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THE QUANTITY OF CORPORATE CREDIT RATIONING WITH MATCHED BANK-FIRM DATA

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Abstract

This paper provides measures of credit rationing in the market of term loans to Italian non-financial firms. We identify non-price allocations of credit by exploiting a unique bank-firm dataset of more than 5 million observations, which matches the quantity and the cost of credit available from the Credit Register with a number of bank- and firm-specific characteristics from different sources of microdata. We propose an approach that endogenously identifies all the bank-firm transactions subject to credit rationing, thus circumventing aggregation biases stemming from the use of less detailed information. The estimates suggest that in the Italian case, rationing mostly reflected an increase in non-performing loans in banks' portfolios and a decline in available collateral. Borrowers' characteristics played a minor role, although banks did switch their supply of funds in favour of firms with greater creditworthiness after the outbreak of the sovereign debt crisis.

JEL Classification: E44, G01, G21.
Keywords: credit rationing, bank-firm relationships, ML estimation.

Contents

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1 Introduction[1]

Is there a cut in lending to the corporate sector? And if so, how relevant are banks' balance sheet conditions? What about the role of borrowers' creditworthiness? These questions are not only key for macroeconomics in general but also for policymakers and regulators that are still managing the legacy of the financial crisis.

Quantifying the relevance of restrictions to credit availability is a well-known difficult task. The identification problem is not only that the supply of credit needs to be disentangled from its demand. The key challenge is to understand whether a supply restriction takes place through an increase in the cost of credit, which in turn transmits to loan quantities via the elasticity of loan demand to lending rates, or through non-price allocation of credit, that is, a condition of excess demand over supply.

Policymakers usually look at qualitative information provided by surveys among banks or firms, which include questions on the terms and conditions of access to credit. In the case of Italy, both the Bank Lending Survey and Istat survey among manufacturing firms provide evidence of quantitative restrictions on business loans occurred during the crisis (see Figure 1). Survey-based methods are timely and ready-to-use but may be biased due to self-reporting.[2] It is therefore useful to cross-check survey-based indicators with measures of credit rationing computed from "hard" information on balance sheets and compulsory reports. However, related evidence based on "hard" data is scant. A major complication is that several economic theories and concepts are consistent with the notion of quantitative credit restrictions. Broadly speaking, credit rationing occurs when, at a given level of the interest rate, the demand for loans exceeds the supply and lenders do not provide additional credit even if the borrowers are willing to pay higher

[1]The views expressed do not necessarily reflect those of the Bank of Italy. This work was started during Lorenzo Burlon's research fellowship at the Bank of Italy. We would like to thank Piergiorgio Alessandri, Ginette Eramo, Alberto Locarno, Francesco Manaresi, Stefano Neri, Giacomo Rodano, Alfonso Rosolia, Alessandro Secchi, Paolo Sestito, Enrico Sette, Luigi Federico Signorini, Stefano Siviero, and participants to seminars at the Banco de Portugal, to the II IAAE conference in Thessaloniki, to the 3rd MBF Workshop in Pavia, to the 1st ECBN conference in Ljubljana, and to the Joint BOE-ECB-CEPR-CFM conference in London. All remaining errors are ours.

[2]One strand of the empirical literature focused on the effects of credit supply restrictions on the intensive margin using matched bank-specific information on lending with survey data, as in Del Giovane et al. (2011) and Bassett et al. (2014). Interestingly, Del Giovane et al. (2013) find that, among the various replies to the Bank Lending Survey, Italian banks' assessment on their capital position is the indicator capturing non-price allocation of credit.

rates.[3]

The theory behind the existence of credit rationing relies primarily on the existence of severe informational asymmetries between the actors of the credit market. This strand of literature stems from the seminal work by Stiglitz and Weiss (1981), in which credit rationing occurs in equilibrium because banks do not raise lending rates above a certain level to avoid financing more risky borrowers (adverse selection) or to discourage firms to take more risk (moral hazard).[4] A different route of empirical research emphasizes the role of banks' capital constraints in determining quantitative restrictions in lending and sometimes used the expression "credit crunch" as an alternative to "credit rationing." Bernanke and Lown (1991), for instance, define a bank credit crunch as "a significant leftward shift in the supply curve for bank loans, holding constant both the safe real interest rate and the quality of potential borrowers," and argue that there is "no necessary connection between a credit crunch and credit rationing in a strict sense." Schreft and Owens (1991) define a credit crunch as "a period of sharply increased non-price rationing" that "may (but need not) be independent of any change in borrowers' risk profile." Notwithstanding the semantic aspects, there is wide consensus that well capitalized banks are less likely to generate strong procyclical changes in credit supply conditions through rationing.

In this paper we propose an approach that uses bank-firm information to compute credit rationing at the aggregate level while imposing as little structure to the data as possible. We provide an extensive application of this method to the case of Italian market for bank term loans to the non-financial corporate sector, with a unique dataset based on more than 5 million observations. To this end, for each bank-firm relationship we match high-quality information on both the quantity and the cost of credit, which are available from two different sections of the Italian Credit Register (CR henceforth). The identification of loan supply and demand curves and the measurement of the quantitative restrictions are obtained by merging the credit variables with bank- and firm-specific variables taken from other sources of micro data, namely the confidential supervisory reports of the Bank of Italy and the Company Accounts Data Service managed by the Cerved Group.

We adopt maximum-likelihood (ML) methods à la Fair and Jaffee (1972),

[3]Typical references for credit rationing are the seminal works by Jaffee and Modigliani (1969), Jaffee and Russell (1976), Stiglitz and Weiss (1981). For a review of the motivations and definitions of credit rationing, see Jaffee and Stiglitz (1990). See also Bellier et al. (2012) for a recent survey.

[4]Previous theoretical approaches stemming from the availability theory of Roosa (1951) treat credit rationing as a temporary misalignment of credit supply and demand which drives the credit market out of equilibrium.

which have been developed to estimate mismatches between demand and supply for various markets and to evaluate the presence of credit rationing at the macroeconomic level.[5] We estimate a system that consists of a demand equation, a supply equation, and a "short-side rule" for which the observed quantity of credit is the minimum between the demand and supplied quantities. Several recent studies use this approach to identify the presence of credit rationing using firm-level panel data from a number of countries.[6] Its main advantage is that it introduces a minimal structure on the data while remaining quite neutral on its theoretical underpinnings. To the best of our knowledge, this is the first paper that applies this methodology to bank-firm data, which is particularly desirable in this framework for a number of reasons.

First, we can circumvent potential aggregation bias problems stemming from the use of macroeconomic information or firm- or bank-level data. The "short-side" rule (i.e., the minimum condition) that characterizes models à la Fair and Jaffee (1972) may indeed hold at the level of the single bank-firm transaction and not necessarily in the aggregate. The averaging process stemming from the use of more aggregate data may signal no credit rationing, while in reality some firms are de facto rationed.[7]

Second, the estimation of supply and demand curves in a unified framework allows us to endogenously identify whether any bank-firm transaction is credit rationed or not, without relying on a-priori exogenous classifications used in previous studies using micro data.[8] Ogawa and Suzuki (2000) and Atanasova and Wilson (2004) point out the need for an endogenous classification of rationed firms. The structure of our matched bank-firm data allows us to distinguish across different cases. In a specific time period a firm may be rationed in the access to credit with certain banks but not with others. At the same time, a bank may ration credit to part of its pool of borrowers but not to the others. Finally, the borrowers may switch between the groups

[5]See, among many others, Amemiya (1974), Fair and Kelejian (1974), Maddala and Nelson (1974), Goldfelfd and Quandt (1975). Laffont and Garcia (1977) and Sealey, Jr (1979) estimate demand and supply functions of commercial bank loans in the US. Ito and Ueda (1981) test the equilibrium versus disequilibrium hypothesis in the US and Japanese business loan markets.

[6]See Ogawa and Suzuki (2000), Atanasova and Wilson (2004), Carbó-Valverde et al. (2009), Shikimi (2013), Kremp and Sevestre (2013), and Farinha and Félix (2015)

[7]See Perez (1998) for an early mention of the aggregation bias problem in the study of credit markets.

[8]On the use of micro data on credit rationing as exogenous variables in macro studies, see for example Fazzari et al. (1987), Berger and Udell (1992), Hoshi et al. (1993), Petersen and Rajan (1994), Gilchrist and Zakrajšek (1995), Gertler and Gilchrist (1994), and Harhoff and Körting (1998).

of rationed and not rationed over time also as a result of their own internal decisions, as they may substitute bank credit with alternative and less costly sources of financing.

An important advantage of our dataset is that we can control for the interest rate at the bank-firm level, which is not available or hardly matched with loan quantities in other credit registers and is crucial to identify non-price allocations of credit. Since for each bank-firm contract the loan interest rate may be the result of a bargaining between the lender and the borrower, it is endogenous in the model, thus providing inconsistent estimates of the supply and demand curve. We carefully address the endogeneity of the loan interest rate by using a two-stage approach. In the first-stage the loan interest rate is regressed on the whole set of demand and supply variables, while in the second stage we estimate the system using the predicted value of the cost of credit. Previous papers usually assume that the loan interest rate does not enter the loan supply curve, thus assuming that banks first decide on the amount they are willing to lend and then bargain the interest rate with firms. Our model allows the cost and the amount of credit to be jointly determined by the two parts involved in the contract and our estimates provide robust evidence that the interest rate enters significantly the supply equation.

Our paper clearly relates to previous studies that provide estimates of the effects of a supply restriction on the intensive margin of lending using high-quality micro data, such as, among others, Khwaja and Mian (2008) and Jiménez et al. (2012). Differently from our paper, these studies focus on general definitions of credit supply restrictions and not necessarily to the identification of credit rationing episodes. In this regard, our matching of the amount and the cost of credit for each bank-firm relationship is crucial to discriminate situations in which supply restrictions take place through an increase in the cost of credit from those stemming from a decline in the availability of loan quantities (i.e., a condition of excess demand).

Since it is particularly important for policy purposes to provide reliable measures of credit rationing that can span an extended period of time and cover as much of the cross-section of banks and firms as possible, we depart from other compelling approaches. In particular, we do not rely on natural experiments that create an easily identifiable supply shock (e.g., Peek and Rosengren (2005) and Khwaja and Mian (2008)) but are feasible only in specific episodes.[9] Moreover, we do not need to narrow the data to the subsample of firms that have multiple lenders so as to control for demand

[9] Gan (2007) and Iyer et al. (2014) explored this issue using CR data for a number of countries, while Albertazzi and Marchetti (2010), Bonaccorsi di Patti and Sette (2012), and Bofondi et al. (2013) used the Italian CR.

conditions with firm or firm-time fixed effects.[10]

In our sample, firm-time fixed effects are highly correlated with firm-specific variables, of which some are supply factors. There is inevitably a trade-off between the need to impose the most restrictive controls for demand conditions and deriving a comprehensive measure of aggregate credit rationing. Apart from the sample coverage issue, there may be additional challenges related to the identification of fixed effects with matched bank-firm data, similarly to what happens with the use of matched employer-employee data since the seminal contribution of Abowd et al. (1999). For example, the inclusion of two-way fixed-effects imposes additivity between firm-time and bank-time fixed effects. Thus, it rules out any heterogeneity in firm-specific credit terms across banks or in bank-specific credit terms across firms, as well as any complementarity between banks and firms, which makes them also incompatible with theoretical models of sorting between banks and firms.[11]

When interpreting our results, it is important to remark that our dataset allows us to identify "weak" credit rationing, which occurs when borrowers are willing to pay the prevailing interest rate but receive a loan amount which is smaller than what they apply for. Following the definition in Jaffee and Stiglitz (1990), weak credit rationing differs from "pure" (strong) credit rationing, which occurs when the borrowers face the rejection of the entire loan amount they applied for. In this regard, our analysis on the intensive margin of lending may be considered complementary to empirical studies on the extensive margin of lending like Puri et al. (2011), Jiménez et al. (2012), Jiménez et al. (2014), and Albertazzi et al. (2015).[12]

Our study suggests that the amount of credit rationing mostly depends on banks' level of non-performing loans and firms' ability to provide collateral against bank loans. Ex-ante credit risk as captured by firm-specific ratings also contribute to a lesser extent to the dynamics of our aggregate credit rationing measures. We also provide evidence of significant aggregation biases stemming from the use of firm- or bank-level information as opposed to bank-firm match-specific data.

The structure of the paper is as follows. In Section 2 we present the model

[10] See Albertazzi and Bottero (2013), Cingano et al. (2013), Bottero et al. (2015), and Rodano et al. (2015) for recent applications of this method using Italian CR data.

[11] Amiti and Weinstein (2013) provide a methodology to solve the first of these limitations. See Bonhomme et al. (2015) for a recent discussion of these issues for the case of matched employer-employee data.

[12] Studies on the extensive margin of credit are based on information from the CR on loan rejection rates and usually estimate the effects of a supply restriction on the probability that the application for a new loan is rejected. Jiménez et al. (2014) propose a two-stage approach aiming at evaluating both the extensive and the intensive margin of lending.

and the methodology. In Section 3 we describe the high-quality dataset used in the empirical analysis and the demand and supply factors used to reach identification. In Section 4 we comment on the benchmark estimates. In Section 5 we develop some indicators of credit rationing that can be used for policy analysis and compare them to those available from survey data conducted among banks and firms. In Section 6 we present a battery of robustness checks. Section 7 offers some concluding remarks.

2 A model for the estimation of credit rationing

We are interested in the intensive margin of credit rationing in the market of term loans to the non-financial corporate sector in Italy over time. With transaction-level data this corresponds to assessing how much of the financing needs of the firms involved in the observed transactions is covered by the supply of credit provided by the banks involved in the same transactions. Since we do not investigate the extensive margin of lending, our estimates of the credit rationing should be considered a lower bound of the overall credit rationing. We are not only interested into the determinants of the demand and supply of credit but also on their evolution over time. Hence, we need to impose some structure to the data in order to extract the information we are interested into.

2.1 Theoretical set-up

We observe the universe of realized transactions between firms and banks in the market of term loans. Since our analysis focuses on this specific market it necessarily reflects a partial-equilibrium perspective. The market for lending to firms is decentralized and bipartite, where each bilateral transaction depends on the realization of the pairwise matches between one bank and one firm. Moreover, the two sides of the market face relevant informational asymmetries and the banks operate in a context that is far from perfect competition. In absence of a central auctioneer the market does not necessarily clear, so the equilibria that arise in it are possibly non-Walrasian. There may be systematic mismatches between the credit demand and credit supply within each bank-firm match and at the aggregate level, thus giving rise to situations of persistent excess demand or excess supply. We are interested in quantifying the excess demand for credit at the aggregate level in the market for term loans.

