Tracing the Impact of Bank Shocks under Bank-Specific Credit Demand*

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Abstract

We propose a method for estimating the effect of bank shocks on credit supply when firms have heterogeneous preferences over banks. We model firms' bank choices in a discrete-choice setting and show that firms prefer banks that are geographically closer, specialized in their industry, and better capitalized. The model yields a predicted probability that a firm borrows from a given bank, capturing firm-specific preferences that can be controlled for in standard credit supply regressions à la Khwaja and Mian (2008). Accounting for these preferences changes the estimated transmission of shocks through banks, revealing a potential bias in the conventional identification strategy.

Keywords: Bank Lending Channel, Credit Supply Identification, Relationship Lending.

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1 Introduction

Over the past two decades, and particularly since the Global Financial Crisis, a large body of research has shown that shocks to banks can disrupt the supply of credit and, in turn, dampen real activity. Using detailed loan-level data, this literature documents how shocks to banks' balance sheets—such as sudden outflows of retail or wholesale (interbank) deposits—affect credit supply. Following the seminal work by Khwaja and Mian (2008), most studies identify shifts in bank credit supply by comparing the changes in amounts lent by affected and unaffected banks to the same firm, filtering out changes in the firm's own credit demand through the inclusion of firm or firm-time fixed effects. The approach assumes that firms are indifferent across their banks, meaning that a firm's demand for credit is not allowed to depend on bank characteristics that are correlated with the shock.

It is not clear whether this assumption always holds in practice. Firms tend to favor banks that are closer geographically, better capitalized, more specialized in their industry, or with which they already have established relationships, for instance. These characteristics relate to a bank's business model, which in turn is likely to be related to its exposure to balance sheet shocks. For example, banks with a smaller network of branches are simultaneously more likely to be distant from many firms as well as being more reliant on wholesale rather than retail deposit funding and thus more exposed to wholesale funding shocks. This raises an important methodological concern, as bank characteristics that determine firms' demand may be correlated with the balance sheet shocks under study, potentially biasing estimates of credit supply effects.

A natural response is to control for the characteristics that matter for firms' choice of banks directly. The challenge is that the choices reflects multiple characteristics, and it is rarely obvious which characteristics matter most or how they should be combined to capture firms' bank-specific demand. We therefore propose to use the bank-firm network itself—who borrows from whom—to infer, for each firm-bank pair, how strongly the firm prefers that bank relative to available alternatives. Our approach builds on the discrete-choice literature and captures firms' preferences for banks based on observable characteristics such as distance, specialization, and capitalization, whose importance may differ depending on firm characteristics. From this model, we derive the probability that a firm borrows from any given bank, which can be interpreted as a (scaled) utility that the firm derives from borrowing from that bank and so is a measure of the firm's bank-specific demand for credit, or *firms' bank preference* for short.

Including this measure in an otherwise standard credit supply regression à la Khwaja and Mian (2008) allows us to assess how controlling for firms' bank preference alters estimated effects, thereby relaxing the standard assumption that firms are indifferent across banks. To illustrate the point, we first replicate the analysis of Iyer, Peydró, da Rocha-Lopes and Schoar (2014) and show how shocks to banks' balance sheet during the global financial crisis affected credit supply in Portugal. We then show that controlling for firms' bank preference changes the magnitude of estimated credit supply effects.

We use several administrative data from the Portuguese central bank, the Banco de Portugal, that provide detailed information on firms and their banks. Our main source is the *Central de Responsabilidades de Crédito* (CRC), a central credit register which records monthly loan exposures for every firm–bank pair in Portugal from 2006 to 2016. The CRC covers all commercial and industrial loans to non-financial firms extended by any bank operating in Portugal. We observe data on credit relationships and balance sheets for both firms and banks from 2006 to 2016. Importantly, because all loans above €50 must be reported, the register effectively captures the universe of firm–bank credit relationships and hence presents a more complete picture of firm-bank relationships than credit registers in other countries which typically have much higher reporting thresholds. We complement these data with bank balance sheets from the *Euro Area harmonized Monetary and Financial Statistics* and firm financial statements from the *Informação Empresarial Simplificada* (IES), which covers the universe of Portuguese nonfinancial firms. Finally, we merge in firm-level probabilities of default estimated by the Banco de Portugal (Antunes, Gonçalves and Prego, 2016; Blattner, Farinha and Rebelo, 2023).

Our main findings are as follows. Firms are more likely to borrow from banks that are geographically closer, better capitalized, more specialized in their industry—meaning the industry accounts for a larger share of the bank's portfolio—or that the bank has a larger share of lending in the industry. Interactions with firm characteristics reveal important heterogeneity, which support the plausibility of our estimates of firms' preferences for banks. For riskier firms, geographical proximity and banks' industry specialization matter more than for safer firms. This is consistent with these firms benefiting relatively more from a bank's ability to gather information on borrowers, through geographical proximity or knowledge and expertise in the industry. By contrast, bank capital matters less for riskier than for safer firms. This is consistent with lowly capitalized banks being more willing to support risky firms through loan evergreening, in order to avoid recognizing loan losses that reduce their already low capital. For larger firms, bank specialization matters more than for smaller firms. This is in line with the possibility that larger firms value banks' specific knowledge of an industry, as this allows banks to provide additional services, including support for M&A activity. This is also consistent with the results in Paravisini, Rappoport and Schnabl (2023), as exporters, who value the expertise of banks towards certain countries or industries, are typically larger firms. By contrast, geographical distance and bank capital are less important than for smaller firms, consistent with larger firms being less opaque and more able to obtain funding across banks, or from non-banks.

We next examine how accounting for firms' bank preferences affects estimates of how bank shocks translate into credit supply shocks. To do so, we replicate the main results of Iyer et al. (2014) as a baseline. They use the framework of Khwaja and Mian (2008) to show that Portuguese banks more dependent on interbank funding contracted credit more sharply after the onset of the interbank market turmoil after mid-2007. When we control for our estimated measure of firms' bank preference, the effect of interbank funding exposure on credit supply remains negative and significant but declines by about 16%. This adjustment is economically meaningful and may affect results of both quantitative macro models and policy simulations, for instance when assessing the impact of monetary tightening on credit supply. A system-of-equations (SUR) test confirms that the difference in estimated coefficients with and without the control for firms' bank preference is statistically significant. Finally, the bank preference measure itself has a positive and highly significant coefficient, indicating that after the start of the crisis, firms demand more credit from their preferred banks.

We conduct several robustness checks, and the results consistently highlight the importance of accounting for firms' bank preference in empirical analyses of credit supply.

Our findings contribute to several strands of the literature. First, we contribute to the empirical literature that estimates the effects of bank balance sheet shocks to credit supply. Since the seminal work of Khwaja and Mian (2008), most studies decompose variation in quantities lent into variation at the bank level, which are interpreted as fluctuations in credit supply, and variation at the firm level, which are intepreted as fluctuations in demand (Jiménez, Ongena, Peydró and Saurina, 2012; Iyer et al., 2014; Bofondi, Carpinelli and Sette, 2018; Bottero, Lenzu and Mezzanotti, 2020; Beck, Da-Rocha-Lopes and Silva, 2021). There are by now three key papers that examine alternatives to this approach.

First, Paravisini et al. (2023) argue that Khwaja and Mian (2008)-style estimates may be biased if firms have bank preferences—for example, if exporters prefer banks specialized in financing exports to their destination markets. In their study of Peruvian firms during the Global Financial Crisis, they focus on firms' bank preferences related to export specialization and show that controlling for these preferences in a Khwaja and Mian (2008)-style regression does not change the estimated effect of bank shocks on credit supply, suggesting that such preferences were uncorrelated with the shocks in that setting. We generalize this idea by modeling firms' bank preferences more broadly in a discrete-choice framework that allows firms to value multiple bank characteristics beyond export specialization, such as proximity, capitalization, and industry focus. In our application to Portuguese firms during the Global Financial Crisis, controlling for firms' bank preferences changes the estimated transmission of bank shocks to credit supply, indicating that these preferences were correlated with the shocks in this context.

Second, Gutierrez, Villacorta and Villacorta (2023) extend the Khwaja and Mian (2008) framework by clustering firms into groups and examining variation in lending at the bank-group level, which could be interpreted as fluctuations in banks' group-specific credit supply. While this approach accounts for differences between groups of firms, it cannot account for the fact that firms within a group may have still different preferences for specific banks. By contrast, our approach allows for this heterogeneity at the relationship level rather than only across groups.

Third, De Jonghe and Lewis (2025) set up a factor structure model in which credit supply shocks and credit demand shocks determine bank-firm specific changes not just in quantities but also in interest rates. Using the idea that increases in demand and increases in supply should push quantities in the same direction but interest rates in opposite directions they can, under some assumptions, recover the underlying supply and demand shocks via spectral decomposition of the variance-covariance matrices. Our work has a different focus: we propose an approach to allow firms' to have a specific preference for banks and assess the consequences for empirical estimates of the effect of shocks to banks on credit supply.

Moreover, none of these three papers explicitly use the information in the network structure itself—that is, the information on which firm borrows from which bank. We further contribute to the literature by showing how this information can be used to infer firms' bank preferences via a discrete choice model and hence refine the Khwaja and Mian (2008) approach.

We also extend the small literature on the determinants of bank–firm match formation (Detragiache, Garella and Guiso, 2000; Chen, 2013; Schwert, 2018). We derive and estimate a structural model of match formation, showing how firms' preference for banks affects credit dynamics in crises and alters empirical estimates of the bank lending channel. Relative to Schwert (2018), who focuses on syndicated loans, we use comprehensive loan-level data covering all firms, including SMEs, thereby avoiding sample selection biases from unobserved smaller relationships.

Our paper further relates to the literature on bank specialization. We show that firms are more likely to borrow from banks with larger market shares in their industry (as in Giannetti and Saidi, 2018) and from banks more specialized in that industry, consistent with evidence in Iyer, Kokas, Michaelides and Peydro (2022) and Blickle, Parlatore and Saunders (2023).

Finally, by identifying the drivers of bank–firm match formation, we contribute to the large literature on relationship lending, particularly studies of the determinants and benefits of stable lending relationships. These include the role of distance (Petersen and Rajan, 2002) and the advantages of persistent ties in downturns (Sette and Gobbi, 2015; Bolton, Freixas, Gambacorta and Mistrulli, 2016; Beck, Degryse, De Haas and Van Horen, 2018; Banerjee, Gambacorta and Sette, 2021). By highlighting the role of firm-specific preferences in shaping credit access, our findings also connect to work on the consequences of relationship termination (Darmouni, 2020; Bonfim, Nogueira and Ongena, 2021; Cohen, Hachem and Richardson, 2021; Goncharenko, Mamonov, Ongena, Popova and Turdyeva, 2022).

