{C}i} = 0$). We find a 1.42% median decrease in the interest rate for unsecured loans, and a significant median drop in the default probability for both secured and unsecured loans, by around 67% and 78% respectively. The demand for secured loans decreases while for unsecured loans increases, but the overall demand is almost unchanged. Banks earn a median 35.39% higher profit from unsecured loans, which leads to a 17.65% increase in total profit because of the higher profit margin generated from eliminating moral hazard risk. Comparing the impact of shutting down adverse selection (Panel B) and moral hazard (Panel C) suggests that moral hazard is quantitatively more important.

6.2. Pricing and rationing responses to the collateral channel

In the last two counterfactuals we use the estimates of our demand and default models, together with our supply-side framework, to 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 first consider banks respond to the collateral value shock only adjusting interest rates and hold the set of available contracts constant at the baseline level. In another scenario, we allow banks to accommodate the drop

Table 9
The Collateral Channel.

	Available	Median Percentage Change				
	Contracts	Interest Rate	Default	Loan Size	Demand	Profit
(A) Pricing						
Secured	7277	2.62	3.03	−12.28	−2.13	−6.51
Unsecured	9575	0.00	0.00	−4.30	0.00	−1.06
Total	16,852	1.37	2.75	−10.43	−3.78	−6.63
(B) Pricing & Rationing						
Secured	4742	0.00	0.00	−0.28	−0.00	−1.59
Unsecured	5549	0.00	−0.21	0.00	0.00	0.00
Total	10,291	0.00	−0.04	0.00	−0.00	−0.00

Note: This table summarizes the median percentage change in equilibrium price (*Interest Rate*), probability of default (*Default*), loan size (*Loan Size*) expected demand (*Demand*) and banks' expected profit (*Profit*) of loans in two counterfactual scenarios compared with the baseline model. Each row stands for secured loans, unsecured loans, and both. The two panels present the scenarios after a 40% collateral value drop compared with the baseline model. Panel A present the case where the set of available contracts is fixed, whereas Panel B 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 loan size is calculated by comparing the average loan size across offers in each borrower's choice set. 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.

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 Eq. (7) is negative. While lenders can potentially ration borrowers also just via pricing, by setting very high interest rates, this strategy can still deliver negative expected profits for some risky borrowers, because the required high rates will lead to higher default probabilities. Hence, for those cases, banks will find more profitable to reject the borrower rather than offering a very high rate. Whereas identifying rationing using data on granted loans is challenging, our counterfactuals allow us to focus on marginal firms that borrow under the normal circumstances of our baseline scenario, but become unprofitable for lenders to serve in the unfavorable scenario of lower collateral value.

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. Panels A and B in Table 9 summarize the new equilibrium after the collateral value shock compared with the baseline model, for the case of banks responding through pricing or through pricing and rationing. We report in Table A.9 in the Appendix the results for the first loan that new borrowers are offered, which are not affected by inertia due to previous relationships.

We find that when banks respond only though pricing (Panel A), a 40% decrease in collateral value generates a median 2.6% and 0% increase in the interest rates of secured and unsecured loans, respectively. This makes economic sense, as secured loans are the ones directly affected by a shock to collateral value. Overall, the median interest rate increase is 1.4%, namely 0.2 percentage points. The median increase in the probability of default is 2.8%. The loan size, expected demand, and profit drop significantly, with a 10.4%, a 3.8%, and a 6.6% median decrease, respectively.[38] 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 (Panel B), 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. While this can appear as a stark reduction in loan supply, it is a reasonable response to the large drop in collateral value that we are simulating, which corresponds in magnitude to the effect of severe crisis events documented in the literature. This also implies that while in the baseline case 43% of firm-bank pairs consisted of both secured and unsecured contracts being offered, after rationing that happens only in 33% of the cases. Moreover, the number of firm-bank pairs with both contracts offered drops by around 42% (Table A.8 in the Appendix). Taken together, these numbers show that once rationing is allowed screening via collateral is used less by banks. 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 (Table A.9 in the Appendix). 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. For this last scenario, we also examine which types of loans are

[38] These results are qualitatively in line with the findings in Cerqueiro et al. (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.

Table 10
The Determinants of Credit Rationing.

	Credit Rationing
Expected Recovery Rate	−0.08*
	(0.05)
Bad Credit Rating	0.21***
	(0.06)
Borrower Controls	Yes
Bank FE	Yes
Region FE	Yes
Quarter FE	Yes
Observations	16,852

*Note:*This table shows how the characteristics of loans and borrowers determine the likelihood of credit being rationed after the collateral value shock. The column reports marginal effects of a probit model, where the dependent variable takes value of one if a loan has negative profit after the collateral value shock, and zero otherwise. *Expected Recovery Rate* is the expected recovery rate in default, defined in Eqs. (9) and (10). *Bad Credit Rating* is a dummy variable taking the value of one if the borrower has a loan with any overdue payment or default. *Borrower Controls* include variables for Corporation, Industry. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

more likely to be rationed when collateral value drops. We regress an indicator variable for a rationed loan on loan and borrower characteristics in a probit model. As illustrated in Table 10, we find that loans with a higher expected recovery rate are less likely to be rationed, while loans granted to borrowers with a bad credit rating are more likely to be rationed. The marginal effects suggest that one standard deviation increase in expected recovery rate decreases the probability of being rationed by 1.9 percentage points, while having a bad credit rating increases the probability of being rationed by 21 percentage points.

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 Eq. (11). As expected, borrowers respond to this by reducing their credit demand and increasing their likelihood of default, through the moral hazard channel $\alpha^{F}_{\mathcal{P}i}$. 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 the riskiness of the marginal borrowers who switch away from secured loans.

6.2.1. 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 (A.3) in the Appendix. 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 11. 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 11, 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 11. This reinforces the results reported in Table 9, 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 11. 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

Table 11
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	5784	5784	3364
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. *Borrower Controls* include variables for Corporation, Industry. 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.) $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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.

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.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2021.12.010.

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