We define a match bft as the association of a bank b and a firm f at time t. An equilibrium credit contract is a match-specific pair (l_{bft}, r_{bft}) of terms, where l_{bft} is the quantity of credit that the firm f borrows from the bank b at time t and r_{bft} is the interest rate at which firm f borrows that amount from bank b at time t. Independently from how the match between the bank and the firm realizes in the first place, this contract is the result of a bargaining between the two agents. Hence, its terms depend on firm characteristics X_{ft}, bank characteristics X_{bt}, as well as other match-specific characteristics X_{bft} at time t, that is,

$$(l_{bft}, r_{bft}) = F(X_{ft}, X_{bt}, X_{bft}),$$

where F is the reduced-form equilibrium mapping between characteristics $(X_{ft}, X_{bt}, X_{bft}) \in \mathbb{R}^P$ of the agents into the pair $(l_{bft}, r_{bft}) \in \mathbb{R}^2$, where P is the sum of the dimensions of X_{ft}, X_{bt}, and X_{bft}. We do not impose any restrictions on how the interest rate may depend on these characteristics, that is, the equilibrium interest rate is a reduced-form generic function f^r of all characteristics,

$$r_{bft} = f^r(X_{ft}, X_{bt}, X_{bft}).$$

However, we need to impose some structure on the data in order to define and quantify the credit rationing. We assume that the loan contracts are incomplete, that is, the value of the contract to any trader who accepts it is not determined entirely by the terms of the contract. Since the equilibrium is non-Walrasian and contracts are incomplete, there may be systematic misallignments of the quantity demanded and the quantity supplied within each match. Firms may prefer to borrow a quantity l^d_{bft} at the observed interest rate r_{bft} that is higher than the quantity l_{bft} that appears in the contract. Similarly, banks may prefer to lend a quantity l^s_{bft} at the observed interest rate that is higher than the observed quantity l_{bft}. However, we suppose that there is no situation in which both the firm and the bank would prefer l_{bft} to be higher for the interest rate r_{bft}. We define a demand function f^d and a supply function f^s as two correspondences between firm, bank, and match-specific characteristics and the amounts l^d_{bft} and l^s_{bft} of credit that the firm f prefers to borrow from bank b and that the bank b prefers to lend to firm f at time t, respectively. In other words,

$$l^i_{bft} = f^i(X_{ft}, X_{bt}, X_{bft}),$$

where $i \in \{d, s\}$ indexes the demand and the supply, and X_{ft}, X_{bt}, and X_{bft} are firm-, bank-, and match-specific determinants of the demand and supply of credit at time t. Note that we abstract from how the equilibrium is determined. Hence, the functions f^d and f^s are simply a characterization of the reduced-form dependence between exogenous variables and equilibrium objects, they are not the structural demand function and the structural supply function. The characteristics can influence the demand and the supply of credit both directly or through their impact on the bargained interest rate. In other words,

$$\frac{\mathrm{d}l^i_{bft}}{\mathrm{d}x} = \frac{\partial l^i_{bft}}{\partial x} + \frac{\partial l^i_{bft}}{\partial r_{bft}} \frac{\partial r_{bft}}{\partial x},$$

where x can be any element of X_{ft}, X_{bt}, or X_{bft}, for $i \in \{d, s\}$. We suppose that the quantity l_{bft} that ends up written in the contract is the minimum between the quantity demanded and the quantity supplied, that is,

$$l_{bft} = \min\{l^d_{bft}, l^s_{bft}\}. \tag{1}$$

Equation (1) describes the characterization of the reduced-form mapping F for the quantity. There are two identifying differences between the demand and the supply functions. First, each characteristic influences the quantity either only through the interest rate or directly as well. The derivative $\partial l^d_{bft}/\partial x$ of the demand function is nil for some characteristic x, and the derivative $\partial l^s_{bft}/\partial x'$ of the supply function is nil for some other characteristic x', and all the characteristics influence the demand only, the supply only, or both. Second, the sign of the impact of the interest rate on the quantity is different between the demand and the supply. In the demand function, $\partial l^d_{bft}/\partial r_{bft}$ is negative. In the supply function, $\partial l^s_{bft}/\partial r_{bft}$ is positive.

2.2 Methodology

In this section we briefly describe our empirical strategy. We suppose that the functions f^r, f^d, and f^s are linear in X_{ft}, X_{bt} and X_{bft} and propose a two-stage estimation approach.

In the first stage, we estimate the interest rate equation by simply regressing our measure of the cost of credit on the entire set of observable and unobservable variables, that is,

$$r_{bft} = \beta^r \left[X_{ft}, X_{bt}, X_{bft}\right]' + \varepsilon^r_{bft}, \tag{2}$$

where β^r is the vector of the OLS estimated coefficients and ε^r_{bft} is a normally distributed error term. We therefore remain agnostic regarding the interest rate dynamics but recognize that changes in this variable may reflect the confluence of demand and supply factors. Recognizing this endogeneity problem is important especially for the identification of the supply curve because we are interested in distinguishing quantitative restrictions from those arising from the interest rate channel. Banks may act as price-takers but set their loan rates taking into account the demand for loans and deposits. Practical considerations also suggest that the interest rate charged on any loan may also depend on the bank cost of retail and wholesale funding, a risk premium charged to compensate the bank for the probability of default risk inherent in the loan request, as well as a profit margin on each loan that provides the bank with an adequate return on the use of capital. Our specification essentially aims at capturing all these features.

In the second stage, we use the predicted values of (2) as a regressor. We can write the demand function f^d and the supply function f^s as

$$l^i_{bft} = \rho^i \bar{r}_{bft} + \beta^i \left[X_{ft}, X_{bt}, X_{bft}\right]' + \varepsilon^i_{bft}, \tag{3}$$

where $i \in \{d, s\}$ and $\bar{r}_{bft} = \beta^r \left[X_{ft}, X_{bt}, X_{bft}\right]$. Thus, β^i is a vector of coefficients that represent the direct impact of each explanatory variable on the loan quantity l^i_{bft}, while ρ^i captures the corresponding impact of the interest rate in the quantity demanded and supplied. Hence, the total derivative of l^i_{bft} with respect to the x-th element of $[X_{ft}, X_{bt}, X_{bft}]$ is $\beta^i_x + \rho^i_x \beta^r_x$, where β^i_x represents the direct impact and $\rho^i_x \beta^r_x$ is the indirect impact through the interest rate channel. In (3) we implicitly suppose that the list of determinants of the interest rate in (2) is exhaustive enough to include all the observables that contribute to the determination of the quantity demanded and supplied, so that ε^r_{bft} does not need to be included in (3).

As ε^r_{bft} is not correlated with ε^i_{bft}, we can estimate (2) separately, derive its predicted value $\hat{r}_{bft} = \hat{\beta}^r \left[X_{ft}, X_{bt}, X_{bft}\right]$, and plug it in (3) instead of $\bar{r}_{bft}$. In this way we are left with a system of three equations, that is, a demand equation

$$l^d_{bft} = \rho^d \hat{r}_{bft} + \beta^d \left[X_{ft}, X_{bt}, X_{bft}\right]' + \varepsilon^d_{bft},$$

a supply equation

$$l^s_{bft} = \rho^s \hat{r}_{bft} + \beta^s \left[X_{ft}, X_{bt}, X_{bft}\right]' + \varepsilon^s_{bft},$$

and the measurement equation (1).

In order to identify the system, we need to impose exclusion restrictions, namely to distinguish some variables that enter only the demand equation from those that enter only the supply equation. Some variables may be hardly identified to be demand or supply factors, thus they enter both equations. Hence, we define subsets X^d_{ft}, X^s_{ft}, and X^{ds}_{ft} that are a partition of X_{ft}, X^d_{bt}, X^s_{bt}, and X^{ds}_{bt} that are a partition of X_{bt}, and X^d_{bft}, X^s_{bft}, and X^{ds}_{bft} that are a partition of X_{bft}. Hence, the first two equations of the system become

$$l^d_{bft} = \rho^d \hat{r}_{bft} + \beta^d X^d_t + \varepsilon^d_{bft}, \tag{4}$$

where $X_t^d \equiv \left[X_{ft}^d, X_{bt}^d, X_{bft}^d, X_{ft}^{ds}, X_{bt}^{ds}, X_{bft}^{ds}\right]'$ and

$$l_{bft}^s = \rho^s \hat{r}_{bft} + \beta^s X_t^s + \varepsilon_{bft}^s, \tag{5}$$

where $X_t^s \equiv \left[X_{ft}^s, X_{bt}^s, X_{bft}^s, X_{ft}^{ds}, X_{bt}^{ds}, X_{bft}^{ds}\right]'$. As long as $X_i^d \neq \varnothing$ for at least an i in $\{ft, bt, bft\}$ and $X_i^s \neq \varnothing$ for at least an i in $\{ft, bt, bft\}$, the system is identified. The size of β^d and β^s depends on the number of observables included in each specification. The system of equations (4), (5), and (1) can be estimated through full-information maximum likelihood methods, as in Maddala and Nelson (1974). See the appendix for details about the estimation procedure.

3 Data and specification

For the empirical analysis we use a unique dataset containing information at the bank-firm level on both terms of the credit contracts, that is, quantities l_{bft} and prices r_{bft}, and other match-specific information X_{bft}. The unique identifiers of banks and firms allows us to merge the bank-firm information with a number of bank- and firm-specific characteristics (X_{bt} and X_{ft}, respectively), which are used to better disentangle the supply from the demand for loans. Data are collected over the period 2006Q1-2015Q2. This allows us to characterize (2), (4), and (5).

3.1 The data

The data on loan quantities and interest rates comes from the Italian CR and covers the universe of loans from a large representative sample of intermediaries operating in Italy (about 200 banks).[13] We consider the end-of-quarter outstanding granted amounts and corresponding interest rates of term loans to firms operating in the industry sector (i.e., manufacturing and construction), which represents more than 60% of total granted term loans to non-financial firms.[14] In Figure 2 we report the total granted amount of term loans in our sample as opposed to harmonized aggregate statistics for the industry sector, which certifies that our panel of firms is highly representative of the whole industry sector. As a measure of the interest rate we

[13] In the appendix we provide more etails about the dataset.

[14] Term loans are more related to firms' investment decisions in the medium-term. They differ considerably from revolving credit lines, which are instead managed day-by-day by firms depending on their liquidity needs. We use granted amounts because drawn credit may be more relevant in empirical analysis of credit lines, where it is a temporary indicator of the firm demand.

use the loan margin, which is the difference between the annual percentage rate and the Eonia rate. We do this to filter out ex-ante any changes in the monetary policy stance and knowing that the EONIA in practice play for intermediaries the role of a floor over which to set the interest rates on loans to non-financial firms.[15] For each single transaction we also observe other characteristics, namely collateralization and maturity.

The firm-level data X_{ft} come from the Company Accounts Data Service (CADS) managed by the Cerved Group, which is one of the largest sources of balance sheet data on Italian firm. The bank-level data X_{bt} come from the Supervisory Reports on banks' balance sheets submitted by each individual bank to the Bank of Italy. We use consolidated balance sheet items. Business strategies are usually decided by the holding of the banking group rather than by the single bank. In addition, regulatory requirements must be computed on consolidated balance sheets and banks belonging to the same group usually exchange funds on the interbank market among them, meaning that funding difficulties are better assessed at the banking-group level. For simplicity, we refer to the banking groups simply as banks henceforth.

The data is at the bank-firm match level. If a firm has more than one distinct term loan granted by the same bank, we compute the total exposure of that firm towards the bank. We compute the weighted averages at the bank-firm level for all the other transaction-level observables, where the weights are the transaction-level amounts. The index bft refers therefore to the uniquely identified bank b-firm f relationship at time t, although from now on we refer interchangeably to the match as a transaction. Our final database consists of over 5.2 million observations from almost $468,000$ bank-firm matches for 38 quarters, which involve 120 banking groups and almost $166,000$ firms. Table 1 reports some summary statistics of the variables contained in the database.

3.2 Demand factors

Bank lending is just one of the multiple sources of funding for firms, which can potentially rely on internal funds, as well as alternative external sources. For example, firms can rely on their internal revenue or on commercial paper, as well as on trade credit or the deep pockets of the business groups they are part of. We include two variables for, respectively, internal and external substitutes of bank lending. The ratio of firms' cash-flow to total sales is a measure of firms' ability to generate internal funds, while the ratio of trade debt to total assets is a measure of firms' reliance to financing from its trade

[15]Results are unaffected if we use the interest rate applied on the loan or taking its deviations from the MRO rate, as all aggregate effects are captured by time fixed effects in the various specifications.

partners by delaying the payment of input purchases. In order to avoid endogeneity we use the one-year lag of each firm-specific variable.

An important aspect of the demand for credit of a firm is its maturity needs. Moreover, due to the presence of re-issuance costs or roll-over risks, firms may prefer higher maturities, other things equal.[16] The bank may alter its supply decisions depending on the average maturity of its overall portfolio but it is unlikely to take these decisions on the basis of the single transaction. Hence, we assign the maturity variable to the credit demand. For each transaction we have some information on the loan maturity. In the CR this variable is recorded only according to two modalities, namely up to and over 12 months (up to and over 18 months before 2009). Since we have aggregated the transaction-level data at the bank-firm level, our maturity variable for each bank-firm pair is the percentage of credit that is flagged to have maturity below 12 months.

3.3 Supply factors

The credit rationing literature emphasizes the importance of borrowers' characteristics. In the case of imperfect and asymmetric information in the credit market, adverse selection and adverse incentive effects are likely to occur. In these cases, as Stiglitz and Weiss (1981) point out, the interest rate does not allow the lender to discriminate between different types of borrower, and it is important to screen and monitor borrowers to reduce the probability that firms fail to repay the loans. In the hypothetical case of perfect screening and monitoring, no firm should be rationed and each borrower should pay the right price to get the loan. However, distinguishing safe from risky firms may be virtually impossible or very costly, and credit rationing may be the outcome. For the purpose of our analysis, we consider the Z-score as an overall measure of the ex-ante risk of firms' default. This score is computed annually by the CADS on balance sheet information.[17] The Z-score takes values ranging from 1 to 9 where firms with assigned values between 1 and 3 are considered a 'low risk', firms with values between 4 and 6 are considered a 'medium risk', and firms with values between 7 and 9 are considered a 'high risk'. The latter firms are more likely to default within the next two years. As the Z-score is an ex-ante measure of credit risk, it may have different information content with respect to the bank loan quality indicators, which are indeed a measure of the ex-post credit risk. Ex-ante credit risk indicators

[16]See Altinkiliç and Hansen (2000) or Bruche and Segura (2015) for the effect of re-issuance costs on maturity and He and Xiong (2012a) or He and Xiong (2012b) for the effect of roll-over risks.

[17]The methodology is described by Altman (1968) and Altman et al. (1994).

reduce the information asymmetry between borrowers and lenders and are expected to have a positive effect on credit availability. To avoid collinearity problems, we include in the system two time-varying dummies, corresponding to 'medium risk' and 'high risk'. The estimated coefficients reflect the premium (or the discount) paid by these firms with respect to those that are considered a 'low risk'. In order to stress the nature of ex-ante credit risk, we use the one-year lag of all firm-level variables.