The rest of the paper is structured as follows: section 2 presents our theoretical framework, section 3 describes the data, section 4 outlines the empirical approach, section 5 presents the results, section 6 concludes.

2 Empirical strategy and framework

This section develops the empirical strategy and framework used in the paper. The seminal contribution of Khwaja and Mian (2008) established a framework that exploits within-firm variation across lenders to identify the effect of bank-specific balance sheet shocks on credit supply, which has become standard in the literature. In this section, we illustrate how systematic differences in firms' bank preferences within the standard framework can lead to omitted variable bias. We then introduce our approach for constructing a proxy for firms' bank preferences, derived from a discrete choice model, which can be incorporated into a Khwaja and Mian (2008)-style regression to mitigate this bias.

2.1 The standard approach

We follow the notation of Khwaja and Mian (2008) in describing their approach. Let L_{ijt} denote the quantity lent by bank i to firm j at time t. Assume that the marginal benefit of the loan to firm j from bank i is given by $A_{jt} - \alpha_L L^t_{ijt}$. Firm j's demand for credit is determined by the condition that the firm equates the marginal benefit of the loan to the marginal cost, which is the interest rate R_{ijt}. The inverse demand curve is therefore linear and given by

$$R_{ijt} = A_{jt} - \alpha_L L_{ijt}. \tag{1}$$

Bank i can raise an amount of funding D_{it} costlessly. Any additional funding produces a marginal cost of funds. If bank i wants to lend a quantity L_{ijt} that exceeds D_{it}, it incurs a marginal cost of funds equal to $\alpha_B (L_{ijt} - D_{it})$. Bank i's supply of credit is determined by the condition that the bank equates the marginal cost of its funds with the marginal benefit of the loan, which is the interest rate R_{ijt}. The inverse supply curve is therefore linear and given by:

$$R_{ijt} = -\alpha_B D_{it} + \alpha_B L_{ijt}. \tag{2}$$

The equilibrium amount L_{ijt} lent by bank i to firm j at time t is given by the intersection of the demand and supply curve:[1]

$$L_{ijt} = \frac{\alpha_B}{\alpha_L + \alpha_B} D_{it} + \frac{1}{\alpha_L + \alpha_B} A_{jt} \tag{3}$$

[1] Khwaja and Mian (2008) simplify their model by implicitly assuming that the demand curve of firm j for funds from bank i is independent from its demand curve for funds from bank $i' \neq i$. This abstracts from the fact that a reduction in credit supply by bank i should increase firm j's residual demand for credit from bank $i' \neq i$. In their regression approach, the coefficient of interest should therefore be interpreted as measuring the difference in the change in credit of banks hit by a shock relative to other banks. For simplicity, we will maintain this assumption here. See also Bergman, Casado, Iyer and Saporta-Eksten (2025), who relax this assumption.

One can take time differences of this equation to obtain:

$$\Delta L_{ij} = \frac{\alpha_B}{\alpha_L + \alpha_B} \Delta D_i + \frac{1}{\alpha_L + \alpha_B} \Delta A_j. \tag{4}$$

Khwaja and Mian (2008) use this equation to motivate the following regression:

$$\Delta L_{ij} = \beta_j + \beta_1 \Delta D_i + \varepsilon_{ij}, \tag{5}$$

where ΔD_i is the bank balance sheet shock and the firm fixed effect β_j controls for credit demand shocks ΔA_j (See Khwaja and Mian, 2008, Eqs. (3) and (5)), as well as for other systematic specific differences across firms borrowing from different banks. The coefficient β_1 describes how the balance sheet shock ΔD_i that shifts the bank's supply curve affects the quantity lent by bank i to firm j.

2.2 Augmenting the standard approach with preferences for a bank

We now modify the standard approach by allowing firms to have a different demand for credit from different banks. Firm j's demand for credit from bank i is determined by its perceived *net* marginal cost of credit R'_{ijt} from that bank, where:

$$R'_{ijt} \equiv R_{ijt} - \alpha_{M,t} M_{ij}. \tag{6}$$

R_{ijt} is the interest rate for loans from bank i to firm j. M_{ij} is a measure of firm j's preference for credit from bank i. This term can capture the proximity of bank i to firm j in geographical space or in product space as in spatial models of product differentiation (Hotelling, 1929), or the degree of "specialization" of bank j in the activities of firm i (Paravisini et al., 2023), which is one of the possible determinants of the "lending advantage" of bank i vis-a-vis firm j. The time-varying coefficient $\alpha_{M,t}$ captures the salience of bank preferences over time. Below, we will describe times with high values of $\alpha_{M,t}$ as crisis times, in which being borrowing from the preferred bank matters greatly, and times with low values of $\alpha_{M,t}$ as good times, in which it does not matter very much.[2]

Consider, for instance, two banks that offer credit to a firm at the same interest rate R, at a given point in time. The bank for which M is larger will be a better match for the firm. The firm will perceive a lower *net* marginal cost of credit R' on loans granted by this bank. In our modified version of the standard approach, firms choose to borrow an amount that equates the marginal benefit of the loan with the *net* marginal cost of credit R'_{ijt}. This means that when considering the two banks, the firm will demand more credit from the bank for which the firms' bank preference, M_{ij}, is larger, everything else being equal.

Equating the net marginal benefit of the loan with the *net* marginal cost of credit implies a modified inverse demand curve:

$$R'_{ijt} = A_{jt} - \alpha_L L_{ijt}. \tag{1'}$$

$$\Leftrightarrow R_{ijt} = \alpha_{M,t} M_{ij} + A_{jt} - \alpha_L L_{ijt}$$

With the same credit supply equation (Equation (2)), we now obtain an equilibrium amount lent of

$$L_{ijt} = \frac{\alpha_B}{\alpha_L + \alpha_B} D_{it} + \frac{1}{\alpha_L + \alpha_B}(\alpha_{M,t} M_{ij} + A_{jt}). \tag{3'}$$

Taking time differences, we can see that

$$\Delta L_{ij} = \frac{\alpha_B}{\alpha_L + \alpha_B} \Delta D_i + \frac{1}{\alpha_L + \alpha_B} \Delta A_j + \frac{M_{ij}}{\alpha_L + \alpha_B} \Delta \alpha_{M,t}. \tag{4'}$$

Suppose $\Delta\alpha_{M,t} \neq 0$ so that the salience of firms' bank preferences varies over time. Then since M_{ij} varies at the level of the firm and bank, in the standard KM-regression (Equation

[2] Firms' bank preferences M could also be time-variant. In general, there are other possible ways to integrate versions of firms' bank preferences (or the "transport costs" of spatial models of product differentiation) into the model. We discuss one specific alternative in Appendix B.

(5)) it would be an omitted variable that would show up in the error term ε_{ij}. If the changes in match preferences are correlated with measures of credit supply shocks ($\text{Cov}(\Delta D_i; M_{ij}) \neq 0$), the estimate of the effects of the credit supply shock β_1 could be biased. This bias arises because the KM estimator attributes all within-firm variation in lending to supply shocks, even when part of this variation reflects variation in a firm's bank-specific demands.

Whether this correlation is empirically relevant is ultimately an open question, but several models of bank lending suggest that it can be important in practice. For example, consider two banks that lend to the same firm. Bank A has a business model based on relationship banking. It has many branches, relies mainly on soft information for credit decisions, and finances itself mainly via retail deposits collected from its branches. By contrast, bank B has fewer branches, relies mainly on credit scoring models, and finances itself mainly via the wholesale money market. The firm borrows from both banks in good times to diversify funding sources. In bad times, when a shock hits the wholesale money market, bank B cuts its credit supply. At the same time, the firm may realize that bank A in fact keeps lending to its relationship borrowers because of an implicit long-term relational contract (see, e.g., Bolton et al., 2016). The firm is therefore also likely to decide that bank A is a better provider of credit, everything else being equal, and to increase its demand for credit from bank A and reduce its demand for credit from bank B.

The reduction in the quantity lent by the bank experiencing the funding shock (bank B) therefore not only reflects a reduction in credit supply by that bank but also a reduction in the firm's demand for funding specifically from that bank. In this case, the standard Khwaja-Mian estimate would overstate the effect of the shock on bank B's credit supply.

An obvious solution is to include a measure of firms' bank preference as a control. Such controls could include, e.g., measures at the bank-level such as bank size, capital ratios, or the density of the branch network, or measures at the bank-firm level, such as dummies that indicate the "main lender" of a firm, the quantity of credit in the form of credit lines to a firm (as credit lines are more information-intensive than other types of loans), a measure of bank specialization in the industry of the firm or similar. We propose to systematically combine all such variables related to firms' bank preferences into a single index m, based on a theoretical model of a firm's choice of a bank. This single index can then be included to control for omitted variable bias, as follows:

$$\Delta L_{ij} = \beta_j + \beta_1 \Delta D_i + \beta_2 m_{ij} + \varepsilon_{ij}. \tag{5'}$$

Here, β_1 describes how balance sheet shocks affect quantities via effects on credit supply and β_2 describes how firms' bank preferences m_{ij} affect their bank-specific credit demand. We note that this is essentially a generalized version of the approach taken by Paravisini et al. (2023) in their Table IX (p. 2079). It turns out that in their setting, banks' balance sheet shocks and their measure of what we call firms' bank preference are not correlated so that the estimate of the coefficient of interest β_1 is not affected.

In other settings, measures of firms' bank preference and bank shocks may be correlated. This is the case in the the setting we consider.

2.3 Measuring firms' bank preferences

Like Crawford, Pavanini and Schivardi (2018) and Paravisini et al. (2023), we model the firm's borrowing decision as a discrete choice problem, whereby each firm selects one bank from the set of feasible lenders.

The discrete choice model is static. Firm j chooses the bank i that provides the lowest net marginal cost of credit $R'_{ij} = R_{ij} - M_{ij}$. We model the net marginal cost of credit as consisting of a linear function of a set of observed match characteristics, X_{ij}, and an unobserved component u_{ij}.