In the existing literature the key bank-balance sheet variables used to identify a supply restriction are the bank liquidity position and the bank capital ratio as a measure of a bank's net worth.[18] As for the former, there is large empirical evidence that banks reduce their supply of loans when hit by liquidity shocks, as predicted by the bank lending channel.[19] Kapan and Minoiu (2013) show that during the 2007-2008 crisis the intensity of the credit supply restriction was related to the degree of banks' reliance on interbank funding. Jiménez et al. (2012) stress the role played by the liquidity ratio, namely the ratio of liquid assets held by the bank (i.e., cash and deposits with central banks and public debt with a maturity up to one year) and the total assets of the bank.

In the case of Italy, the shocks to banks' funding occurred in two distinct phases of the financial crisis and originated from different components of banks' liabilities. During the global crisis of 2007-2008 the financial shocks originated abroad and hit the Italian banking system through a dramatic liquidity drought in interbank markets.[20] As a result, the reliance of banks on interbank funding, as captured by the interbank-to-assets ratio, represents an important source of variation in banks' exposure to liquidity shocks (Bonaccorsi di Patti and Sette (2012)) and may then be a valid instrument to assess the effects of a credit supply tightening on the real economy (Cingano et al. (2013)).[21] During the sovereign debt crisis, the financial shocks stemmed from the increase in the sovereign risk, which rapidly transmitted to the banking sector. Identifying this effect is challenging, since banking and sovereign crisis are closely intertwined through several channels, reinforcing each other through strong feedback effects. However, between November 2011 and February 2012 Italian banks' funding was hit by a dra-

[18]See, e.g., Holmstrom and Tirole (1997), Bernanke (2007), and Diamond and Rajan (2011).

[19]See for example Stein and Kashyap (2000) and Khwaja and Mian (2008).

[20]See Angelini et al. (2011) and Affinito (2013) for a focus on the Italian banking system in the aftermath of the global financial crisis.

[21]For banks belonging to groups the use of consolidated balance sheet items allows to exclude interbank transactions made by banks belonging to the same banking group, which cannot be considered genuine interbank funding.

matic fall in non-residents' deposits (Banca d'Italia (2012)), which comprise mainly interbank funds raised abroad, owing to the heightened perception of country risk from foreign lenders. As a result, drop in non-residents' deposits may be also considered as a source of liquidity shocks.[22] In light of these considerations, we consider a single interbank funding variable that comprises the interbank exposure of the banking group with both domestic and foreign intermediaries.[23] In the benchmark model we do not consider the liquidity obtained by the Eurosystem through the ordinary and the exceptional long-term refinancing operations. Since banks have used this liquidity to substitute the decline in the wholesale funding, we explore the role played by the funding obtained from the Eurosystem in the robustness check section.

As for banks' capital position, conclusive evidence of a capital-related contraction of credit supply is still unresolved in the existing literature.[24] In the case of Italy the evidence is mixed as well, albeit confined to event studies for the global crisis of 2007-2008.[25] In this study we consider the bank capital position as measured by the Tier 1 capital ratio over risk-adjusted assets.

We also consider the credit quality in banks' balance sheets, measured by the ratio of non-performing loans to total loans standing in each bank's consolidated balance sheet. As already discussed, this is an ex-post measure of the average credit risk. In addition, the impairment in the quality of bank assets induces a drop in bank profitability, which in turn leads to capital losses and deleveraging needs. During the recent financial crisis, it has been considered one the most relevant factors affecting both the cost and the availability of credit.[26]

The existence of collateral is expected to increase credit availability, since it mitigates the ex-ante problems of adverse selection and moral hazard. Hence, we allow the supply to depend on the percentage of collateralized

[22] An alternative measure of a liquidity shock is the funding gap indicator (i.e., the fraction of loans to the private sector not financed by customers' deposits). When included in the estimated regressions, the funding gap results to be not statistically significant meaning that this variable has no marginal information content beyond the already mentioned indicators for the bank liquidity position.

[23] In order to rule out intra-group domestic interbank exposures we use the bank-to-bank liabilities from the Supervisory Reports and the list of mergers and acquisitions across banks in our sample. Thus, we know which bank belongs to which group in each period, and we can exclude the liabilities towards domestic members of the same banking group for each bank. We then aggregate the domestic extra-group liabilities across banks of the same banking group to create a consolidated measure together with the liabilities towards foreign entities.

[24] See, e.g., Rosengren and Peek (2000), Puri et al. (2011), Jiménez et al. (2012), and Udell (2009).

[25] See Bonaccorsi di Patti and Sette (2012) and Albertazzi and Marchetti (2010).

[26] See Banca d'Italia (2013).

loan, i.e., the percentage of credit that is flagged to be guaranteed in the CR.

3.4 Other control variables

We consider a number of variables that cannot be uniquely classified as demand or supply factors. In this regard, they are not used to reach the identification of demand and supply curves by means of the exclusion restrictions, but are included in both equations as relevant control variables for observed and unobserved factors.

Firm size, which is measured by the logarithm of total assets, may affect the demand for loans to the extent that the financing needs of firms depend on their size for a standard scale effect. Larger firms face larger operating costs and larger need of external financing in absolute terms. Firm size may also help to explain the supply of credit. Large firms are usually considered less risky than smaller ones. Petersen and Rajan (1994) showed that credit constraints become more severe as firm size decreases because the effects of adverse selection and moral hazards are larger when the company is smaller. Using data from a national survey of small businesses, Levenson and Willard (2000) find that the smallest firms in the US are both more discouraged and more rationed than other firms. By comparing large firms with SMEs in the Capitalia surveys on Italian manufacturing firms, Agostino et al. (2008) also find that larger firms are less credit rationed than small firms.

The system specification also includes a number of fixed effects. We include a series of time-invariant 2-digit subsector dummies to capture sectoral differences in demand and supply conditions. We also include a series of time-invariant geographical dummies that correspond to firms' macroarea (NUTS1) to control for spatial differences in supply and demand conditions. Finally, we consider an appropriate set of time-specific and bank-specific fixed effects to control, respectively, for macro variables and unobservable bank characteristics.

We do not include firm fixed effects for two reasons. The first reason is that by including firm fixed effects we would limit our sample to multiple-lender firms, which may be the most likely to experience rationing of their demand for credit. The second reason is technical and refers to the nature of our ML estimation procedure. For a successful estimation of the model, each single value of categorical variables like firm-specific dummies or bank-ID dummies needs to have a sufficient amount of valued observations. Otherwise, the ML estimation assigns a disproportionate weight to that observation on the demand or the supply side, leading to exploding magnitudes of the estimated coefficients corresponding to the variable. This limitation relates to a well-known problem of corner solutions in the estimation of models à la Fair and Jaffee (1972), see Maddala (1986) for further details. Our simulations suggest that, to avoid corner solutions, we would need at least 1000 observations for each firm ID. Since a firm ID can reach at most a few hundreds observations, we would end up dropping almost all our sample. This is not the case for bank fixed effects or sector-specific fixed effects as the number of observations for each bank or sector ID is high enough.[27] We give an idea of the amount of information we lose without firm fixed effects in Subsection 4.2, where we evaluate the empirical correlation between firm-time fixed effects and the firm-level variables we include in the specification.

3.5 The benchmark specification

We allocate observables between the demand function and the supply function depending on whether that observable is likely to be a demand shifter, a supply shifter, or both. On the basis of what we discuss in Subsection 3.2 and Subsection 3.3, our benchmark system of equations is

$$\begin{aligned} l^d_{bft} = \rho^d \hat{r}_{bft} + \beta^d \Big[& \text{Cash-flow/Sales}_{ft}, \text{Trade debt/Assets}_{ft}, \\ & \text{Short maturity}_{bft}, \\ & \text{Firm assets}_{ft}, \\ & \text{Sector}_f, \text{Macroarea}_f, \text{Bank}_b, \text{Quarter}_t \Big]' + \varepsilon^d_{bft} \end{aligned} \tag{6}$$

for the demand and

$$\begin{aligned} l^s_{bft} = \rho^s \hat{r}_{bft} + \beta^s \Big[& \text{Average rating}_{ft}, \text{Bad rating}_{ft}, \\ & \text{Bad loans/Loans}_{bt}, \text{Tier 1 capital}_{bt}, \\ & \text{Interbank/Assets}_{bt}, \\ & \text{Collateralization}_{bft}, \\ & \text{Firm assets}_{ft}, \\ & \text{Sector}_f, \text{Macroarea}_f, \text{Bank}_b, \text{Quarter}_t \Big]' + \varepsilon^s_{bft} \end{aligned} \tag{7}$$

for the supply. Hence, our identification scheme is as follows. First, the demand is identified by $X^d_{ft} = \Big[\text{Cash-flow/Sales}_{ft},\ \text{Trade debt/Assets}_{ft}\Big]$ and

[27] In the benchmark model we solve this limitation by dropping from our sample sectors with less than $50,000$ observations and bank-IDs with less than $1,000$ observations. This leads to an overall loss of around $90,000$ observations out of a sample of more than 5.2 million observations.

by $X^d_{bft} = \big[\text{Short maturity}_{bft}\big]$. Second, the supply is identified by $X^s_{ft} = \big[\text{Average rating}_{ft}, \text{Bad rating}_{ft}\big]$, by $X^s_{bt} = [\text{Interbank/Assets}_{bt}, \text{Tier 1 capital}_{bt}, \text{Bad loans/Loans}_{bt}]$, and by $X^s_{bft} = [\text{Collateralization}_{bft}]$. There are covariates that serve only as controls and not for identification. For example, $X^{ds}_{ft} = [\text{Firm assets}_{ft}, \text{Sector}_f, \text{Macroarea}_f]$, $X^{ds}_{bt} = [\text{Bank}_b]$. Moreover, the time dummies Quarter_t appear on both sides as well.[28]

Lastly, the specification (2) of the interest rate comprises all covariates of demand and supply, that is,

$$
\begin{aligned}
r_{bft} = \beta^r \Big[& \text{Cash-flow/Sales}_{ft}, \text{Trade debt/Assets}_{ft}, \\
& \text{Average rating}_{ft}, \text{Bad rating}_{ft}, \\
& \text{Bad loans/Loans}_{bt}, \text{Tier 1 capital}_{bt}, \\
& \text{Interbank/Assets}_{bt}, \\
& \text{Short maturity}_{bft}, \text{Collateralization}_{bft}, \\
& \text{Firm assets}_{ft}, \\
& \text{Sector}_f, \text{Macroarea}_f, \text{Bank}_b, \text{Quarter}_t \Big]' + \varepsilon^r_{bft}.
\end{aligned} \tag{8}
$$

4 Estimation results

In Table 2 we present the estimation results for the benchmark model. We compute standard errors in all estimated equations by a two-way clustering at the firm-sector and bank-category level. We assign banks to five categories (first 5 groups, large groups, medium groups, small groups, and minor groups). The structure of our data is complex and characterized by several dimensions, so that many clustering schemes are possible. We offer a robustness check about the statistical significance of the coefficients based on alternative clustering schemes in Section 6.6.

The first column reports the estimated coefficients of the loan margin equation. Demand factors are in general weakly correlated with the loan margin, while supply factors are highly significant. The cost of credit indeed declines with the borrowers' creditworthiness. The dummies for averagely and badly rated firms enter with a positive sign, meaning that these firms pay a premium with respect to the best rated firms (about 30 and 70 basis points, on average, respectively). The loan margin is also lower for larger firms, which are usually considered less risky than smaller ones. Firm size

[28] As mentioned before, we use the one-year lag of all firm-level variables in X^d_{ft}, X^s_{ft}, and X^{ds}_{ft}.

has therefore marginal predictive content beyond the rating, which should capture all relevant characteristics related to firms' riskiness.

All considered bank-specific variables are significant. Lower interest rate margins are associated to banks with a higher capital ratio and with a better credit quality in their loan portfolios. The cost of credit is also lower for banks with access to the interbank market.[29] Finally, collateralized loans are charged, on average, about 30 basis points less than unsecured loans. Long-term loans are cheaper than short-term by about 70 basis points, on average.

In the second column we report the estimation result of demand equation. The predicted loan margin from the first-stage equation has a negative coefficient, thus identifying a downward-sloping demand curve. An increase of one percentage point in the interest rate corresponds to a 30% decrease in credit demand. The two substitutes to bank lending that we consider, namely, the ratio of cash-flow over sales and the ratio of trade debt over assets, enter with the expected sign. The elasticity of substitution is higher for external financing, maybe capturing payment delays by the customers of the firm that the latter transmits to the providers. The negative coefficient on the duration dummy suggests a preference for long-term debt. This outcome is consistent with re-issuance costs, as in Altinkiliç and Hansen (2000) and Bruche and Segura (2015), or roll-over risks, as in He and Xiong (2012a). Firm size captures scale effects and the large estimated coefficient is the outcome of the level-specification of the model.[30]

In the third column we report the estimated coefficients of the supply equation. The predicted loan margin enters with a positive sign, thus describing an upward-sloping supply curve. This outcome suggests that studies that typically assumed a flat supply curve maybe not consistent with the data. Interestingly, the credit supply seems to be more elastic to changes in the cost of credit than the credit demand. This result is a novelty in the literature that uses models a' la Fair and Jaffee (1972), since previous contributions either do not have match-specific data on the cost of credit or include it only in the demand equation. We explore the relevance of this

[29]Our estimates suggest large heterogeneity with respect to previous studies for Italy. Gambacorta (2008) used bank-level data and found that higher interest rates were associated to lower asset quality (a higher bad loan-to-total loan ratio) and bank efficiency (as measured by the cost-to-total asset ratio). The results also suggested a positive correlation with a number of macroeconomic variables, such as inflation, permanent income, and money market rate volatility, which, in our model might be captured by the time dummies. However, this study focused on a different sample period, which was not characterized by a financial crisis.

[30]In Atanasova and Wilson (2004) loan quantity is normalized by firm's assets to filter out scale effects, so that the estimated coefficient can be interpreted as a true size effect.

assumption for our estimates in Section 4.1 in addition to other econometric issues related to the identification of the supply equation.

Borrowers'characteristics are pivotal in explaining the supply of credit, thus providing empirical support to standard theoretical models of asymmetric information à la Stiglitz and Weiss (1981). Compared to the best rated firms, the reduction in credit supply to firms with an average and bad rating is, on average, 19% and 31% larger.

However, banks' balance sheet composition plays indeed an important role. A decrease of one percentage point in the Tier 1 capital ratio may force the bank to reduce its loans to the corporate sector of almost 1% in order to comply with the regulatory requirements. Later we present some evidence on the nonlinear effects that these requirements may have on banks' behaviour. Moreover, an increase of one percentage point in the ratio of bad loans over total loans leads to a 2.7% decrease in credit supply, as banks tighten their supply when they become too exposed to defaults. Considering that on average this ratio passed from 3% before the crisis to over 13% at the end of our sample, we can gauge approximately a decrease in aggregate credit supply of around 30% due to the rapid accumulation of bad loans in banks' balance sheets. Banks' access to cheap funding is relevant as well, although the statistical significance is less strong and the magnitude is relatively small. A reduction of one percentage point in intermediary's exposure to the interbank market leads to a 0.4% decrease in its supply of credit.

The size of the firm has a positive impact on credit supply, which may capture again a simple scale effect. However, there is a difference of 0.3 percentage points in the increase of credit supply relative to the increase of credit demand that corresponds to an increase of 1% in firm size. This may reflect the fact that the size of firms' balance sheets may be among the characteristics that the bank takes into account to evaluate the risk profile of a borrower beyond its credit rating. Finally, posting collateral in the transaction reduces informational asymmetries and the credit supply triples with respect to transactions with no collateral.

4.1 The treatment of the loan margin

The inclusion of a transaction-level interest rate in our estimation deserves an in-depth discussion, as it raises relevant econometric issues.

First, recent contributions that use models à la Fair and Jaffee (1972) to study the credit market like Kremp and Sevestre (2013) or Farinha and Félix (2015) include the interest rate only on the demand function. Hence, column 1 of Table 3 reports the estimation of an alternative model where we assume that the supply curve is not affected by the interest rates.[31] The estimates for the coefficients of the demand equation do not change significantly in magnitude, except for the short-term maturity dummy that loses statistical significance and exhibits a wrong sign. The supply equation instead is significantly affected. The estimated effects of all covariates decline in magnitude to the reduced-form coefficients, which can be computed by a back-of-the-envelope calculation on the basis of Table 2 as the values that sum up the direct effect on the supply and the indirect effect through the interest rate. In particular, the bank interbank exposure now enters with a negative sign. This result points at the crucial role that imposing a structure on the data may have in the study of the market for term loans. Access to funding from the interbank market may appear associated to a lower credit supply to the corporate sector in reduced-form but that may be the results of its effect on the cost of funding and, in turn, on loan interest rate rather than a factor affecting the credit availability.

The second issue is related to the endogeneity problem. Column 2 of Table 3 reports the results of an alternative experiment in which we estimate the model by replacing the predicted loan margin with its actual value. We, therefore, do not estimate the first-stage regression and evaluate the effects of considering r_{bft} endogenous in the model. The semi-elasticity of the demand curve to the loan margin is less than 1/4 of that obtained with the benchmark estimate, while the semi-elasticity of the supply curve becomes negative, raising concerns about the identification of the supply function. Hence, addressing the endogeneity of interest rate is crucial for the identification of the system.[32]

4.2 Decomposition of the data

The use of bank-firm data for the cost and the amount of credit and their matching with bank-specific and firm-specific characteristics represent the major novelty of this paper with respect to previous studies that relied on the approach à la Fair and Jaffee (1972) to identify the credit rationing. In this regard, what is the relative importance of observable and unobservable firm-specific and bank-specific characteristics in explaining our endogenous variables?

To answer these questions, we first decompose the overall variance in

[31] We report only the coefficients associated with the variables of main interest, for sake of brevity. The other estimated coefficients are available upon request.

[32] Results are similar in case we include the endogenous version of the loan margin only on the demand side. In this case, however, the semi-elasticity on the demand curve doubles in magnitude. These results are also available upon request.

loan quantities and prices in its fundamental components, namely bank-time fixed effects and firm-time fixed effects.[33] We then compare how much of each component of variability is explained by the observables we include in our model. We regress bank-time fixed effects on the observable bank-level variables, and firm-time fixed effects on the observable firm-level variables. As a measure of their ability to capture their respective dimension of variability, we look at the R-squared of these regressions. This exercise also informs us about the amount of information we lose by not considering firm fixed effects in the benchmark specification.

A regression of the observable credit quantities on bank-time and firm-time fixed effects leads to the drop of 1.8 million singleton observations, which correspond mostly to single-lender firms at a given time. The R-squared on the remaining 3.5 million observations resulted to be 69%, of which bank-time fixed effects explain 2% of the variation in credit quantities whereas firm-time fixed effects explain the remaining 67%. This asymmetry lies at the heart of the reduced-form evidence on the predominance of borrowers' characteristics as drivers of loan quantities.

Under the assumption that bank-time fixed effects capture all the variation of credit quantity that is due to bank characteristics, we want to understand how much of such variation we capture with the variables we include in our benchmark model. We find that our time-varying bank-level covariates together with the bank fixed effects, time fixed effects, and the dummies for firms' sectors and geographical location explain 93% of bank-time fixed effects. We do the same for firm-time fixed effects and firm-level characteristics included in our benchmark specification, and obtain an R-squared of 67%. We can therefore conclude that our specification accounts for a sufficiently high share of overall bank-time and firm-time variation.

We perform the same analysis for the cost of credit. We obtain that bank-time and firm-time fixed effects explain 21% and 39% of overall variance of the interest rates, for a total of 60%. Our bank-level variables explain 93% of bank-time fixed effects, and our firm-level variables explain 15% of firm-time fixed effects. Hence, it seems that interest rate developments are mostly explained by bank-level variables than by firm-level variables.

Among the explanatory variables we include in the model a particular attention should be paid to the bank-firm-time variables, namely the maturity and the level of collateralization of the loan contracts. Interestingly, these observables add 7 percentage points to the overall variance of loan quantities

[33] We do not consider bank-firm fixed effects because the matches themselves are not stable over time, so the variation in their number and distribution would capture important time-varying effects. We leave the exploration of this dimension to future research.

and 2 percentage points of the overall variance of the loan prices.

Overall, our analysis suggests some important considerations. First, there may be a relevant loss of information when analyzing the loan markets with dataset that do not comprise both firm- and bank-specific variables. Second, the identification of the effects of a supply restriction on lending dynamics by including firm-time fixed effects to control for demand conditions is powerful but it may be too conservative. We showed that firm-time fixed effects are not independent from firm characteristics, of which some are supply factors. Similar considerations may apply when bank-time fixed effects are included in the regression which relies on multiple-borrower banks, although that may be less of an issue empirically.[34]

There are additional challenges related to the identification with matched bank-firm data, as it is well-known in the literature on matched employer-employee data since the seminal contribution of Abowd et al. (1999). For example, the inclusion of two-way fixed-effects imposes additivity between firm- and bank-specific fixed effects. Thus, it rules out any heterogeneity in firm-specific credit terms across banks or in bank-specific credit terms across firms, as well as any complementarity between banks and firms, which makes them also incompatible with theoretical models of sorting between banks and firms.[35]

4.3 Explaining aggregate demand and supply

We now compute aggregate demand and supply and decompose their evolution in its time-varying observable and unobservable determinants. For the purpose of our analysis we are particularly interested in evaluating the contributions of the variables that directly affected the loan supply while condensing together those affecting the loan market through the interest rate channel.

We use the benchmark estimates for (6) and (7) to compute the predicted demand and predicted supply at the level of the single transaction. Then, we sum the predicted demand and the predicted supply across all bank-firm matches within each quarter. Figure 4 reports the two time series. Aggregate demand grew from the beginning of the sample to 2009Q2 when the global financial crisis drove the economy into recession. It fell into a persistent decline during the sovereign debt crisis. Aggregate supply instead grew until the first quarter of 2008 when the financial turmoil in the interbank market

[34] Bank-firm fixed effects would rely on the existence of the same match in at least two quarters.

[35] See Bonhomme et al. (2015) for a recent discussion of these issues in the case of the labour market.

and the Lehman collapse led to a supply contraction. Then, loan supply turned to increase until the breakout of the sovereign debt crisis.

Given the estimated coefficients and the time variation of the explanatory variables, in Figure 5 and Figure 6 we report the cumulative contribution of demand and supply factors at each point in time. The most striking result is that non-performing loans are the main driver of the fall in the supply factor during the sovereign debt crisis. The availability of collateral also provided a negative contribution in the last part of the sample period reflecting the decline in the availability of collateral. The deterioration of the borrowers' creditworthiness played a minor role. The positive contribution of the firm rating during the crisis reflect a change in the borrowers' composition with banks that switched the supply of funds in favor of firms with a higher creditworthiness. Interestingly, bank capital did not contribute to the fall in loan supply, thus suggesting the banks' recapitalization occurred during the crisis did not have perverse effects on loan supply. As for the reduction of aggregate demand, it is mostly explaining by the unobservable characteristics of the model. Time dummies play a dominant role in this regard, maybe capturing the effects of the aggregate business cycle on the demand for loans.

5 Indicators of credit rationing

In this section we describe some credit rationing indicators that can be used for policy analysis.

The maximum likelihood estimation of the system (6)-(7)-(1) provides us with the predicted demand $\hat{l}^d_{bft}$,

$$\hat{l}^d_{bft} = \hat{\rho}^d \hat{r}_{bft} + \hat{\beta}^d X^d_t,$$

and the predicted supply l^s_{bft},

$$\hat{l}^s_{bft} = \hat{\rho}^s \hat{r}_{bft} + \hat{\beta}^s X^s_t,$$

for each bank-firm relationship. We can also compute the estimated probability that each bank-firm match is credit rationed as an analog $\hat{\pi}_{fbt}$ of the actual probability π_{fbt}, that is,

$$\begin{aligned}
\hat{\pi}_{bft} &= Pr\left(\hat{\rho}^d \hat{r}_{bft} + \hat{\beta}^d X^d_t - \left(\hat{\rho}^s \hat{r}_{bft} + \hat{\beta}^s X^s_t\right) > \varepsilon^s_{bft} - \varepsilon^d_{bft}\right), \\
&= Pr\left(\hat{l}^d_{bft} - \hat{l}^s_{bft} > \varepsilon^s_{bft} - \varepsilon^d_{bft}\right),
\end{aligned}$$

which under the assumption of independently and normally distributed errors implies that

$$\hat{\pi}_{bft} = \Phi \left[\frac{\hat{l}^d_{bft} - \hat{l}^s_{bft}}{\sqrt{(\hat{\sigma}^d)^2 + (\hat{\sigma}^s)^2}} \right],$$

where Φ is the normal cumulative distribution function and $(\hat{\sigma}^d)^2$ and $(\hat{\sigma}^s)^2$ are the realized variances of the residuals of the demand and the supply equations, respectively.

Once we have $\hat{\pi}_{bft}$ we can analyze its distribution over time and across firms and banks. For example, Figure 3 reports the distribution of $\hat{\pi}_{bft}$ in different years. A credit rationing probability close to 1 ($\hat{\pi}_{bft} \approx 1$) means that the predicted demand for that particular transaction is considerably higher than the predicted supply while a credit rationing probability close to 0 ($\hat{\pi}_{bft} \approx 0$) means that the predicted demand is considerably lower than supply. The situation of equality between demand and supply corresponds to a probability of 50%, represented by the vertical bar at the $\hat{\pi}_{bft} = 50\%$ level. The distribution seems to tilt slightly towards the right, especially when the sovereign debt crisis hit the Italian economy in 2011. This evidence is consistent with the identification of "weak" credit rationing during the financial crisis.

5.1 Head counts of transactions and weighted measure

We propose two macroeconomic indicators of credit rationing. The first measure simply counts the number of observations that, for each period t, resulted to have a credit rationing probability $\hat{\pi}_{bft}$ above a threshold. In order to be conservative, we fix this threshold to 80%, so that in case $\hat{\pi}_{bft} > 0.80$ we are far away from the situation of perfect equality between demand and supply. The indicator can be computed as follows:

$$I^1_t = \% \text{ observations with } \pi_{bft} > 80\%_t \equiv \frac{\sum_{bf \in N_t} \mathbb{1}\left(\hat{\pi}_{bft} > 0.80\right)}{\#(N_t)}, \quad (9)$$

where $\mathbb{1}\left(\hat{\pi}_{bft} > 0.80\right)$ is an indicator function that takes value 1 if $\hat{\pi}_{bft} > 0.80$, N_t is the set of transactions at time t, and $\#(N_t)$ is the number of transactions at time t. This indicator is similar in the spirit to the indicators of supply conditions that can be drawn from survey data among firms or banks, where "net percentages" essentially reflect head counts.

A second indicator can be based on the quantity of rationed credit, namely on the percentage of credit demand that is satisfied by the supply at each point in time. Precisely, this measure weighs the excess demand at the bank-firm level with the probability that the same bank-firm match is rationed.

This indicator has the advantage of not relying on any arbitrary threshold for the selection of the rationed bank-firm relationships and provides a different perspective with respect to head counts-based measures. The indicator can be computed as follows:

$$I_t^2 = \text{Weighted credit rationing ratio}_t \equiv \frac{\sum_{bf\in N_t}\left(\hat{l}^d_{bft} - \hat{l}^s_{bft}\right)\hat{\pi}_{bft}}{\sum_{bf\in N_t}\hat{l}^d_{bft}}. \qquad (10)$$

In Figure 7 we compare the two credit rationing indicators. Not surprisingly, both measures reach the maximum values in the most acute phases of the global and the sovereign debt crises. The credit rationing measures jump from an average of 10% before the crisis (involving around 6% of the granted loans) to about 20% (10% by head count) in the global financial crisis and to about 17% (8% by head count) at the peak of the sovereign debt crisis.[36] Notice that the two measures may exhibit different levels and dynamics since they are related to different aspects of credit rationing. For example, there may be several small bank-firm transactions that are not rationed and a few large transactions that are rationed, which would result into a low level for I_t^1 but a high level for I_t^2.

5.2 Comparison with survey-based measures of credit rationing

We can construct measures of credit rationing that help the comparison with sources of soft information such as surveys across banks or firms. The main difference is that our measures are based on hard information and are not self-reported.

We first compute the percentage of firms that result to be rationed according to the definition of I_t^1. Since we can derive the firm-level probability of credit rationing as

$$\hat{\pi}_{ft} \equiv \frac{1}{\#(B_t(f))}\sum_{b\in B_t(f)} l_{bft}\hat{\pi}_{bft},$$

where $B_t(f)$ is the set of banks that lend to firm f at time t and $\#B_t(f)$ is the size of the set $B_t(f)$, the firm-level version of indicator I_t^1 is given by

$$I_t^{1F} = \%\text{ observations with } \hat{\pi}_{ft} > 80\%_t \equiv \frac{\sum_{f\in F_t}\mathbb{1}\left(\hat{\pi}_{ft} > 0.80\right)}{\#(F_t)},$$

[36]The pre-crisis level accounts also for "equilibrium" credit rationing due to informational frictions.

where $\mathbb{1}\left(\hat{\pi}_{ft} > 0.80\right)$ is an indicator function that takes value 1 if $\hat{\pi}_{ft} > 0.80$, F_t is the set of firms in period t, and $\#(F_t)$ is the number of firms at period t. The indicator I_t^{1F} counts the firms that resulted to be rationed according to our estimates. Hence, it is comparable in nature with survey-based indicators based on the number of firms that declare to be rationed.