The interest rate charged by bank i to firm j should be included in X_{ij} if it is observed. Unfortunately, many older credit registers contain only information on quantities but not on interest rates. This is also the case for the Portuguese CRC in 2007-2008 that we use to replicate the work of Iyer et al. (2014), so that we need to treat the interest rate as an unobserved characteristic. Since estimation of the discrete choice model requires that $E[u_{ij}|X_{ij}] = 0$, we need to make the assumption that $E[R_{ij}|X_{ij}] = 0$. This assumption ensures that the unobserved component of the match absorbs both the true interest rate and any remaining unmeasured features of the bank–firm relationship, allowing the model to be estimated on quantity-only data without violating the orthogonality condition. We stress that it is not necessary to make this assumption when data on R_{ij} are observed, in which case they should simply be included in the observed characteristics of the match, X_{ij}, and possibly instrumented, for example with Hausman-type instruments as in Crawford et al. (2018), to account for the endogeneity of prices to demand.

Under our assumption, choosing the bank with the lowest net marginal cost of credit is equivalent to choosing the bank with the highest M_{ij}, where this is given by the linear function

$$M_{ij} = X_{ij}\gamma + u_{ij}, \tag{7}$$

where X_{ij} are the observed characteristics and the u_{ij} the unobserved characteristics of the bank-firm match. Under the assumption that the u_{ij} are i.i.d. and follow a Gumbel distribution, the setting is that of conditional logit. The probability that bank i is chosen when firm j is faced with a set of $k = 1, ..., N$ banks to choose from (which includes bank i) is given by

$$P_{ij} = \frac{e^{X_{ij}\gamma}}{\sum_{k=1}^{N} e^{X_{kj}\gamma}} \tag{8}$$

and the parameters γ can be estimated via maximum likelihood.

Once parameters are estimated, the observed part of the firms' bank preferences, $X_{ij}\hat{\gamma}$, can be computed. However, like a utility index, this quantity has no natural scale or interpretation and is really only meaningful when comparing across the different banks a firm can choose. For this reason, we take as our measure $\hat{m}_{ij}$ of firm j preference for bank i the estimate of the probability in Equation (8):

$$\hat{m}_{ij} \equiv \frac{e^{X_{ij}\hat{\gamma}}}{\sum_{k=1}^{N} e^{X_{kj}\hat{\gamma}}} \equiv \hat{P}_{ij}. \tag{9}$$

This is effectively a scaled version of the estimated, observed part of the utility $X_{ij}\hat{\gamma}$ that is constrained to be between 0 and 1. A number close to one indicates that the firm derives a very high utility from borrowing from that bank; a number close to zero indicates that the firm derives a very low utility from borrowing from that bank.

3 Implementation of the empirical strategy

This section describes how we implement the framework developed in Section 2.

3.1 Estimating firms' bank preferences

We estimate firms' preferences over potential lenders from the actual choices of firms.

Firms' choices of banks. We define a "choice event" as occuring when a firm initiates a new lending relationship with a bank. We identify new relationships directly from the Portuguese credit registry (CRC). We classify a firm–bank pair as new when it appears in the registry for the first time or when it reappears after at least 12 months of inactivity. This definition follows the standard approach in the literature and ensures that the event reflects an active decision by the firm rather than mechanical continuation of an existing loan (Degryse and Ongena, 2005; Degryse, Karapetyan and Karmakar, 2021). When a firm establishes more than one new relationship in the same year, we follow Crawford et al. (2018) and treat the bank providing the largest share of credit as the chosen alternative for estimation purposes.[3] We focus on firms experiencing at least one choice event during the

[3]In our data, approximately 68% of firms borrow from a single bank, while the remaining 32% borrow from multiple banks.

period used to estimate match preferences.

Constructing the firm–bank choice set. To estimate the discrete-choice model of bank selection, we restrict the set of banks that firms can choose from to banks that provide at least 1% of total corporate credit. This yields 18 banks that together intermediate more than 90% of corporate credit in Portugal (Section 4 provides detailed information on these institutions). For every firm with a choice event in year t, we construct a balanced choice set in which the firm is paired with the full set of 18 potential lenders. The bank with which the firm initiates a new lending relationship is coded as the chosen alternative, while the remaining banks in the choice set are coded as unchosen alternatives. The resulting indicator variable equals one for the chosen bank and zero otherwise, and serves as the dependent variable in the conditional logit estimation.

Match characteristics. We augment each bank-firm-year in the data with observed match characteristics that are the explanatory variables in our discrete choice model. There are several categories of match characteristics that we include.

The first category consists of variables that vary at the bank level. Schwert (2018) shows that bank capitalization influences firms' lender choices, as more strongly capitalized banks are perceived as safer counterparties. We therefore include the logarithm of bank capital (defined as book equity and reserves), as reported in supervisory balance sheets, to capture cross-bank differences in financial strength. We also include bank fixed effects to ensure that the predicted choice probabilities match the empirical frequencies with which different banks are selected.

The second category consists of variables that vary at the bank–firm match level. A growing theoretical and empirical literature highlights the role of geographic distance in shaping credit relationships. Distance erodes banks' ability to acquire soft information because it captures proximity to the information source in several guises. Firms located farther from their lenders face greater informational frictions (Hauswald and Marquez, 2006) and, in some cases, higher transportation or monitoring costs (Acharya, Hasan and Saunders, 2006). In the Portuguese context, Bonfim et al. (2021) document that distance is a significant determinant of credit conditions. These mechanisms imply that banks derive an ex-ante cost advantage when they are physically closer to borrowers, making distance a natural match characteristic in our framework. We therefore include the distance between a firm and the nearest branch of the bank for each bank–firm pair.

Previous work also demonstrates that bank specialization and market presence in the borrower's industry influence lending outcomes (Giannetti and Saidi, 2018; De Jonghe, Dewachter, Mulier, Ongena and Schepens, 2020; Iyer et al., 2022; Blickle et al., 2023). Consequently, we include the share of the firm's industry in the bank's loan portfolio (*Industry Specialization*) and the bank's market share in the firm's industry (*Industry Market Share*). Both variables are computed using total drawn credit, rather than committed amounts, to ensure that the measures reflect the actual distribution of outstanding credit exposures. As discussed in Subsection 2.3, we do not include interest rates because the portion of the CRC used by Iyer et al. (2014)—which forms our benchmark sample—does not report pricing information.

The last category captures interactions between bank-level and firm-level characteristics. We encode firm size and an estimate of the firms' probability of default as dummies and interact these with the bank-level variables to allow the sensitivity of lender choice to vary with firm size and firm risk.

Estimation. We estimate a conditional logit model of lender choice, in which firms select among the 18 potential banks based on observed match characteristics. The model maps these characteristics into the probability that firm j selects bank i at time t. We compute the fitted choice probability $\hat{P}_{ijt}$ using the estimated coefficients and the contemporaneous values of the match characteristics X_{ijt}. We use these fitted probabilities as our empirical measure of firm j's preference for bank i, denoted $\hat{m}_{ijt} \equiv \hat{P}_{ijt}$ (eq. 9).

3.2 Estimating effects of bank shocks to credit supply

Once we have estimated each firm's bank preference using the discrete choice model, we examine whether incorporating this measure alters standard estimates of how bank-level shocks affect the supply of credit. As a benchmark, we replicate the analysis of Iyer et al. (2014), who apply the Khwaja and Mian (2008) identification strategy to an earlier version of the Portuguese CRC.[4] Importantly, for the credit supply shocks, the match-preference index is estimated using lending relationships observed in 2007, i.e., before the interbank funding shock. This ensures that the preference measure reflects pre-crisis match quality and is not contaminated by crisis-driven relationship dynamics.

We begin by estimating a version of the standard Khwaja and Mian (2008) within-firm specification, as in Iyer et al. (2014). We then augment this regression by adding our estimated $\hat{m}_{ij}$ index (cf. Equation (5')) to test whether firm–bank match quality alters the estimated effect of bank exposure to the interbank shock on credit supply.

Formally, following the framework in Section 2, we estimate:

$$\Delta \ln Credit_{ij} = \alpha_j + \beta_1 Interbank\,Borrowing_i + \beta_2 \hat{m}_{ij} + Controls + \varepsilon_{ij} \tag{10}$$

We measure the change in log credit between 2007:Q2 and 2009:Q2 and relate it to banks' exposure to interbank markets in 2007:Q2, captured by the *Interbank Borrowing* ratio, controlling for firm j's preference for bank i, $\hat{m}_{ij}$, which is fixed at its 2007 value in all specifications.[5] In the replication of Iyer et al. (2014), β_2 is implicitly constrained to zero; in our augmented specification, we allow it to vary freely. Following Iyer et al. (2014), we include the bank-level controls *Capital ratio*, *Bank liquid assets*, and *Bank size* and double cluster standard errors at both the bank and firm levels. The coefficient β_1 captures the effect of the

[4] Methodological changes at Banco de Portugal since Iyer et al. (2014) imply that our version of the CRC is not identical; accordingly, we match their qualitative findings but cannot reproduce their exact numerical estimates.

[5] In this specification, the sample naturally contracts because identification requires firms with multiple bank relationships observed in both 2007:Q2 and 2009:Q2. The resulting dataset contains 31,202 unique firms.

interbank shock on credit supply, while β_2 measures whether firms' utility from matching with a particular bank affects the evolution of credit from that bank during the crisis.

We expect β_2 to be positive: during the crisis, firms should reallocate borrowing toward banks that are better matches for them. We also expect β_1 to be negative and significant, consistent with Iyer et al. (2014). The key question is whether the estimated supply effect β_1 changes, by an economically and statistically significant magnitude, once firms' bank preference $\hat{m}_{ij}$ is included.

4 Data and summary statistics

4.1 Data sources

We use proprietary administrative data from the Banco de Portugal. The data contain information on credit relationships and balance sheets for both firms and banks from 2007 to 2012. This window provides sufficient relational history to estimate firm–bank match preferences and includes the 2007–2009 period exploited by Iyer et al. (2014) for identifying credit supply shocks. The dataset is constructed from three main sources.

The first is the Portuguese credit registry (*Central de Responsabilidades de Crédito*, CRC), which includes monthly loan exposures for every firm-bank pair. This comprehensive dataset records all commercial and industrial loans to non-financial companies by all banks operating in Portugal. It is a legal requirement for all financial institutions granting credit in Portugal to report all loans above €50 to CRC on a monthly basis. This implies implies that the credit register effectively records the universe of outstanding loans to corporations and individuals. When the reporting threshold is higher, as in the vast majority of other credit registers (Belgium, Euro Area, France, Germany, Italy, United States), if a relationship is not observed it could be both because it is truly not realized, but also because it involves a loan below the reporting threshold. This distinction is particularly relevant for smaller firms, which typically borrow small amounts but are also the most bank-dependent segment of the corporate sector. The CRC also contains information about the amount of the loan and its status, namely whether it is performing, renegotiated, non-performing, or defaulted.

To match all loans with the corresponding bank-specific characteristics, we use the Banco de Portugal's *Estatísticas Monetárias e Financeiras*, a database reporting balance sheet information for financial institutions operating in Portugal. The bank-level data are monthly in frequency. In addition, firm balance sheets and income statements come from the *Informação Empresarial Simplificada* (IES), which covers the entire universe of Portuguese non-financial firms. The firm-level data are available at an annual frequency. We also use firms' probability of default from a credit risk prediction model calculated by the Banco de Portugal (Antunes et al., 2016) and subsequently used in the literature (e.g., Farinha, Spaliara and Tsoukas 2019; Blattner et al. 2023).

The CRC contains the addresses of firms and bank branches, which contain post codes. We use the Google Maps API to geolocate these post codes. This allows us to compute distances between firms and bank branches as we describe below.

4.2 Data filtering

The CRC contains information on loans granted by 261 distinct banks to 600,472 distinct firms. Because most loans in our dataset are relatively small, it is more appropriate in our context to model the matching decision as borrowers choosing banks. This implies that banks do not ration borrowers, in line with the literature adopting a structural approach to bank lending, for example Crawford et al. (2018).[6]

As described in section 3, to reduce the dimensionality of the firms' choice set, we restrict the analysis to the 18 banks that each provide at least 1% of the overall credit and for which balance sheet information is available in the supervisory reports during our sample period. These banks together account for slightly more than 90% of total credit extended in Portugal,

[6] In settings involving larger loans, one could instead model banks as choosing borrowers, or adopt a bilateral matching framework similar to those used in the mergers and acquisitions literature (Bena and Li, 2014).

ensuring that we retain the institutions that meaningfully compete in the corporate credit market while excluding fringe lenders that account for negligible volumes and would just add noise to the discrete-choice estimation. These 18 banking groups include both large nationwide institutions and smaller agricultural savings banks ("caixas agrícolas"), which historically play an important role in supplying credit to small and regionally concentrated firms.

As standard in the literature, we also exclude companies that do not have complete records on our explanatory variables and firm-years with negative sales. To control for the potential influence of outliers, we remove observations in the 1% upper and lower tails of the distribution of the regression variables.

Our final estimation sample for the discrete-choice model consists of 255,604 firms and 18 banks over the 2007–2012 window. These 255,604 firms account for 730,001 choice events over this time period.

Our final estimation sample for the credit supply regression comprises 72,864 firm-bank pairs.

4.3 Variable definitions and construction

We define and construct the main variables for our analysis as follows (see Appendix A for a summary).

For the discrete-choice analysis, the dependent variable is defined at the firm-bank-year level and constructed using information from the CRC. It is an indicator for a new firm–bank relationship, equal to one when a firm initiates a lending relationship with a given bank in year t and zero otherwise, as described in Section 3.

The main explanatory variables capture bank characteristics and firm-bank match attributes. *Industry market share* is defined as the share of total credit in a given industry accounted for by a bank, while *Industry specialization* measures the share of a bank's loan portfolio allocated to the firm's industry. *Ln(capital)* describes bank capitalization and is defined as the logarithm of book equity and reserves. *Distance* is measured as the geographic distance (in tens of kilometers) between a firm's headquarters and the nearest branch of each bank, which we compute as follows. We rely on information from the CRC on the addresses of bank branches and firms' headquarters. The addresses vary in the amount of information they provide. To maximize coverage, we restrict ourselves to the four-digit post code, which is present for most of the addresses. The four-digit post code describes an irregularly-shaped area associatedwwith a postal distribution center. The size of these areas varies; maximal distances within the areas can be less than 3 kilometers in big cities but also more than 30 km in the less densely populated rural areas. We geolocate the four-digit postal codes and compute the distance between them in kilometers. If a firm and bank branch are located in the same postal code, our measure of distance is zero (approximately 70% of firms have at least one bank with a branch in the same postal code). For each firm–bank pair, we compute the distance to every branch of the bank and retain the minimum value, yielding a single, proximity measure for each alternative. Firm risk is measured using a predicted probability of default constructed by the Banco de Portugal and widely used in the literature, which we encode into the *High PD* indicator equal to one if the firm's default probability is above the sample median.[7] The indicator *Big Firm* is equal to 1 when the firm's total assets are above the sample median.

For the credit-supply analysis, the dependent variable is defined at the firm-bank level and constructed using information from the CRC. $\Delta \ln Credit_{ij}$ is the logarithmic change in outstanding credit between 2007:Q2 and 2009:Q2 for the firm-bank pair. Bank balance-sheet explanatory variables used in the credit-supply regressions are measured as of 2007:Q2 and include: the *Interbank borrowing* ratio, defined as ratio of total interbank borrowing to total

[7]The default indicator follows the definition implemented by the Banco de Portugal and introduced by Antunes et al. (2016). A firm is flagged as being in default if overdue credit exceeds 2.5% of total outstanding credit for at least three consecutive months. A default event is recorded in the third consecutive month above this threshold. A firm is considered to have defaulted in a given year if a default event occurs at any point during that year. To avoid overweighting recurrent defaulters, we exclude all firm observations after the first default event. The construction is based on monthly information from the Central Credit Register and is embedded in the CRC default module used by the Banco de Portugal.

assets; the *Capital ratio*, measured as total bank capital as a fraction of total assets; *Bank liquid assets*, defined as the ratio of short-term to total assets; and *Bank size*, defined as the natural logarithm of the banks' total assets.

4.4 Summary statistics

Panel A of Table 1 reports descriptive statistics for the variables used to estimate the discrete-choice model of firm–bank matching. The unit of observation is the firm–bank–year pair in the balanced choice set constructed for the discrete-choice estimation. This sample contains 255,604 firms paired with the 18-bank choice set over 2007–2012. About 5.5% (or $\frac{1}{18}$) of firm–bank pairs correspond to a new lending relationship, as defined by the credit register records. The average firm is located 33 kilometers from the nearest branch of a given bank. The median distance is zero because many firms borrow from banks with a branch in the same postal code, while geographically distant matches generate a long right tail. This pattern is consistent with evidence for Portugal documented in Bonfim et al. 2021, who also report substantial dispersion in bank–firm distances.

Industry market share and industry specialization average 4.5% and 10.4%, respectively, exhibit meaningful cross-bank variation. The mean of Ln(capital) is 8.49, corresponding to roughly €4.9 billion in book equity, a magnitude consistent with the balance-sheet size of the major Portuguese banking groups in our sample. Capital levels also vary substantially across institutions. Approximately half of firm–bank pairs involve firms classified as high default risk, generating additional heterogeneity for the interaction terms included in the specification.

Panel B presents summary statistics for the variables entering the Khwaja and Mian (2008) credit-supply regression. The average change in log credit over the 2007:Q2–2009:Q2 window is 0.845, with substantial dispersion across firm–bank pairs. Interbank borrowing averaged 24% of liabilities before the shock, consistent with the measure used in Iyer et al. (2014). The mean of the match-preference index is 0.103, indicating that firms assign relatively high predicted choice probabilities to a small subset of lenders. The bank-level controls (capital ratio, liquid assets, and size) display substantial cross-bank variation, which allows the empirical design to separate bank balance-sheet conditions from firm-specific credit demand.

Overall, the descriptive evidence indicates: (i) substantial heterogeneity in the characteristics that shape firm–bank matching, and (ii) meaningful cross-sectional variation in bank exposures relevant for credit supply during the crisis.

5 Results

5.1 Firms' Bank Preference: Drivers and Effects on Access to Credit

We begin by examining firms' bank preferences. Table 2 reports estimates from the discrete-choice model described in Equation (8), with bank and match characteristics added sequentially across columns. Each column corresponds to a conditional logit specification in which firms choose among the same set of 18 potential lenders when initiating a new lending relationship. Identification comes from within–choice-set variation in the relative attractiveness of alternative banks for a given firm. All specifications include bank fixed effects. Following the discrete-choice and bank-firm matching literature, we interpret coefficients in terms of relative odds of selection within firm choice sets, rather than absolute probability changes.

Column (1) relates match formation to geographic distance, measured at the firm–bank level as the distance between the firm's location and the nearest branch of each bank. Distance enters with a negative and highly significant coefficient, indicating that firms are substantially less likely to initiate new lending relationships with more distant banks. A one-unit increase in distance (10 kilometers) reduces the log-odds of a new lending relationship by $-0.02.$, which corresponds to a 0.5% lower probability of observing a match, roughly one–tenth of the average match probability of 5.5%. Column (2) examines the role of industry market share, which varies at the bank–industry level and captures the importance of the bank in total lending to the firm's sector. The coefficient is positive and highly significant, indicating that banks with a stronger presence in a firm's industry are substantially more likely to attract new borrowers. The implied odds ratio, $\exp(2.55) \approx 12.8$, indicates that industry market share multiplies the odds of forming a new lending relationship by more than twelve times, holding the rest of the choice set fixed.

Column (3) focuses on bank industry specialization, following Blickle et al. (2023) and Iyer et al. (2022). More specialized banks are significantly more likely to be chosen, consistent with sectoral expertise conferring an advantage in screening and lending. Column (4) shows that better-capitalized banks are significantly more likely to attract new borrowers. This finding is consistent with Schwert (2018), who shows that bank-dependent borrowers, in particular, tend to prefer well-capitalized lenders. Finally, Column (5) includes all bank and match characteristics simultaneously. The coefficients retain their sign, statistical and economic significance, indicating that distance, industry market share, specialization, and capitalization each capture distinct and economically relevant dimensions of firm–bank matching. Together, the results show that firms' lender choices reflect a combination of informational frictions, sectoral fit, and bank balance-sheet strength, consistent with the mechanisms emphasized in the literature.

We will use this specification to estimate the firms' preferred bank measure that we will use to test its predictive power on credit growth (Table 6), and its role in affecting estimates of the effects of bank shock on credit supply (Section 5.2).

The time-series behavior of firms' bank preferences is shown in Figure 1. The average remains rather stable over time, as it increases mildly from slightly above 0.06 to a peak of about 0.067 in 2010. This is consistent with our measure capturing structural preferences of firms across lenders, as this is not really affected by idiosyncratic shocks in certain years, nor by the business cycle.

Finally, Appendix Figure OA1 presents the distribution of firms' bank preference by year.

While the bulk of the distribution remains stable over time, the right tail becomes fatter during the crisis years, indicating a growing concentration of credit among strongly matched bank–firm pairs. The broad stability of the distribution indicates that the estimated firms' bank preferences capture structural characteristics of bank-firm relationships rather than just time-varying shocks.