Similarly, we can define the bank-level probability that a single bank rations its pool of borrowers as

$$\hat{\pi}_{bt} \equiv \frac{1}{\#(F_t(b))} \sum_{f \in F_t(b)} l_{bft} \hat{\pi}_{bft},$$

and, therefore, the bank-level version of indicator I_t^1 is given by

$$I_t^{1B} = \% \text{ observations with } \hat{\pi}_{bt} > 80\%_t \equiv \frac{\sum_{b \in B_t} \mathbb{1}\left(\hat{\pi}_{bt} > 0.80\right)}{\#(B_t)},$$

where $F_t(b)$ is the set of firms that borrow from bank b at time t, $\#(F_t(b))$ is the number of the firms in $F_t(b)$, B_t is the set of banks in period t, and $\#(B_t)$ is the number of banks in period t. The indicator I_t^{1B} counts the banks whose average transaction resulted to be rationed according to the 80% threshold. Hence, it is comparable in nature with survey-based indicators based on the number of banks that declare to have tightened their credit standards via quantitative restrictions.

In Figure 8 we report both the firm- and bank-level head-count-based indicators of credit rationing and compare them with our indicator based on bank-firm level information. This allows to give an assessment of the bias stemming from data aggregation.

Figure 9 compares our measure with the indicator stemming from the Istat's survey, which is available only since 2010. The dynamics of the two indicators are quite correlated during the sovereign debt crisis, albeit some differences arise in the first part of the sample period. The Istat's survey reports a peak of credit rationing in 2012, when the number of rationed firms reached 3.6%. The level of our measure in that year is 3.3%.

The percentage of rationing banks increases throughout the sample but reaches 1.1% only towards the end of the sample. This coincides with the evidence from the Bank Lending Survey for Italian banks, that reports a steady increase of credit rationing throughout the sample, with two acceleration in the most acute phases of the financial crisis. Figure 10 reports the comparison between our measure and BLS's, whose evolution is similar.

6 Robustness

6.1 Alternative estimation techniques

Table 4 reports the estimated coefficients of the benchmark model obtained with alternative econometric techniques. In column 1 we report the OLS estimates of demand and supply functions. The simple OLS regressions are able to capture qualitatively the correlations in the demand function but miss on identifying the supply function. The semi-elasticity on the supply for the OLS regression is positive, which is a clear signal of misspecification.

In column 2 we report the same estimates using separate IV regressions, where the first stage equation consists of the estimation of the interest rate equation. The semi-elasticity on the demand curve to the interest rate is three times that of the benchmark model. The semi-elasticity of the supply curve is positive but not significantly different from zero. The interbank exposure's and the Tier 1 capital ratio's coefficients are not significant either. The use of IV regressions therefore leads to the conclusion that the loan supply does not depend neither on the interest rate nor on bank-specific variables and is mostly related to borrowers' characteristics. The difference between IV and ML estimates is due exactly to potential non-price allocations of credit. Suppose that for certain transactions the demand is high and the supply is low, which means that the observed quantity is the result of supply determinants. The IV assigns to these observations the same weight in the estimation of the supply function that it assigns to observations most likely driven by demand determinants. Our model instead assigns to these observations more weight than observations driven by demand determinants. The IV estimates a supply equation treating in the same way observations that are structurally driven by demand factors and observations that are structurally driven by supply factors, thus mixing up direct effects on the supply with effects that pass through the interest rate.

6.2 Alternative specifications of the supply

We explore the role played by other variables that the recent empirical literature pointed out as important drivers of the credit supply. Table 5 summarizes the results.

First, we include the ratio of government bonds over total assets in both the interest rate equation and the supply equation. In a recent contribution, Bottero et al. (2015) show that the Italian banks' exposure to the sovereign debt significantly affected the supply of loans to non-financial firms. Moreover, government bonds may simply substitute corporate lending in banks' investment strategies. Banks' exposure to the sovereign risk significantly affected both the cost and the availability of credit. An increase of one percentage point in the ratio of government bonds over total assets leads to a -1.5% direct decrease in credit supply which remains as high as -1.2% once we take into account also its effect through the interest rate, as a 1-pp higher government bond ratio is associated with a 0.7-bp lower loan margin. However, its inclusion does not affect significantly our measures of non-price allocations of credit.

Second, we control for the role played by the Eurosystem refinancing operations. There is no doubt that these operations offset the liquidity risk in the most acute phases of the financial crisis and have been used by banks to substitute the drop in the wholesale funding. In the cross-section we find a high and negative correlation between banks' interbank exposure and their reliance to Eurosystem liquidity, which tend to offset one another when included simultaneously in our model. If we included the ratio of Eurosystem funding over banks' total assets in the supply function, we would not identify the effect of unconventional monetary policy. Given their complementarity we include in the model the sum of banks' interbank exposure and their use of the Eurosystem funding. Interestingly, this variable has no significant effect on credit supply, thus suggesting no role for banks' funding conditions in the evolution of credit rationing.[37]

Third, we check the role played by banks' profitability. We consider the ratio of bank profits over total assets. The profitability of banks seems to affect negatively the supply of credit, which may be a consequence of tighter and more selective lending standards. This interpretation is confirmed by the fact that higher profitability is associated also with higher rates, which makes it a standard supply shifter. The rest of the covariates are broadly unaffected, except for the access to the interbank funding, which becomes not statistically significant.

6.3 Alternative specifications of the demand

Our demand curve does not include a measure of firms' ex-ante investment decisions, which may be important in explaining the dynamics of term loans but is not observed. We can just consider firms' realized investments, as captured by the change in fixed assets, which is, however an ex-post measure of investment decisions. This raises a relevant problem of endogeneity

[37]It may be interesting to disentangle domestic and foreign components of banks' interbank exposure. The domestic net exposure has a negative effect on supply, while non-resident deposits do not have a significant impact on either the credit supply or the interest rate. We do not report these results for the sake of brevity.

since firms investment depend on their access to bank lending.[38] The use of the one-year lag that characterizes our firm-level information may help but cannot guarantee pure exogeneity. It is useful nonetheless to assess the robustness of the results by including in the demand curve investments as measured by the ratio of gross variation of fixed assets over total assets. The first column of Table 6 shows that investments enter significantly and with the expected sign but do not alter relevantly the rest of the coefficients. Moreover, the evolution of the credit rationing indicators is the same.

Our estimation relies on the joint determination of both terms of a credit contract, that is, quantities and prices. However, we also stress how crucial it is for our procedure to focus on the market for a single credit product such as the term loans to non-financial corporations by bank entities. Hence, it is important to check that our benchmark specification is effective even within a subsample of relevant characteristics that may describe a further segmentation of the market. Column (2) of Table 6 presents the same estimation within the subsample of uncollateralized short-term financing. In order to construct this subsample, we consider only transactions with a percentage of short-term amount above 50% but with a percentage of collateralized amount below 50%. In this way, we separate around half of the benchmark sample. Within this subsample, the estimated coefficients are not relevantly different from the benchmark, despite the absence by construction of two key determinants of demand and supply, that is, the maturity and the level of collateralization.

Another potential determinant of the demand for credit is credit availability from the other lenders. Firms that do not rely solely on one intermediary may be less rationed than single-lender firms and their demand for credit to a given intermediary could depend negatively on the number of additional counterparts. Hence, we include in the demand function the number of banks that each firm borrows from at each point in time and report the estimation results in the third column of Table 6. The transaction-specific demand for credit depends negatively on the number of additional lenders that a firm may have. The benchmark estimation and the indicators of credit rationing are, however, robust to the inclusion of this variable.

In Figure 11 we compare the credit rationing indicator for single-lender firms with that for multiple-lender firms. The intensity of credit rationing is persistently stronger for single-lender firms than for multiple-lender peers over the considered sample period. This finding points at the importance of including single-lender firms in our sample for the purpose of a more compre-

[38] See Cingano et al. (2013) for an event study on the effect of bank-lending shock on investment in Italy.

hensive estimation of credit rationing at the aggregate level. It also suggests that estimates based on the subsample of multiple-lender firms may provide a lower bound. It is important to note, however, that the credit rationing indicators are all based on the estimated coefficients of the benchmark model. In this regard, column (4) of Table 6 shows that estimated coefficients using only the subsample of multiple-lender firms are not remarkably different from the benchmark, with the exception of the semi-elasticity of supply to the interest rate.

6.4 Structural breaks

In the benchmark estimation we do not consider potential breaks in the estimated relationships over time. Hence, we reestimate the model by augmenting our benchmark specification with interaction terms between all demand and supply factors and year-specific dummies. The time-varying estimates highlight some intertemporal differences in the magnitudes for certain variables but qualitatively the benchmark model remains valid. In particular, the coefficient of the interbank exposure remains statistically significant only up until 2008. The global financial crisis seems to favor initially a pooling of the clientele with respect to their credit rating, with the difference between firms with an average rating and firms with a bad rating narrowing in 2009. However, average- and bad-rating firms diverge from good-rating firms from then on, reaching their joint maximum distance from zero at the end of the sample. Lastly, the indicators of credit rationing using the time-varying estimates do not change relevantly, and their evolution over time is virtually identical.

6.5 Bootstrap evidence

Our estimation imposes as little structure on the data as we deem necessary for the purpose of estimating a measure of credit rationing. Hence, our estimates are conditional upon our sample and in particular upon the distribution of characteristics across observations in our sample. Thus, we try to control for the biases that the composition of our sample may entail by considering a bootstrap procedure. In particular, we set-up a bootstrap for the maximum-likelihood estimation of our system of equations. The bootstrap estimates coincide in magnitude with our benchmark, and the statistical significance is substantially higher. Hence, our benchmark estimation appears to be robust to variations in the composition of our sample, at least to the extent that such variations are random.

6.6 Clustering schemes

The richness of our dataset implies that there are several potential dimensions of correlation in the estimated residuals. Hence, we make sure that the significance of our estimated coefficients do not depend on the clustering structure we adopt in the benchmark specification. In particular, we check clusters by firms' sector, by banks' type, by time, and three-way clustering by firms' sector, banks' type, and time. Finally, we also check the case of no clustering. The statistical significance of the estimated coefficients is robust to the adoption of the clustering scheme.

7 Conclusion

Largely due to the use of reduced-form specifications, empirical models of the credit market do not discriminate situations in which the supply restriction takes place through an increase in the cost of credit from situations of credit rationing, i.e., a condition characterized by excess demand over supply. Episodes of credit rationing may be due to higher banks' risk aversion, severe asymmetric information problems between lenders and borrowers, as well as significant banks' balance-sheet constraints.

Our contribution to the literature lies in meeting this identification challenge and in providing estimates of non-price allocation of credit. We use an unexplored and high-quality dataset comprising about 5 million observations by merging bank-firm information about the quantity and the cost of credit, available in the Italian Credit Register. We use maximum likelihood methods to estimate a model for the market of term loans, in which we control for a number of bank- and firm-specific characteristics. The model endogenously identifies all the rationed bank-firm relationships and provides measures of credit rationing at the aggregate level.

As for the dynamics of the market of term loans, we find some important results. Credit rationing is mostly explained by lenders' exposure to raising non-performing loans and borrowers' ability to provide collateral against bank loans. Other characteristics like the ex-ante credit risk contribute to the evolution of credit rationing, thus confirming a major role played by information asymmetries among banks and firms. Moreover, banks switched their supply of funds in favor of firms with a higher creditworthiness after the breakout of the sovereign debt crisis. Banks' funding conditions deteriorated significantly in the most acute phases of the financial crisis but do not seem to have induced strong restrictions in the availability of lending.

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A Appendix: Estimation method

Our maximum likelihood estimation method is based on Maddala and Nelson (1974). Our system of equations consists of a demand equation

$$l^d_{bft} = \rho^d \hat{r}_{bft} + \beta^d X^d_t + \varepsilon^d_{bft}, \tag{11}$$

a supply equation

$$l^s_{bft} = \rho^s \hat{r}_{bft} + \beta^s X^s_t + \varepsilon^s_{bft}, \tag{12}$$

and the measurement equation from 1,

$$l_{bft} = \min\{l^d_{bft}, l^s_{bft}\}.$$

The errors ε^d_{bft} and ε^s_{bft} have zero mean and variance σ_d and σ_s, respectively. We say that an observation fbt of a given loan *belongs* to the supply equation if the observation-specific demand l^d_{bft} is higher than the supply l^s_{bft}. Then, the probability π_{bft} that a given observation belongs to the supply function is

$$\begin{aligned}\pi_{bft} &\equiv Pr\left(l^d_{bft} > l^s_{bft}\right)\\ &= Pr\left(\rho^d\hat{r}_{bft} + \beta^d X^d_t - \rho^s\hat{r}_{bft} - \beta^s X^s_t > \varepsilon^s_{bft} - \varepsilon^d_{bft}\right),\end{aligned}$$

which under the assumption that the error terms ε^d_{bft} and ε^s_{bft} are independently and normally distributed becomes

$$\pi_{bft} = \int_{\left(\rho^d\hat{r}_{bft}+\beta^d X^d_t-\rho^s\hat{r}_{bft}-\beta^s X^s_t\right)/\sigma}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right)\mathrm{d}u,$$

where σ is the standard deviation of the difference $\varepsilon^s_{bft}-\varepsilon^d_{bft}$ of the error terms. Since the errors are independently and normally distributed, $\sigma^2 = \sigma^2_d + \sigma^2_s$. We can rewrite π_{bft} as

$$\pi_{bft} = \int_{-\infty}^{\infty} f_s(l_{bft})F_d(l_{bft})\mathrm{d}l_{bft},$$

where

$$f_s(l_{bft}) \equiv \frac{1}{\sqrt{2\pi}\sigma_s}\exp\left[\frac{-1}{2\sigma^2_s}\left(l_{bft} - \rho^s\hat{r}_{bft} - \beta^s X^s_t\right)^2\right] \tag{13}$$

and

$$F_d(l_{bft}) \equiv \int_{l^d_{bft}}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_d}\exp\left[\frac{-1}{2\sigma^2_d}\left(L^d - \rho^d\hat{r}_{bft} - \beta^d X^d_t\right)^2\right]\mathrm{d}L^d. \tag{14}$$

In this way, we can define the density of l_{bft} conditional on the observation bft belonging to the supply equation, that is, $l_{bft} = l^s_{bft}$, as

$$\frac{Pr\left(l^d_{bft} > l_{bft}\right)}{Pr\left(l^d_{bft} > l^s_{bft}\right)} = \frac{f_s(l_{bft})F_d(l_{bft})}{\pi_{bft}}.$$

If instead the observation bft belongs to the demand equation, its conditional density is

$$\frac{Pr\left(l_{bft} < l^s_{bft}\right)}{Pr\left(l^d_{bft} < l^s_{bft}\right)} = \frac{f_d(l_{bft})F_s(l_{bft})}{1-\pi_{bft}},$$

where

$$f_d(l_{bft}) \equiv \frac{1}{\sqrt{2\pi}\sigma_d} \exp\left[\frac{-1}{2\sigma_s^2}\left(l_{bft} - \rho^d \hat{r}_{bft} - \beta^d X_t^d\right)^2\right] \tag{15}$$

and

$$F_s(l_{bft}) \equiv \int_{l_{bft}^s}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left[\frac{-1}{2\sigma_s^2}\left(L^s - \rho^s \hat{r}_{bft} - \beta^s X_t^s\right)^2\right] \mathrm{d}L^s. \tag{16}$$

Since the observation l_{bt} belongs with probability π_t to the supply equation and with probability $1 - \pi_t$ to the demand equation, we can derive the unconditional density of l_{bft} given $\hat{r}_{bft}$, X_t^d, and X_t^s, that is,

$$\begin{aligned} h(l_{bft}) &= (1 - \pi_{bft})\frac{f_d(l_{bft})F_s(l_{bft})}{1 - \pi_{bft}} + \pi_{bft}\frac{f_s(l_{bft})F_d(l_{bft})}{\pi_{bft}} \\ &= f_d(l_{bft})F_s(l_{bft}) + f_s(l_{bft})F_d(l_{bft}). \end{aligned} \tag{17}$$

Hence, the log-likelihood L of the system is

$$L = \sum_{bft} \log f_d(l_{bft})F_s(l_{bft}) + f_s(l_{bft})F_d(l_{bft}),$$

whose maximum we compute in full-information. See Maddala and Nelson (1974) for details.

B Appendix: Data

The data on loan quantities are monthly and come from the Italian CR, which covers the universe of all banks operating in Italy. We consider the granted amounts of term loans to firms operating in the industry sector (i.e., manufacturing and construction), which represents more than 60% of total granted term loans to non-financial firms. There exists a reporting thresholds at €75,000 (€30,000 from 2009) for the quantity of credit in the CR. However, this threshold does not impact the sample as much as we may expect. In fact, this threshold refers to the overall exposition of a borrower towards an intermediary. Hence, if a firm has two loans of €20,000 each with the same bank, that firm appears in our sample with the two loans. We can find almost 1.3 million observations below the €75,000 threshold and 0.5 million observations below the €30,000 threshold, with no noticeable change of this sample over time and specifically not around the change in threshold for the CR data between 2008 and 2009. Moreover, there is no bunching of observations around the threshold, which lies on the far left tail of the observed distribution in any period of time.

The data on loan interest rates come from the TAXIA database, which is a sub-sample of the CR reported at quarterly frequency for a large representative sample of intermediaries (about 200 Italian banks and 10 branches and subsidiaries of foreign banks). We compute the annual percentage rate of interest for each loan on the basis of the actual interests paid by firms. For consistency with the credit quantity variable, we consider the observed interest rates net of fees and commissions, since these may be at least partly charged on the actual drawn amounts. To merge loan interest rate and quantities, we consider the end-of-quarter outstanding amounts from the monthly CR database.

The firm-level data X_{ft} come from the Company Accounts Data Service (CADS) managed by the Cerved Group, which is one of the largest sources of balance sheet data on Italian firms and covers about $700,000$ firms per year, of which over $160,000$ operate in the industry sector. The bank-level data X_{bt} come from the Supervisory Reports on banks' balance sheets submitted by each individual bank to the Bank of Italy. In order to construct banks' consolidated balance sheets, we carefully manage merges and acquisitions among banks. The two banks involved in each merge operation are considered as separate entities until the effective date of the operation and as a new single one afterwards. At the same time, if a firm has a relationship with a specific bank and this bank disappears from the database because of a merge or an acquisition by another intermediary, we can track whether there is a new relationship with the newly formed bank or with the acquirer. In this case we consider the relationship as a new one since both the characteristics of the "new" bank and its business model can be very different from the previous ones. Hence, we collapse all bank-firm matches at the banking group level.

C Appendix: Tables

Table 1: Variable description and summary statistics.

Variable	**Unit**	**Definition**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Loan quantity$_{bft}$	log(EUR)	Log of granted credit	12.291	1.625	0	20.834
Loan margin$_{bft}$	%	Spread between loan rate and EONA rate	2.921	1.896	-4.253	25.100
Firm assets$_{ft}$	log(000 EUR)	Log of firm's total assets	8.184	1.443	4.927	11.546
Cash-flow/Sales$_{ft}$	%	Firm's ratio of cash-flow over total sales	2.438	20.673	-326.923	56.944
Trade debt/Assets$_{ft}$	%	Firm's ratio of trade debt to total assets	23.235	16.979	0	80.088
Average rating$_{ft}$	0/1	1 if firm's rating is between 4 and 6	0.598	0.490	0	1
Bad rating$_{ft}$	0/1	1 if firm's rating is between 7 and 9	0.303	0.460	0	1
Sector$_{f}$	Cat.	Firm's sector	-	-	1	22
Macroarea$_{f}$	Cat.	Firm's macroarea	-	-	1	3
Bad loans/Loans$_{bt}$	%	Bank's ratio of bad loans over total loans	5.642	3.846	0.369	41.080
Interbank/Assets$_{bt}$	%	Bank's ratio of interbank exposure to total assets	8.144	7.372	0	57.926
Tier 1 capital$_{bt}$	%	Bank's Tier 1 capital ratio	13.566	4.927	0	61.567
Collateralization$_{bft}$	%	Percentage of loan which is collateralized	28.274	43.340	0	100
Short maturity$_{bft}$	%	Percentage of loan with maturity less than 12 months	22.291	37.984	0	100
Bank$_{b}$	Cat.	Bank's ID	-	-	1	120
Quarter$_{t}$	Cat.	Quarter	-	-	2006Q1	2015Q2

Notes: All variables have 5231134 non-missing observations. The firm index f ranges from 1 to 165878. The bank index b ranges from 1 to 120. The time index t ranges from 2006Q1 to 2015Q2 for a total of 38 quarters.

Table 2: Benchmark model

	(1) Interest rate equation	(2) Demand equation	(3) Supply equation
Dependent variable	Loan margin	Loan quantity	Loan quantity
Loan margin		-0.290 ***	0.478 ***
		(0.043)	(0.091)
Cash-flow/Sales	0.000	-0.003 ***	
	(0.000)	(0.000)	
Trade debt/Assets	0.002 **	-0.010 ***	
	(0.001)	(0.001)	
Average rating	0.327 ***		-0.187 ***
	(0.013)		(0.025)
Bad rating	0.678 ***		-0.515 ***
	(0.026)		(0.051)
Bad loans/Loans	0.024 ***		-0.027 ***
	(0.005)		(0.003)
Interbank/Assets	-0.017 ***		0.004 *
	(0.003)		(0.002)
Tier 1 capital	-0.013 ***		0.010 ***
	(0.003)		(0.002)
Collateralization	-0.003 ***		0.024 ***
	(0.000)		(0.001)
Short maturity	0.007 ***	-0.001	
	(0.000)	(0.001)	
Firm assets	-0.246 ***	0.711 ***	0.749 ***
	(0.008)	(0.020)	(0.030)
Pseudo R-squared	0.275		
Log-likelihood		-7848774.3	-7848774.3
Observations	5231134	5231134	5231134

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. $*$, $**$ and $***$ denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

Table 3: Alternative treatment of the loan margin

	Excluded from supply equation (1)	**Endogenous loan margin (2)**
Demand equation		
Loan margin	-0.262 ***	-0.070 ***
	(0.039)	(0.009)
Cash-flow/Sales	-0.003 ***	-0.003 ***
	(0.000)	(0.000)
Trade debt/Assets	-0.010 ***	-0.010 ***
	(0.001)	(0.001)
Short maturity	0.001	0.000
	(0.001)	(0.000)
Firm assets	0.717 ***	0.764 ***
	(0.020)	(0.017)
Supply equation		
Loan margin		-0.118 ***
		(0.006)
Average rating	-0.033	-0.033
	(0.028)	(0.031)
Bad rating	-0.199 ***	-0.197 ***
	(0.039)	(0.045)
Bad loans/Loans	-0.016 ***	-0.015 ***
	(0.003)	(0.004)
Interbank/Assets	-0.003 **	-0.003 *
	(0.001)	(0.001)
Collateralization	0.022 ***	0.022 ***
	(0.001)	(0.001)
Tier 1 capital	0.004	0.004 *
	(0.002)	(0.002)
Firm assets	0.642 ***	0.618 ***
	(0.023)	(0.022)
Log-likelihood	-7852057	-7799702.9
Observations	5231134	5231134

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. $*$, $**$ and $***$ denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

Table 4: Benchmark model: alternative estimation techniques

	OLS estimation		**IV estimation**	
	Demand equation	**Supply equation**	**Demand equation**	**Supply equation**
	(1)		**(2)**	
Loan margin	-0.119 ***	-0.100 ***	-0.935 ***	0.004
	(0.004)	(0.005)	(0.066)	(0.052)
Cash-flow/Sales	-0.002 ***		-0.004 ***	
	(0.000)		(0.001)	
Trade debt/Assets	-0.009 ***		-0.006 ***	
	(0.001)		(0.001)	
Average rating		-0.016		-0.054 *
		(0.015)		(0.024)
Bad rating		-0.111 ***		-0.186 ***
		(0.019)		(0.033)
Bad loans/Loans		-0.008 ***		-0.011 ***
		(0.002)		(0.003)
Interbank/Assets		-0.001 *		0.000
		(0.001)		(0.001)
Tier 1 capital		0.002 *		0.004
		(0.001)		(0.003)
Collateralization		0.011 ***		0.012 ***
		(0.000)		(0.001)
Short maturity	-0.002 ***		0.004 ***	
	(0.000)		(0.001)	
Firm assets	0.684 ***	0.677 ***	0.473 ***	0.701 ***
	(0.013)	(0.013)	(0.024)	(0.036)
Observations	5231134	5231134	5231134	5231134

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. $*$, $**$ and $***$ denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

Table 5: Robustness. Alternative specification of the supply

	Government bonds (1)	**Eurosystem liquidity (2)**	**Bank profits (3)**
Demand equation			
Loan margin	-0.295 ***	-0.294 ***	-0.308 ***
	(0.044)	(0.044)	(0.046)
Cash-flow/Sales	-0.003 ***	-0.003 ***	-0.003 ***
	(0.000)	(0.000)	(0.000)
Trade debt/Assets	-0.010 ***	-0.010 ***	-0.010 ***
	(0.001)	(0.001)	(0.001)
Short maturity	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Firm assets	0.710 ***	0.710 ***	0.708 ***
	(0.020)	(0.020)	(0.020)
Supply equation			
Loan margin	0.479 ***	0.479 ***	0.474 ***
	(0.091)	(0.092)	(0.092)
Average rating	-0.185 ***	-0.186 ***	-0.183 ***
	(0.025)	(0.025)	(0.025)
Bad rating	-0.513 ***	-0.514 ***	-0.510 ***
	(0.051)	(0.051)	(0.051)
Bad loans/Loans	-0.024 ***	-0.028 ***	-0.025 ***
	(0.003)	(0.003)	(0.004)
Interbank/Assets	0.005 *		0.000
	(0.002)		(0.002)
Interbank+Eurosystem/Assets		0.000	
		(0.002)	
Bank profits/Assets			-0.041 *
			(0.018)
Tier 1 capital	0.009 ***	0.009 ***	0.007 ***
	(0.002)	(0.002)	(0.002)
Government bonds/Assets	-0.016 ***		
	(0.002)		
Collateralization	0.024 ***	0.024 ***	0.024 ***
	(0.001)	(0.001)	(0.001)
Firm assets	0.750 ***	0.749 ***	0.758 ***
	(0.030)	(0.030)	(0.030)
Log-likelihood	-7848026.5	-7848814.7	-7593123.6
Observations	5231134	5231134	5063414

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. $*$, $**$ and $***$ denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

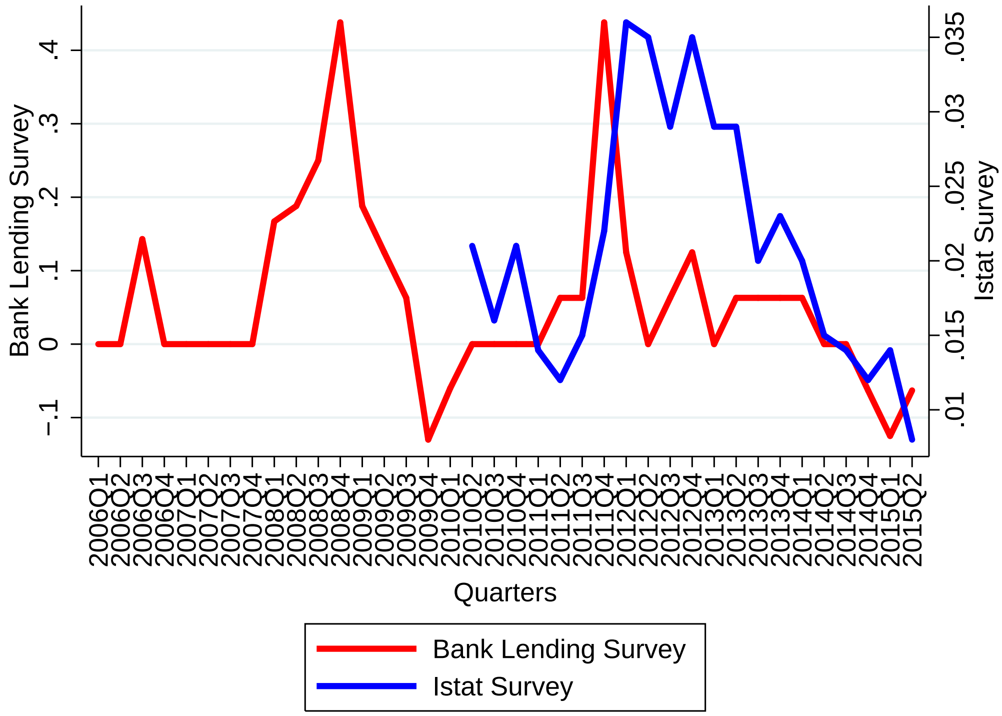
Table 6: Robustness. Alternative specifications of the demand

	Fixed investment (1)		**Short term uncollateralized (2)**		**# lenders (3)**		**Multiple lender data (4)**	
Demand								
Loan margin	-0.314	***	-0.234	***	-0.221	***	-0.397	***
	(0.038)		(0.037)		(0.043)		(0.038)	
Cash-flow/Sales	-0.003	***	-0.003	***	-0.003	***	-0.003	***
	(0.000)		(0.000)		(0.000)		(0.000)	
Trade debt/Assets	-0.009	***	-0.010	***	-0.010	***	-0.008	***
	(0.001)		(0.001)		(0.001)		(0.001)	
Investment/Assets	0.391	***						
	(0.093)							
# bank counterparts					-0.086	***	-0.058	***
					(0.012)		(0.007)	
Short maturity	-0.001				-0.002	*	-0.003	***
	(0.001)				(0.001)		(0.001)	
Firm assets	0.709	***	0.575	***	0.800	***	0.796	***
	(0.019)		(0.024)		(0.023)		(0.016)	
Supply								
Loan margin	0.484	***	0.472	*	0.510	***	0.913	***
	(0.094)		(0.187)		(0.088)		(0.133)	
Average rating	-0.189	***	-0.229	***	-0.140	***	-0.362	***
	(0.025)		(0.057)		(0.027)		(0.046)	
Bad rating	-0.534	***	-0.439	***	-0.500	***	-0.888	***
	(0.052)		(0.110)		(0.053)		(0.087)	
Bad loans/Loans	-0.027	***	-0.027	***	-0.029	***	-0.036	***
	(0.003)		(0.006)		(0.003)		(0.004)	
Interbank/Assets	0.004	*	0.012	*	0.006	**	0.010	***
	(0.002)		(0.005)		(0.002)		(0.002)	
Tier 1 capital	0.009	***	0.013	**	0.024	***	0.015	***
	(0.002)		(0.005)		(0.001)		(0.002)	
Collateralization	0.024	***		0.011	***	0.023	***	
	(0.001)			(0.002)		(0.001)		
Firm assets	0.760	***	0.937	***	0.761	***	0.929	***
	(0.030)		(0.051)		(0.031)		(0.039)	
Log-likelihood	-7557150.9		-4039593.7		-7825697.9		-5010810.3	
Observations	5042664		2629670		5231134		3359951	

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. $*$, $**$ and $***$ denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

D Appendix: Figures

Figure 1: Indicators on weak credit rationing in Italy: evidence from business and bank surveys.