To distinguish persistent matching preferences from crisis-driven reallocation, Table 3 re-estimates the discrete-choice model using only pre-crisis data (2007–2008), a period characterized by normal credit market conditions.[8] The estimates closely mirror those in the full sample: distance, industry market share, specialization, and capitalization remain strong predictors of lender choice, with similar magnitudes. This stability indicates that the determinants of firm–bank matching primarily reflect structural preferences rather than crisis-induced distortions.

Heterogeneity in firms' bank preferences. As a next step, we examine whether firm characteristics influence firms' bank preferences. To do so, we re-estimate the conditional logit specification in equation (8) and interact all match characteristics with indicators for firm risk and size. Because firm-level variables are absorbed by the firm–year fixed effects inherent in the conditional logit framework, heterogeneity is identified exclusively through these interactions. We use the indicators *High PD* and *Big firm*, which indicate a predicted probability of default or a firm size that is above the median, respectively, as measures of firm risk and firm size.

Table 4 reports the results. Columns (1)–(4) focus on interactions with our measure of

[8] We treat the 2007–2008 period as a benchmark characterized by relatively weak financial constraints, in which firms and banks form lending relationships without binding balance-sheet stress. This assumption is reasonable in the Portuguese context. Prior to the global financial crisis, Portugal experienced moderate and stable economic growth (average real GDP growth of 1.4% per year between 2004 and 2008), with no evidence of housing or credit bubbles. To corroborate this view, we construct indicators of credit and asset price booms following Greenwood, Hanson, Shleifer and Sørensen (2022). As shown in Appendix Figures OA2 and OA3, neither non-financial business credit nor household credit exhibits signs of financial overheating in the pre-crisis years. By contrast, the crisis period is marked by a sharp contraction in economic activity and a pronounced tightening of credit conditions, with real GDP falling by 1.6% per year on average between 2009 and 2013 and unemployment rising to 16.1% in 2013.

firm risk, *High PD*. In Columns (1) to (3), we find that the effects of distance, industry market share, and industry specialization are economically and statistically stronger for riskier firms. This pattern is consistent with the notion that lending to high-risk firms relies more heavily on soft information, which is more readily available when the bank is geographically closer (Degryse and Ongena, 2005), more specialized in the firm's industry (Iyer et al., 2022), or holds a larger market share in that industry (Giannetti and Saidi, 2018). By contrast, the effect of bank capitalization is significantly attenuated for high-risk firms (Column (4)). Within the framework of our model, where firms select banks, this result suggests that firms with higher default risk place less weight on banks' long-term balance-sheet strength. These firms may anticipate a shorter survival horizon or expect that, in downturns, even well-capitalized banks will curtail credit. Consistent with this interpretation, less-capitalized banks may have stronger incentives to continue lending to risky firms through loan evergreening to avoid further capital erosion (Caballero, Hoshi and Kashyap, 2008).

Columns (5)–(8) examine heterogeneity by firm size (*Big firm*), a key dimension in financial intermediation (Berger and Udell, 2002) and in macroeconomic dynamics (Crouzet and Mehrotra, 2020; Kalemli-Özcan, Sørensen, Villegas-Sanchez, Volosovych and Yeşiltaş, 2024). Distance and bank capitalization matter less for larger firms when forming new lending relationships. This pattern is consistent with larger firms being less reliant on soft information and better able to absorb the fixed costs associated with searching for and accessing distant lenders. The weaker sensitivity to bank capitalization further suggests that larger firms are less bank dependent and better positioned to diversify their external financing sources, making them less sensitive to a bank's ability to sustain lending during adverse conditions. By contrast, banks' industry market share and industry specialization matter more for larger firms, indicating that firms with greater scale place relatively more weight on sectoral expertise and market presence when selecting lenders. This pattern likely reflects larger firms' greater ability to substitute across financing sources and to actively select banks with specialized industry knowledge.

5.2 Match preference and access to credit

We now turn to examining whether the estimated match preference index matters in determining credit availability and, crucially, if it modifies estimates of how bank balance sheet shocks affect credit supply.

5.2.1 Firms' bank preference and credit outcomes

As a preliminary step, we assess whether our measure of firms' bank preference correlates with credit outcomes. The purpose of this exercise is not to estimate causal effects, but to validate that the index captures persistent features of bank-firm relationships that are relevant for credit allocation.

Table 5 reports regressions relating credit outcomes to the firms' bank preferences measure.

Panel A examines the extensive margin of credit relationships, where the dependent variable is an indicator for whether an existing bank-firm relationship continues in the next year. Columns (1)-(3) show that relationships characterized by higher firms' bank preferences are significantly more likely to persist over time. The estimates remain stable as we saturate the specification with fixed effects (bank, firm, year, bank-year, and firm-year fixed effects), ensuring that the results are not driven by time-varying bank balance-sheet conditions or firm-level credit demand. A one standard deviation increase in firms' bank preference is associated with a 3 to 4% (depending on the specification) higher probability that a bank-firm relationship continues. Columns (4)-(6) focus on an out-of-sample validation exercise. Using coefficients estimated from the pre-crisis lender-choice model (2007-2008), we compute the firms' bank preference index for the post-crisis period (2009-2012) and relate it to the extensive margin. The positive and significant coefficients indicate that relationships formed on the basis of strong pre-crisis firms' banks preference were more likely to survive after the crisis, providing support to the ability of our model to identify relationships that firm prefer, also out of sample.

Panel B shows the same exercise on the intensive margin of lending, measured by the logarithm of outstanding credit. Across specifications, firms receive significantly more credit from banks they prefer to be matched with. The estimates are robust to alternative fixed-effect structures. a one standard deviation increase in fimrs' preference for a bank is associated with 14.5 to 24.1% higher credit, a sizeable effect. Finally, columns (4)-(6) repeat the out-of-sample test and results are analogous to those for the extensive margin of lending.

To further assess how firms' bank preferences relate to bank lending over the business cycle, Figure 2 plots year-specific estimates of the marginal effect of firms' bank preference on outstanding credit. The figure is based on regressions that interact the firm–bank preference index with year indicators, while absorbing bank–year and firm-year fixed effects. The estimates indicate that firm–bank preference has a positive and statistically significant association with credit outcomes throughout the sample period, but that its marginal importance declines during the crisis. While better-matched firms consistently receive more credit from a given bank in a given year, the sensitivity of credit allocation to firms' bank preference is attenuated in crisis times. This pattern is consistent with the notion that relationship-specific drivers of bank lending play a smaller role when banks face binding balance-sheet constraints (see, e.g., Sette and Gobbi, 2015).

5.2.2 Tracing the impact of bank shocks under bank-specific credit demand

As a next step, we include our measure of firms' bank preference in a regression estimating the effects of bank effects to balance sheet shocks on their credit supply. Our goal is to assess whether controlling for bank-specific credit demand has a material effect on the estimates of the effects of banks' exposure to shocks, as described in Subsection 2.2 (see Equation (5')).

We first replicate the results of Iyer et al. (2014), who use Portuguese credit registry data to show that banks more reliant on interbank borrowing before the 2007-2008 crisis reduced their credit supply more sharply during the crisis. Results, shown in Column (1) and (2) of Table 6 confirm the findings of Iyer et al. (2014): banks with higher interbank borrowing ratio contract credit supply more than banks with lower interbank ratios. This result becomes even stronger when controlling for bank characteristics, namely, capital, liquidity, size, non-performing loan ratio, and profitability. We note that we do not exactly replicate the result of Iyer et al. (2014), probably due changes in the methodology of the data construction in the CRC over time, even though our results are very similar.

Next, in Column (3) we include our estimated firms' bank preference measure, $\hat{m}_{ij}$ (see Equation (9)). We find that the coefficient on firms' bank preference is positive and highly significant, indicating that firms shift to obtaining more credit from their preferred banks over the course of the crisis. The coefficient is also economically meaningful: a one–standard–deviation increase in bank preference is associated with an increase in credit growth of approximately 24 percent.[9]

Importantly, while the point estimate of the coefficient on the interbank borrowing ratio remains negative and strongly significant, it drops in magnitude by around 16% from -3.289 to -2.751. We run a test of equality of these coefficients by using an approach akin to SUR,[10]and results indicate that the two coefficients are statistically different at the 8% level. This shows that the interbank borrowing, Iyer et al.'s 2014 measure of banks' exposure to a balance sheet shock, is correlated with our measure of firms' bank-specific demand for credit. Hence, controlling for firms' bank-specific demand for credit allows obtaining more accurate measures of the impact of bank balance sheet shock on credit supply. We note that whether a given measure of a bank balance sheet shock is correlated with firms' bank-specific demand for credit will depend on the empirical setting. For instance, in Paravisini et al.

[9]To gauge economic magnitude, we scale the estimated coefficient by the standard deviation of the bank-preference index and convert from log points. A one–standard–deviation increase in bank preference (0.05) implies $\exp(4.324 \times 0.05) - 1 \approx 24\%$ higher credit.

[10]We stack the data with a copy of itself and include a dummy to indicate the copied dataset. We then estimate a version of the model where all explanatory variables that involve our measure of firms' bank preference are multiplied by that dummy. This allows us to check whether the coefficient on interbank exposure are statistically significantly different when excluding or including our measure of firms' bank preference.

(2023), controlling for their measure of bank specialization which can be interpreted as a (less general) measure of firms' bank-specific demand for credit does not affect the coefficient of interest because bank specialization is mostly uncorrelated with the shock variable in their data. In general, though, it is difficult to predict ex-ante whether a shock to banks' balance sheet is correlated with firms' preference for that bank. Hence, it is advisable to control for a measure of firms' bank preferences, using for example the approach we propose in this paper, to make sure that estimates of the effects of shocks to banks' balance sheet on credit supply are not affected by the bias arising from firms having a preference for certain banks.

Finally, as a robustness test, in Column (4), we introduce an interaction term between the interbank borrowing ratio and our measure of firms' bank preference. This may be an interesting extension for at least two reasons. First, it can arise in a model with non-linear demand and supply functions, e.g., in a direct extension of the model of Paravisini et al. (2023), see Appendix B. Second, it allows for nonlinearities in the effect of both variables, which could be relevant in practice. The results indicate that the estimates of interbank exposure and firms' bank preference are virtually unchanged and the interaction term is positive but not statistically significant at conventional levels.

Overall, these findings indicate that firms' bank-specific demand for credit is a key determinant of credit dynamics and, importantly, that its inclusion may substantially affect estimates of the effect of bank balance sheet shocks on credit supply.[11]

6 Conclusion

Firms may prefer to borrow from particular banks for reasons beyond loan pricing, including a bank's industry expertise, geographic proximity, or financial strength. Such bank-specific preferences can affect empirical estimates of how bank shocks influence the supply of credit.