Notes: The Istat's survey is the "Business confidence survey conducted in the manufacturing sector". The indicator refers to the net percentage of firms that reported to have received a lower-than-asked amount of credit. The Bank Lending Survey is conducted among banking groups. The indicator refers to the net percentage of banks that reported a tightening/easing of their terms and conditions via a change in the "size of the loan or credit line" with respect to the previous quarters.

Figure 2: Representativeness of the sample: evolution of aggregate granted credit (in billions of euros).

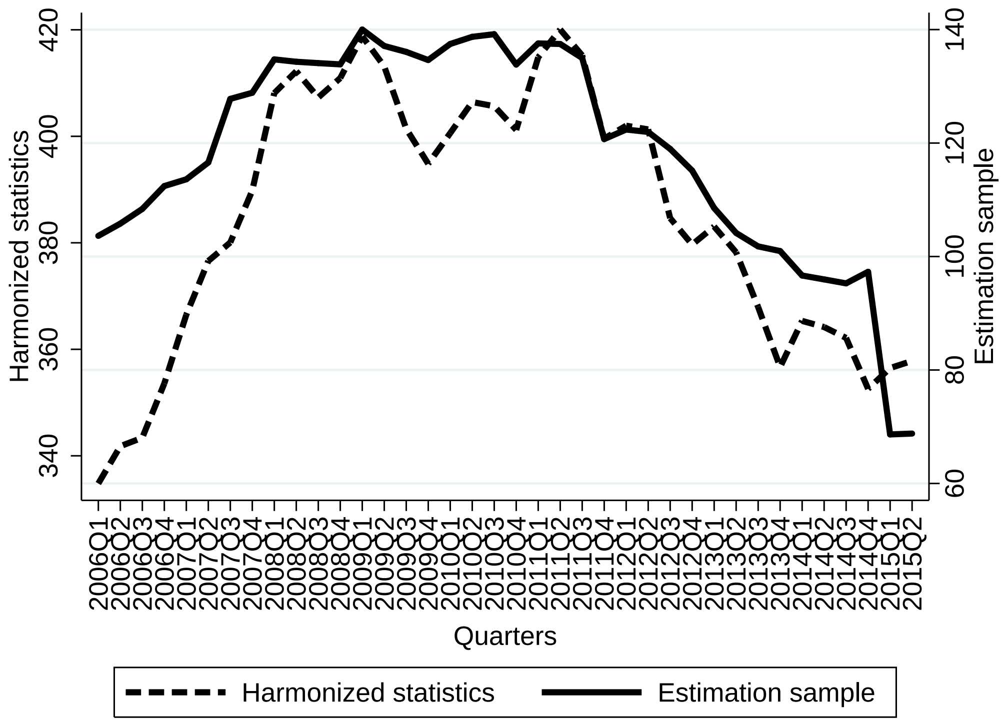
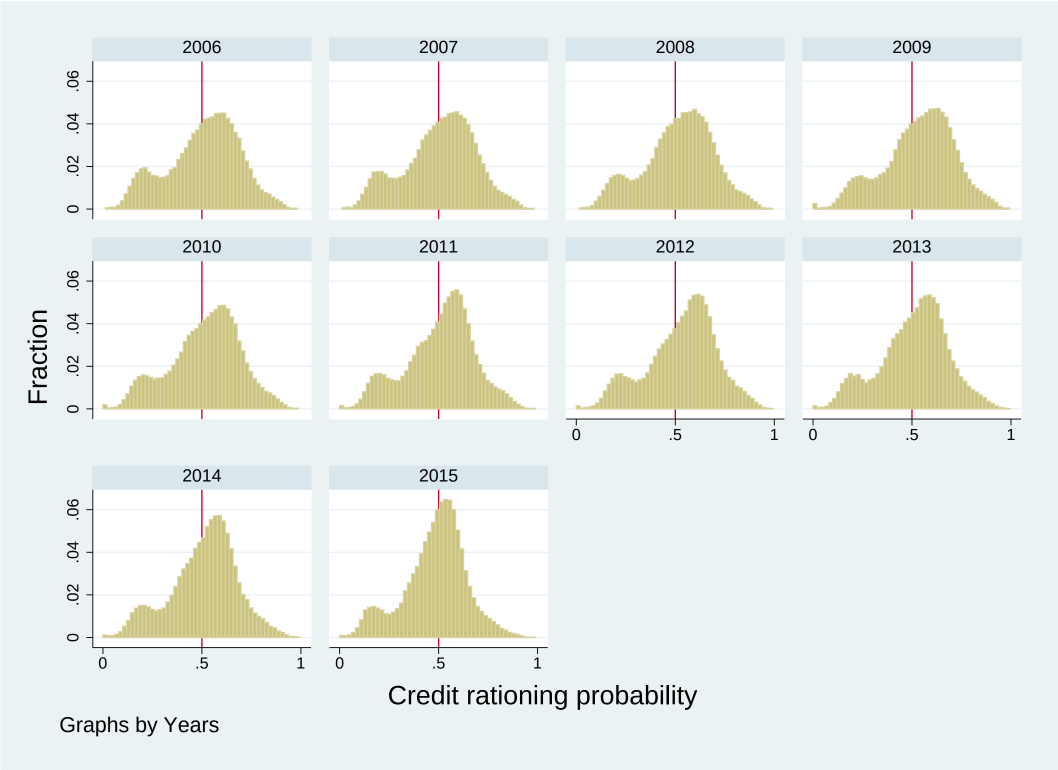


Figure 3: Distribution of match-level credit rationing probability $\hat{\pi}_{bft}$ over time.



Notes: We report the distribution conditional on the first quarter of each year. The vertical line corresponds to $\hat{\pi}_{bft} = 50\%$.

Figure 4: Evolution of aggregate predicted demand and aggregate predicted supply.

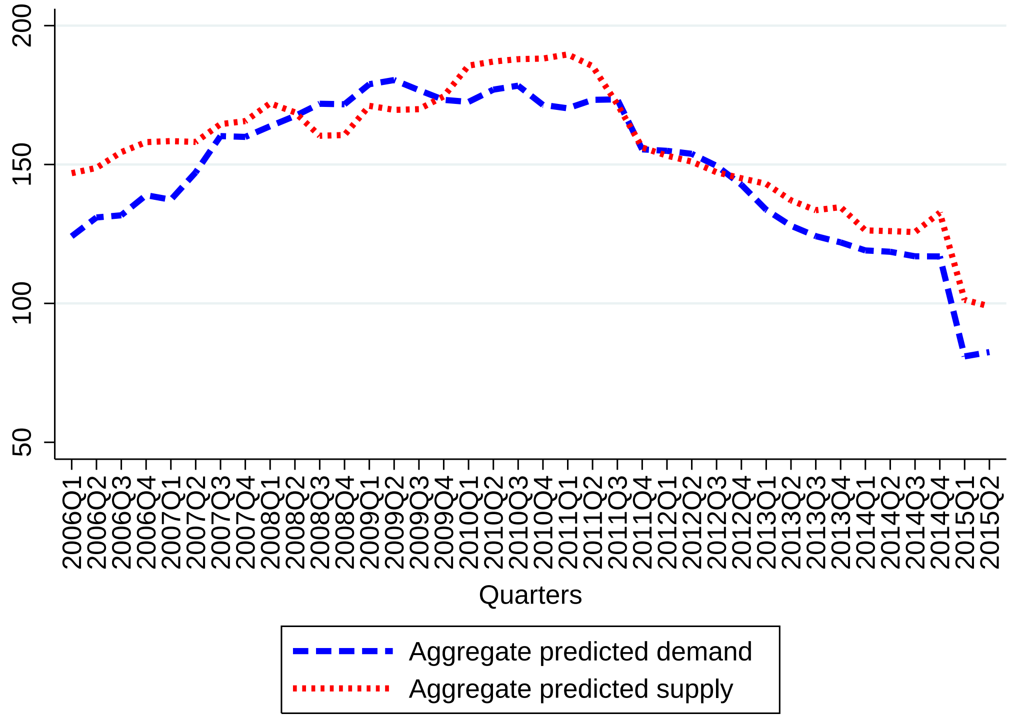
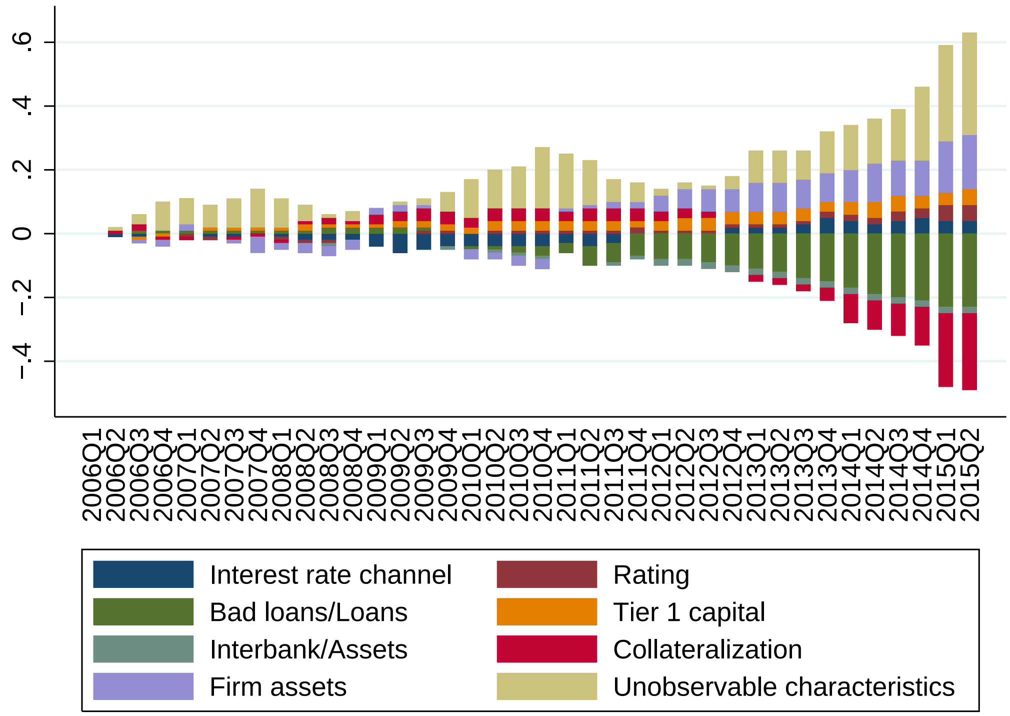
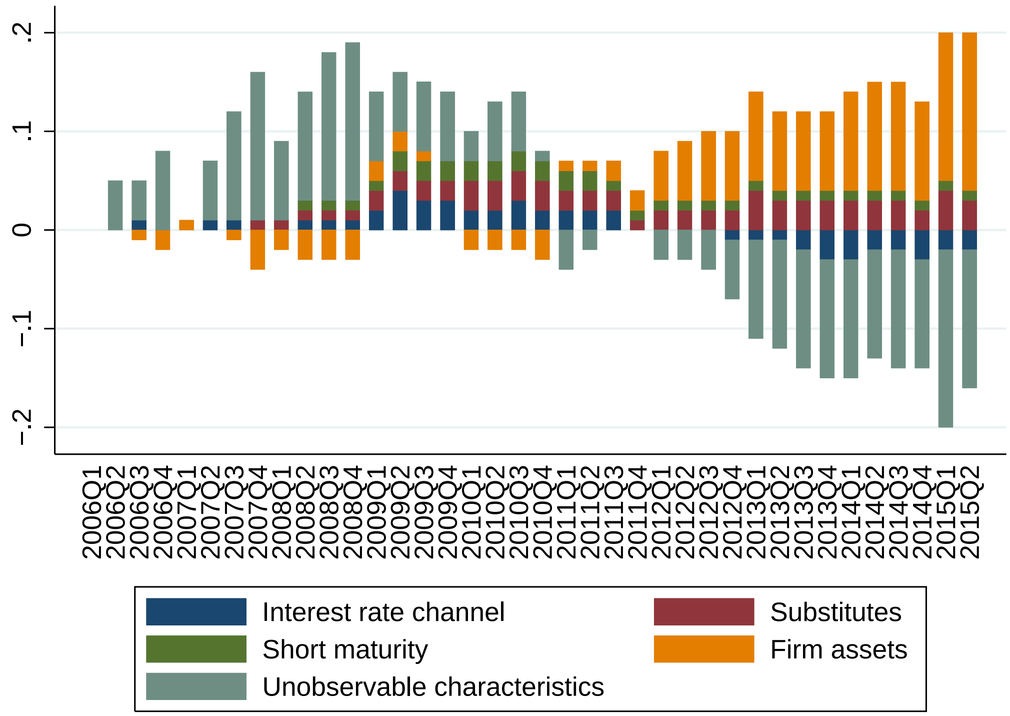


Figure 5: Decomposition of aggregate predicted supply.