[11] We are currently implementing additional tests to measure the relevance of the bias coming from the correlation between firms' preferences and banks' exposure to the shock. One of these tests involve running the regressions shown in Table 6 over sample splitted according to whether the correlation between our preferred bank measure and bank exposure to interbank funding is particularly high.

The empirical literature typically assumes that firm (or firm-time) fixed effects absorb credit demand and that firms' preferences across banks are orthogonal to banks' exposure to shocks.

We develop a conceptual framework to examine the consequences of relaxing this assumption. We estimate a structural model of how firms choose banks, which yields a predicted probability of a given firm choosing a given bank. We use a scaled version of this probability as a measure of firms' bank preference. Our model identifies four key bank characteristics that systematically affect firms' preferences: geographic distance, the bank's market share in the firm's industry, the bank's specialization in the firm's industry, and bank capital.

Importantly, our measure of firms' bank preference predicts future credit growth and affects estimates of the effect of bank shocks on credit supply. This is consistent with firms having bank–specific credit demand driven by bank characteristics that correlate with measures of banks' exposure to shocks.

Our findings contribute to a better understanding of the drivers of firms' bank-specific demand for credit and provide a simple, general approach for taking this bank-specific demand into account when estimating the impact of bank shocks on credit supply.

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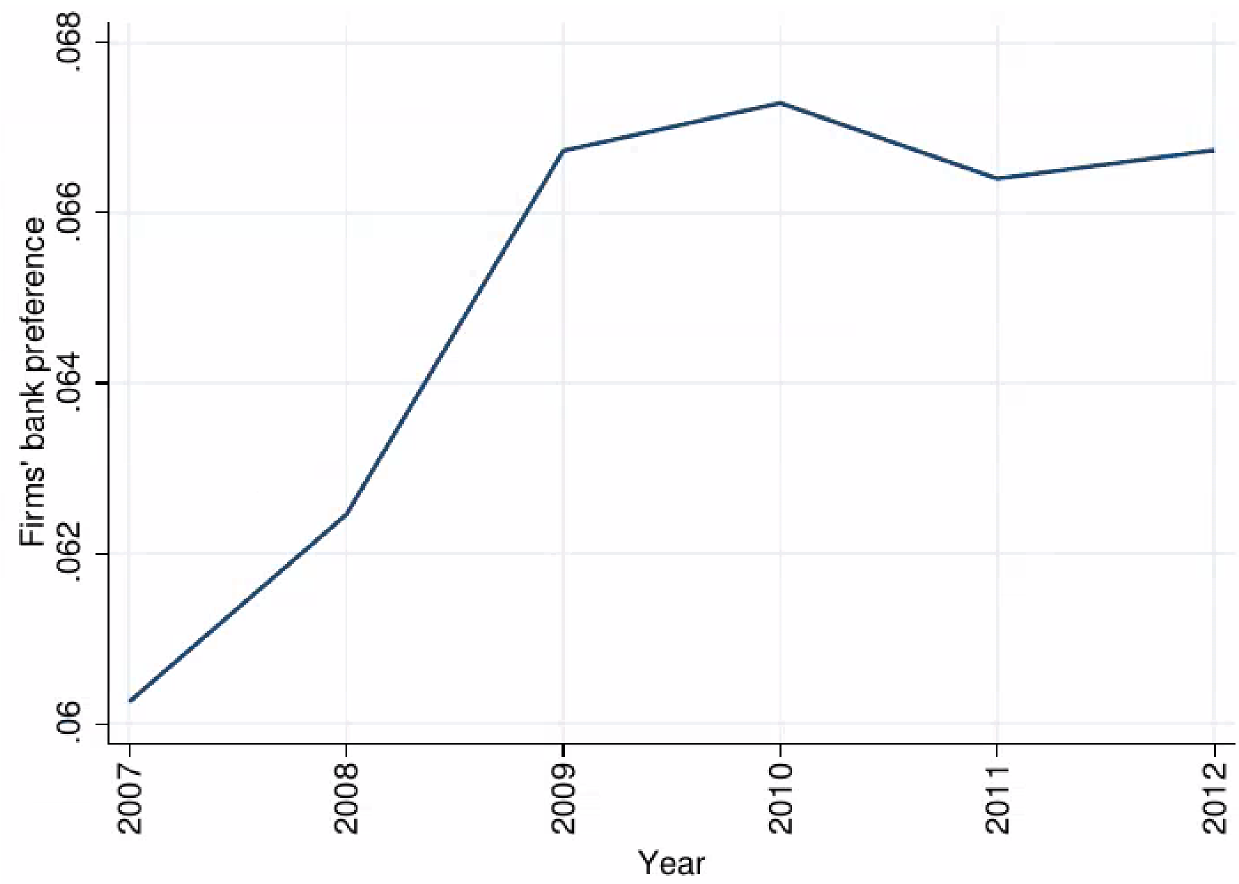
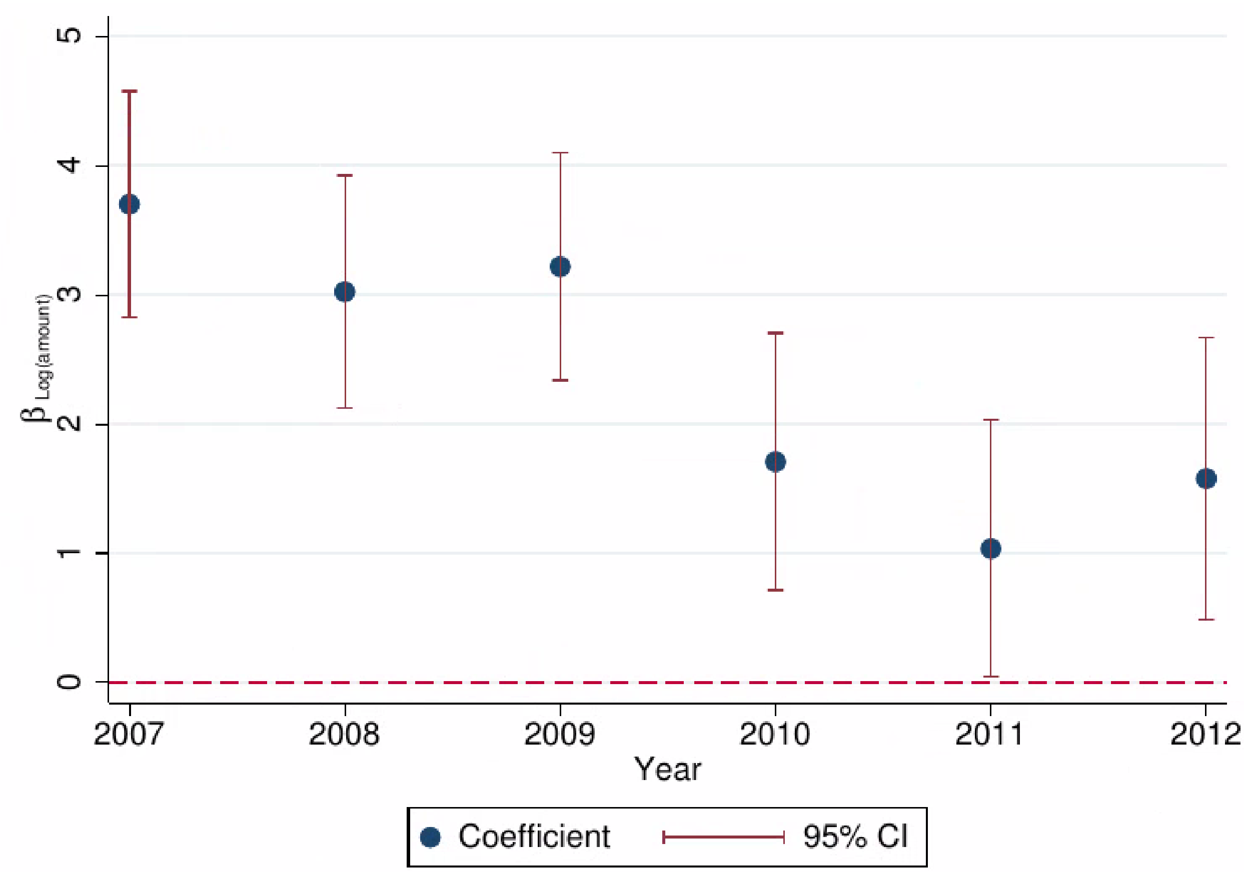
Figures

Figure 1: Evolution of the firms' bank preference



Notes: This figure plots the annual average of firms' bank preference, measured as the predicted match probability $\hat{m}_{ij}$ from the conditional logit model of firm-bank matching. For each year, we compute the mean predicted probability across all firm-bank pairs in the estimation sample.

Figure 2: Evolution of the effect of firms' bank preference on credit allocation



Notes: This figure plots year-specific coefficient estimates and 95% confidence intervals for firm–bank preference from regressions that interact the firms' bank preference index with year indicators. The dependent variable is the logarithm of outstanding credit at the bank-firm-year level. Firms' bank preference is measured as the predicted choice probability from the discrete-choice model of bank selection. All specifications include bank-year and firm-year fixed effects, and standard errors are clustered at the bank-firm level.

Tables

Table 1: Summary statistics

	Observations	Mean	SD	Min	P50	Max
Panel A: Variables used for estimating firms' bank preferences						
New bank-firm relationship (0/1)	13,140,027	0.055	0.223	0.000	0.000	1.000
Distance (per 10Km)	13,140,027	3.292	12.489	0.000	0.000	190.594
Industry market share	13,140,027	0.045	0.046	0.000	0.039	0.580
Industry specialization	13,140,027	0.104	0.144	0.000	0.049	0.884
Ln(capital)	13,140,027	8.489	2.153	3.563	8.476	11.874
High PD (0/1)	13,140,027	0.509	0.500	0.000	1.000	1.000
Distance × High PD	13,140,027	1.724	9.272	0.000	0.000	190.594
Industry market share × High PD	13,140,027	0.023	0.037	0.000	0.000	0.580
Industry specialization × High PD	13,140,027	0.055	0.116	0.000	0.000	0.884
Ln(capital) × High PD	13,140,027	4.327	4.514	0.000	3.593	11.874
Panel B: sample used for the replication of Iyer et al. 2014						
$\Delta Credit$	72,864	0.845	0.111	-11.147	0.820	15.424
Interbank borrowing	72,864	0.241	0.111	0.000	0.236	0.387
Firms' preferred bank	72,864	0.103	0.050	0.000	0.108	0.463
Capital ratio	72,864	0.067	0.044	0.004	0.050	0.159
Bank liquid assets	72,864	0.315	0.093	0.059	0.293	0.665
Bank size	72,864	12.978	0.950	9.325	13.387	13.763

Notes: Panel A reports descriptive statistics for the variables used in estimating the discrete-choice model of firm-bank matching over 2007-2012. The unit of observation is the firm–bank–year pair in the balanced choice set used for the conditional logit estimation. Panel B reports summary statistics for variables entering the Khwaja and Mian (2008) credit-supply specification. Following Iyer et al. (2014), the regression is estimated on a cross-section of firm–bank pairs, where the change in log credit is computed between 2007:Q2 and 2009:Q2 while the interbank borrowing ratio and all bank-level controls (capital ratio, liquid assets, and size) are measured as of 2007:Q2. All variables are defined in Appendix A.

Table 2: Bank-firm matching

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	New bank-firm relationship				
Distance (per 10Km)	-0.020***				-0.020***
	[-20.409]				[-20.337]
Industry market share		2.553***			1.609***
		[53.666]			[29.979]
Industry specialization			1.715***		1.258***
			[42.404]		[28.461]
Ln(capital)				0.115***	0.110***
				[30.362]	[28.908]
Observations	13,140,027	13,140,027	13,140,027	13,140,027	13,140,027
R-squared	0.157	0.157	0.157	0.156	0.158
Bank FE	Y	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm	Firm

The table reports coefficients and z-statistics (in brackets). We estimate all specifications using a conditional fixed-effects logit model, where the dependent variable is a dummy that equals one if the bank (b) - firm (f) matching is identified in the credit registry within a four-digit post-code (l) at time t, and zero if they do not match. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,** and *** marks denote the statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Table 3: Bank-firm matching in good times

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	New bank-firm relationship				
Distance (per 10Km)	-0.009***				-0.009***
	[-11.694]				[-11.731]
Industry market share		2.351***			-0.142
		[37.166]			[-1.412]
Industry specialization			2.404***		2.449***
			[54.724]		[47.072]
Ln(capital)				0.312***	0.336***
				[17.769]	[19.076]
Observations	5,103,633	5,103,633	5,103,633	5,103,633	5,103,633
R-squared	0.167	0.168	0.170	0.167	0.170
Bank FE	Y	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm	Firm

The table reports coefficients and z-statistics (in brackets). We estimate all specifications using a conditional fixed-effects logit model, where the dependent variable is a dummy that equals one if the bank (b) - firm (f) matching is identified in the credit registry within a four-digit post-code (l) at time t, and zero if they do not match. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,** and *** marks denote the statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Table 4: Bank-firm matching: The role of firm characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	New bank-firm relationship							
Distance (per 10Km)	-0.017***	-0.020***	-0.020***	-0.020***	-0.053***	-0.020***	-0.020***	-0.021***
	[-16.207]	[-20.347]	[-20.350]	[-20.311]	[-8.305]	[-20.377]	[-20.348]	[-20.602]
Industry market share	1.599***	1.196***	1.675***	1.601***	1.611***	-0.348***	1.719***	1.591***
	[29.798]	[18.365]	[31.180]	[29.844]	[29.864]	[-3.482]	[32.183]	[29.523]
Industry specialization	1.260***	1.205***	0.519***	1.242***	1.258***	1.292***	-0.019	1.172***
	[28.518]	[27.284]	[9.103]	[28.115]	[28.434]	[28.981]	[-0.325]	[26.391]
Ln(capital)	0.110***	0.109***	0.110***	0.138***	0.110***	0.111***	0.111***	0.190***
	[28.921]	[28.592]	[28.806]	[35.072]	[28.782]	[29.013]	[28.989]	[45.362]
Distance× High PD	-0.008***							
	[-4.296]							
Ind. market share× High PD		1.167***						
		[14.493]						
Industry spec.× High PD			1.265***					
			[20.482]					
Ln(Capital)× High PD				-0.059***				
				[-27.625]				
Distance× Big firm					0.040***			
					[6.316]			
Ind. market share× Big firm						3.434***		
						[32.926]		
Industry spec.× Big firm							2.183***	
							[29.718]	
Ln(Capital)× Big firm								-0.141***
								[-55.813]
Observations	13,140,027	13,140,027	13,140,027	13,140,027	13,140,027	13,140,027	13,140,027	13,140,027
R-squared	0.158	0.158	0.158	0.159	0.158	0.159	0.159	0.160
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Notes: The table reports coefficients and z-statistics (in brackets). We estimate all specifications using a conditional fixed-effects logit model, where the dependent variable is a dummy that equals one if the bank (b) - firm (f) matching is identified in the credit registry within a four-digit post-code (l) at time t, and zero if they do not match. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,** and *** marks denote the statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Table 5: Firm's bank preference and credit outcomes

	Panel A: Extensive margin					
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Relationship continuation (0/1)					
Bank preference	0.676***	0.838***	0.580***			
	[8.233]	[8.825]	[5.011]			
Bank preference * Crisis period						
Bank preference (post crisis)				0.431***	0.569***	0.409***
				[7.078]	[5.531]	[3.315]
Observations	1,486,906	1,486,906	907,615	957,830	957,830	592,607
R-squared	0.526	0.529	0.33	0.574	0.578	0.334
	Panel B: Intensive margin					
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Ln(credit)					
Bank preference	4.324***	2.710***	2.912***			
	[12.975]	[7.035]	[6.446]			
Bank preference * Crisis period						
Bank preference (post crisis)				0.420*	1.238***	1.714***
				[1.801]	[3.082]	[3.662]
Observations	1,446,742	1,446,742	871,848	948,208	948,208	579,616
R-squared	0.662	0.665	0.646	0.717	0.718	0.649
Year FE	Y			Y		
Bank FE	Y			Y		
Firm FE	Y	Y		Y	Y	
Bank*Year FE		Y	Y		Y	Y
Firm*Year FE			Y			Y
Cluster SE	Bank-Firm	Bank-Firm	Bank-Firm	Bank-Firm	Bank-Firm	Bank-Firm

Notes: This table examines the relationship between firm–bank match quality and credit outcomes along the extensive and intensive margins. Panel A reports linear probability models where the dependent variable is an indicator equal to one if the firm-bank relationship continues in the next year, and zero otherwise. Panel B reports regressions where the dependent variable is the logarithm of outstanding credit at the bank-firm-year level. Credit outcomes are constructed from monthly observations in the Central Credit Register and aggregated to the annual level following Iyer et al. (2014). The key explanatory variable (*bank preference*) is a firm-bank match-quality index based on predicted choice probabilities from a conditional logit model of firm-bank matching. Columns (1)-(3) use an index estimated over the full sample period (2007-2012). Columns (4)-(6) use an out-of-sample index constructed by applying coefficients from a pre-crisis matching model (2007–2008) to post-crisis observations (2009-2012). All specifications include fixed effects as indicated in the table. Standard errors are clustered at the bank-firm level. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Table 6: Bank preference and credit supply

	(1)	(2)	(3)	(4)
Dependent variable:	$\Delta \ln Credit_{ij,2009:Q2-2007:Q2}$			
Interbank borrowing	-1.406***	-3.289***	-2.751***	-2.888***
	[-5.780]	[-5.358]	[-4.459]	[-14.571]
Capital ratio		-3.202**	-4.514***	-4.197***
		[-2.450]	[-3.720]	[-8.701]
Bank liquid assets		0.412	0.341	0.397***
		[0.811]	[0.738]	[4.105]
Bank size		-0.102*	-0.224***	-0.229***
		[-1.950]	[-3.533]	[-14.090]
Bank preference			4.342***	5.049***
			[3.290]	(6.810)
Bank preference × interbank borrowing				2.498
				[1.130]
Observations	72,864	72,864	72,864	62,771
R-squared	0.466	0.469	0.470	0.461
Firm FE	Y	Y	Y	Y
Cluster	Bank-Firm	Bank-Firm	Bank-Firm	Bank-Firm

The table reports coefficients and t-statistics (in brackets). We estimate all specifications using OLS, where the dependent variable the bank-firm logarithmic difference between the post-crisis (2009:Q2) and pre-crisis (2007:Q2) values of credit granted to firm j by bank i. We include fixed effects as noted in the lower part of the table to control for different levels of unobserved heterogeneity. The *,** and *** marks denote the statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Appendix

"Tracing the Impact of Bank Shocks under Bank-Specific Credit Demand"

This appendix provides supplementary information and results to support the main paper.

The content is organized as follows:

Appendix A provides definition of the main variables used in the paper.

Appendix B presents an alternative theoretical model.

Appendix C includes additional figures that complement the main results.

A Definitions of the variables used

- $New\ bank - firm\ relationship$: is a dummy that equals one if the bank (b) - firm (f) matching is identified in the credit registry at time t, and zero if they do not match.
- $Distance$: is the distance between a firm and the nearest branch of the bank for each bank-firm pair per 10Km.
- $Industry\ market\ share$: is the total credit granted in 2007Q2 by bank i in sector s/ total credit granted in 2007Q2 in sector s.
- $Industry\ specialization$: is the total credit granted in 2007Q2 by bank i in sector s/ total credit granted in 2007Q2 in sector s.
- $Ln(capital)$: is the logarithm of the bank's ratio of book equity to total assets.
- PD: is measured as the probability that any given firm will have a significant default episode within a one-year horizon using information from the central credit register and comprehensive balance sheet data.
- $High\ PD$: is a dummy that equals one if the firm's probability of default, is above the median probability of default of all firms, and zero otherwise.
- $Big\ firm$: is a dummy that equals one if the firm's real total assets are above the median size of all firms, and zero otherwise.
- $\Delta \ln Credit_{ij,2009:Q2-2007:Q2}$: is the bank-firm logarithmic difference between the post-crisis (2009:Q2) and pre-crisis (2007:Q2) values of credit granted to firm j by bank i.
- $Interbank\ borrowing$: is the ratio of total interbank borrowing in 2007:Q2 for a bank.
- $Capital\ ratio$: is the total bank capital as a fraction of total assets.
- $Bank\ liquid\ assets$: is the ratio of short-term to total assets of the bank.
- $Bank\ size$: is the log of total assets of the bank. Liquid assets is the ratio of short-term to total assets of the bank.

B Alternative model

There are many ways to include match preference akin to a notion of transport costs in spatial models of product differentiation into a Khwaja and Mian (2008) style empirical model.

Here, we discuss an additional approach that suggests that one should try interacting demand and supply shifters with match preference. Also, we proceed with the model of Paravisini et al. (2023) as a starting point to highlight the similarities to our approach.

In the model of Paravisini et al. (2023), firms are defined as a collection of activites, and banks specialize in supporting specific activities. We simplify by assuming that each firm only engages in a single activity. Firms finance all production via borrowing, the funds they borrow are the only input into production, and the interest rate they pay on the borrowed funds are the only cost of production. The specialization of bank b in firm f's activity is described by a parameter m_{fb}, which enters the firm f's production function: When borrowing funds L_{fb} from bank b, the firm can produce output

$$q_f = m_{fb} L_{fb}. \tag{11}$$

The more specialized bank b is in the activity of the firm, the higher m_{fb} and the lower the funding required to produce a given unit of output.

If the firm borrows a quantity L_{fb} at interest rate R_b, the cost to the firm is $R_b L_{fb}$. This total cost can also be expressed as a function of q_f by using the production function (11):

$$R_b L_{fb} \equiv \frac{R_b}{m_{fb}} q_f. \tag{12}$$

From this expression of the total cost, we can see that $\frac{R_b}{m_{fb}}$ is the marginal cost per unit of output if firm f chooses bank b. Firm f will therefore choose the bank that minimizes this marginal cost:

$$b = \arg\min_{b'} \frac{R_{b'}}{m_{fb'}} \tag{13}$$

This describes a discrete choice model, which, under some assumptions, can be estimated on data on firms' actual choices of bank(s), as we discuss in the next subsection.

In essence, the approach of Paravisini et al. (2023) describes firms that treat credit from different banks as imperfect substitutes. The model is again a type of spatial model of product differentiation (Hotelling, 1929), with $\frac{R_b}{m_{fb}}$ being the "price" (R_b) that firms pay, but adjusted for a form of transport costs – in the space of firms' activities. In the approach presented in the main text, we subtracted match quality, here we divide by match quality. In both cases, the firm perceives a lower cost of credit whenever the index m_{fb} is higher.

Banks that specialize in the activity of a firm are, in that sense, closer to that firm, have a lending advantage vis-a-vis the firm, or are simply a better match for the firm. Below, we will therefore refer to m_{fb} as match preference, or "match quality."

We now introduce demand and supply curves to examine how match preference affects equilibrium quantities. Suppose that the firm faces a linear demand curve in its product market described by $p(q_{ft}) = A_{ft} - \frac{1}{2}aq_f$, where $a > 0$ and $A_{ft} > 0$ describes the time-varying demand for the output of firm f. Suppose furthermore that the interest rate R_{bt} that the bank has to pay can vary over time. Given a choice of bank b, the firm will choose output q_{ft} to maximize profits $\pi(q_{ft}; b) = p(q_{ft})q_{ft} - \frac{R_{bt}}{m_{fb}}q_{ft}$.

A first-order condition pins down the optimal choice of output q_{ft}. Using the production function (11), we can rearrange this first-order condition to obtain firm f's inverse credit demand function when borrowing from bank b:

$$R_{bt} = m_{fb}A_{ft} - am_{fb}^2 L_{fbt}. \tag{14}$$

This linear demand function is the analogue of the linear demand function in Khwaja and Mian (2008). We can equate this demand with the standard supply function (Equation (2)) to obtain the equilibrium quantity of credit that firm f obtains from bank b, which is now:

$$L_{fbt} = g(m_{fb})A_{ft} + h(m_{fb})D_{bt}, \tag{15}$$

where $g(m_{fb}) = \frac{m_{fb}}{\left(am_{fb}^2+c\right)}$ and $h(m_{fb}) = \frac{c}{\left(am_{fb}^2+c\right)}$ are functions of match quality m_{fb}. Taking time differences, we obtain

$$\Delta L_{fb} = g(m_{fb})\Delta A_f + h(m_{fb})\Delta D_b \tag{16}$$

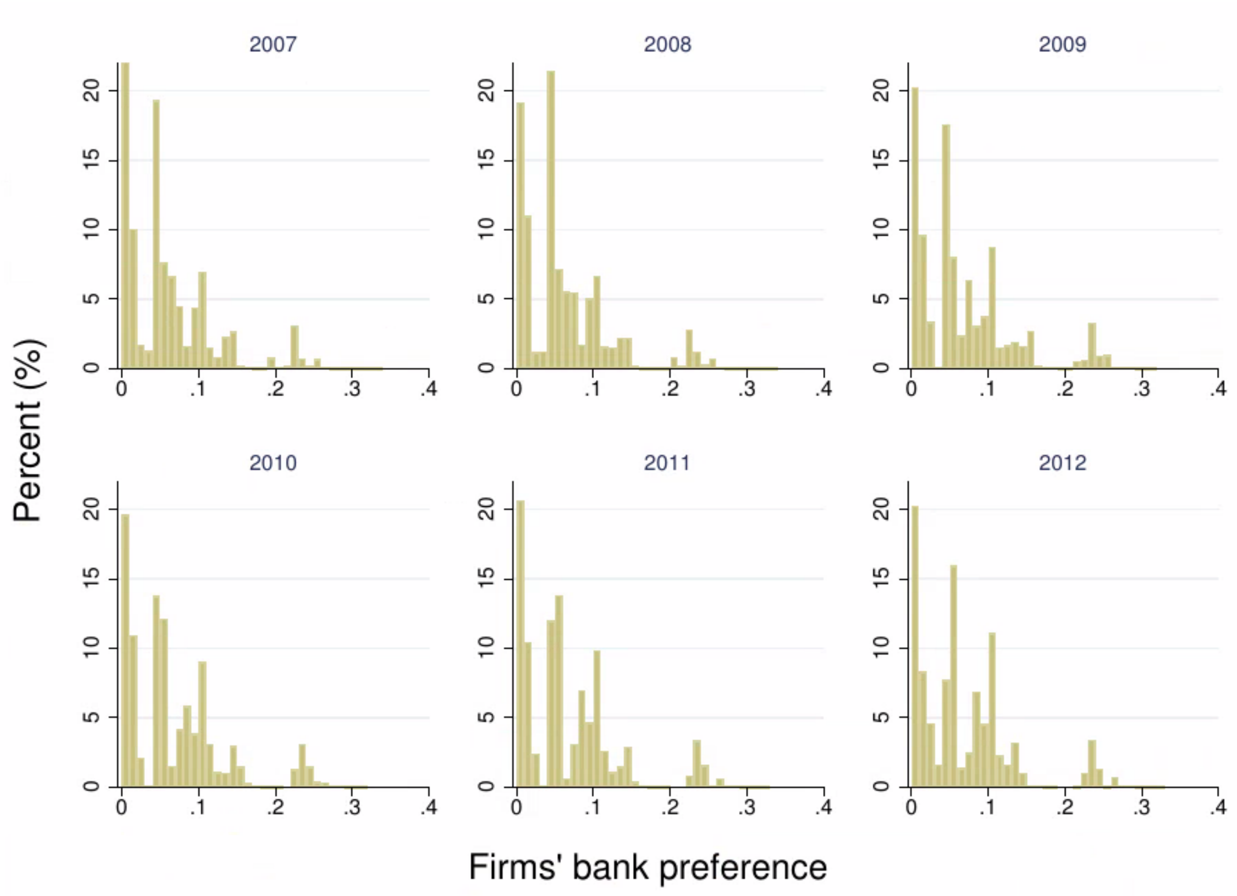
Since Equation (16) suggests that the effect of the demand shifter ΔA_f and the supply shifter ΔD_b can depend on m_{fb}, we obtain the following, linearized model:

$$\Delta L_{fb} = \alpha_f + \gamma_1 \hat{m}_{fb} + \gamma_2 \alpha_f \hat{m}_{fb} + \theta_1 \Delta D_b + \theta_2 \hat{m}_{fb} \Delta D_b + \varepsilon_{fb}. \tag{17}$$

We have assumed linear demand and supply functions throughout, but in this appendix, like Paravisini et al. (2023), that match quality enters multiplicatively rather than additively. In general, depending on the functional forms for demand and supply and how match preference enters the cost of credit, different expressions for g and h can arise – and these can be independent of m like in the model presented in the main text. If one wants to maintain an agnostic approach, however, it is probably prudent to allow for interactions and the possibility that g and h may depend on m.

C Additional figures

Figure OA1: Distribution of firms' bank preference by year



Notes: This figure shows yearly histograms of firms' bank preference, measured as the fitted choice probability $\hat{m}_{ij} = \hat{P}_{ij}$ from the conditional logit model of firm-bank matching. Each panel reports the distribution of $\hat{m}_{ij}$ across firm-bank observations in the corresponding year.

Figure OA2: Business credit and asset prices growth

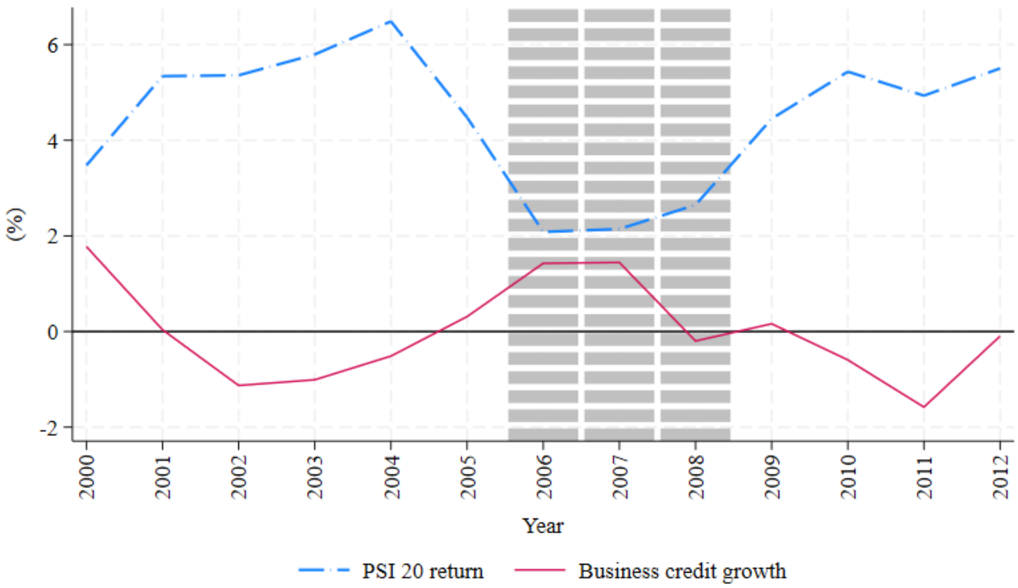


Figure OA3: Household credit and household prices growth