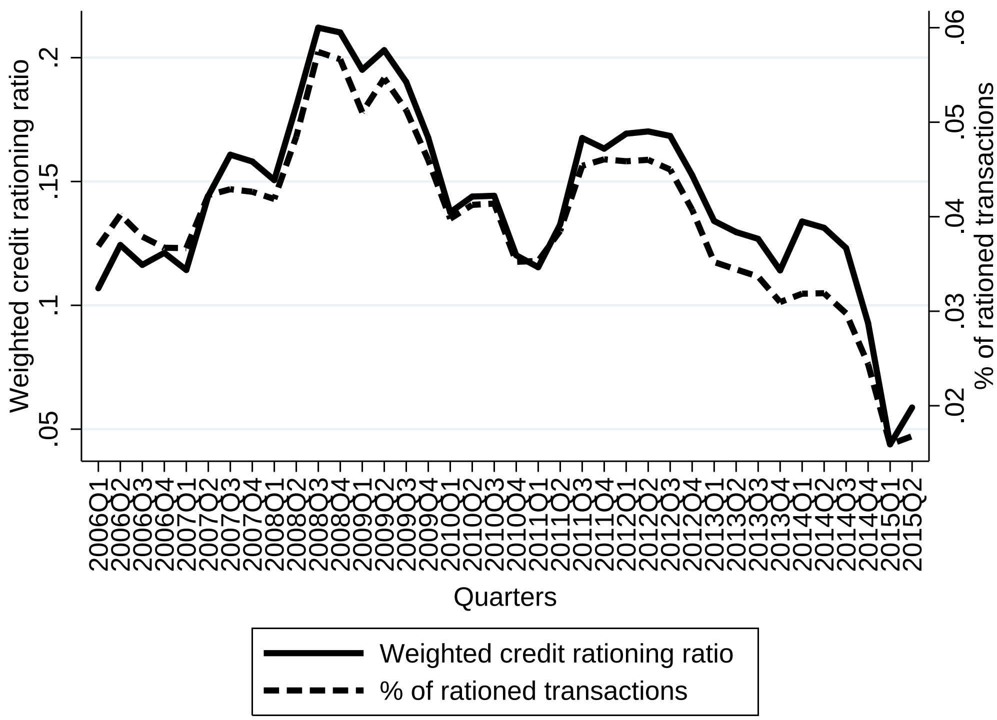
Notes: We report the estimated contribution of our observable and unobservable variables to the dynamics of the estimated aggregate supply. The ”interest rate channel” inlcude the estimated effects of all observable variables that enter the loan margin equation. The ”unobservable characteristics” comprise the effects of all specific fixed effects included in the model.

Figure 6: Decomposition of aggregate predicted demand.



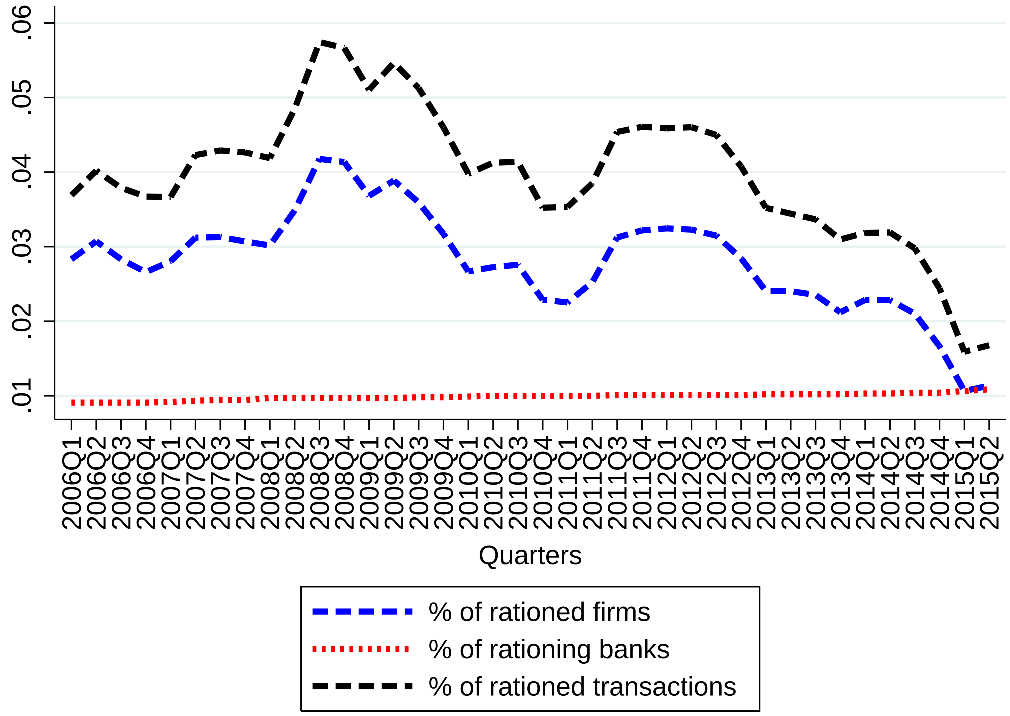
Notes: We report the estimated contribution of our observable and unobservable variables to the dynamics of the estimated aggregate demand. The "interest rate channel" inlcude the estimated effects of all observable variables that enter the loan margin equation. The "unobservable characteristics" comprise the effects of all specific fixed effects included in the model. The "substitutes" comprise the effects of the firm-specific variables that are substitutes for bank lending, namely the ratio of cash-flow over total sales and the ratio of trade debt to total assets.

Figure 7: Evolution of the credit rationing indicators.



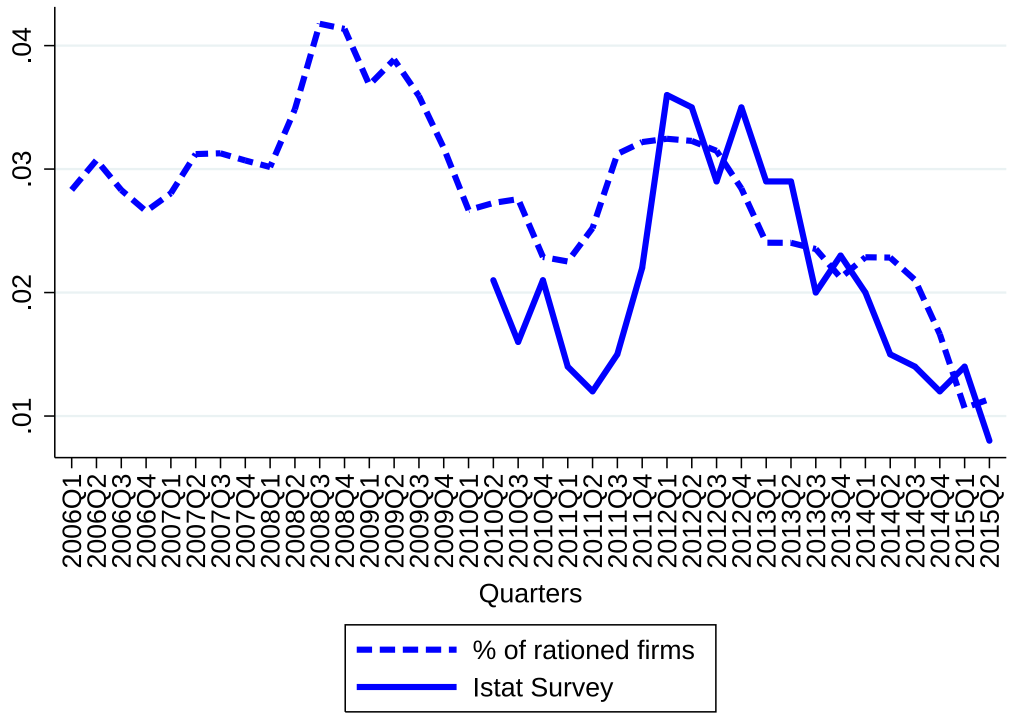
Notes: We report on the left axis the indicator I_t^1, which measures the percentage of transactions in each period that have a predicted probability $\hat{\pi}_{bft}$ of being rationed above 80%. We report on the right axis the indicator I_t^2, which measures the amount of credit rationing as a percentage of aggregate demand. In the latter case each transaction-level excess demand, $\hat{l}^d_{bft} - \hat{l}^s_{bft}$, is weighted according to the predicted probability of being rationed.

Figure 8: Evolution of alternative credit rationing indicators.



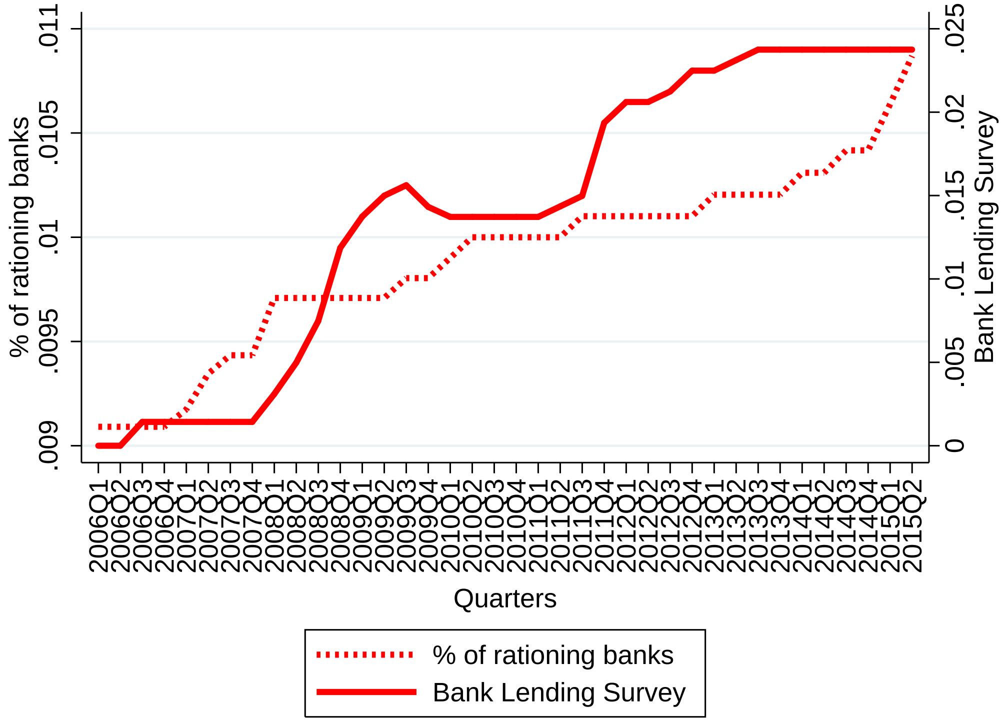
Notes: We report the percentage I_t^1 of rationed transactions(dashed black), the percentage I_t^{1F} of rationed firms (dashed blue), and the percentage I_t^{1B} of rationing banks (short-dashed red). We classify a firm as rationed if the weighted average across all its transactions of the probability $\hat{\pi}_{bft}$ of credit rationing is above 80%. We classify a bank as rationing in the same way.

Figure 9: Comparison between our firm-level credit rationing, I_t^{1F}, and Istat's survey.



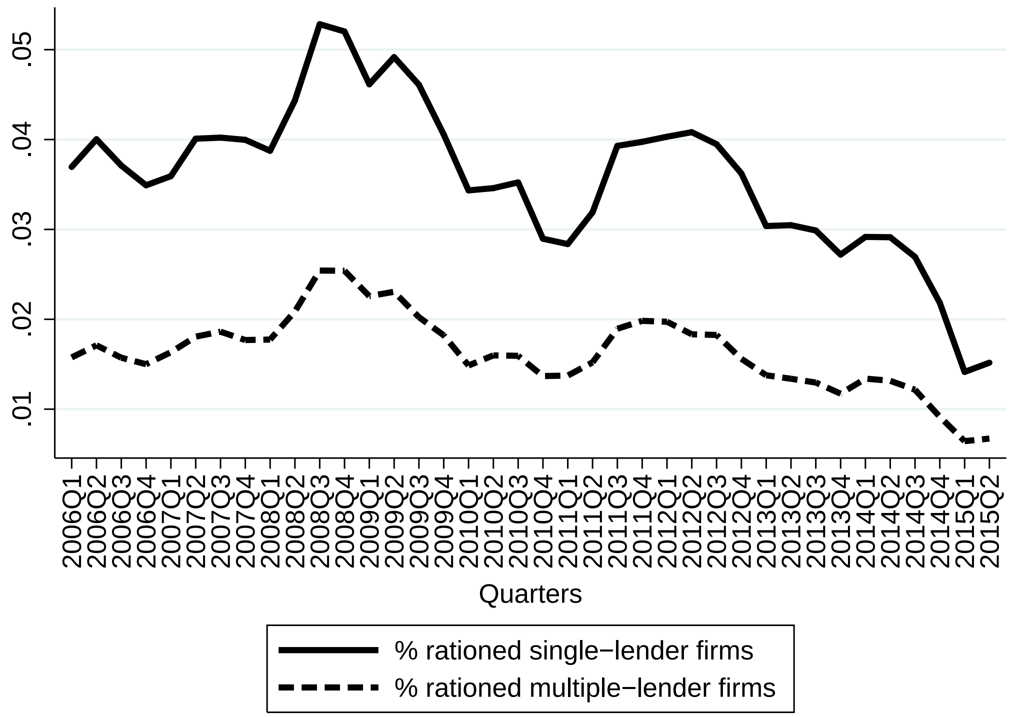
Notes: The Istat's survey is the "Business confidence survey conducted in the manufacturing sector". The indicator refers to the net percentage of firms that reported to have received a lower-than-asked amount of credit.

Figure 10: Comparison between our measure I_t^{1B} of bank-level credit rationing and the Bank Lending Survey.



Notes: The Bank Lending Survey provides the net percentage of banks that report a tightening or easing of their terms and conditions by a change in the size of the loan or credit line with respect to the previous quarters. For comparison purposes with our indicator in levels we take 2006Q1 as the base quarter and cumulate the net percentages.

Figure 11: Credit rationing indicators: single- vs. multiple-lender firms.



Notes: We report the percentage I_t^{1F} of rationed firms for the subsamples of single-lender and multiple-lender firms. Estimates are based on the benchmark model.

Online appendix

Structural breaks

In the benchmark estimation we implicitly assume that the average operator on both sides of the market for term loans does not modify its behavior over time. However, since in our sample two major economic crises occurred, it is natural to wonder whether the relations that we explore in our benchmark model do not evolve in response to changes in the regulatory framework or to shifts in the medium-to-long-term growth prospects of the economy. Hence, from Figure 12 to Figure 19 we report the estimates obtained by augmenting our benchmark specification with interactions with year dummies. We limit the interactions to key observable covariates and use 2006 as the base year. Our model consists again of an interest rate equation and a system of demand and supply equations, where we include year interactions for interest rate, firm assets, bank lending substitutes, rating dummies, interbank exposure, Tier 1 capital ratio, non performing loans over loans, maturity, and collateralization.

The bands in each subgraph of Figures 12 to 19 correspond to the confidence intervals of the coefficients associated with each variable and its interaction with the year dummies. We do not report the estimates for the interest rate equation and focus only on the direct estimates for the demand and supply function. The time-varying estimates highlight important intertemporal differences in the magnitudes for certain variables but qualitatively the model remains valid. We observe important variations in the interbank exposure, whose coefficient remains significantly different from zero only up until 2008. The capital position matters only at the beginning and at the end of the sample, although the central estimates never reach zero. The coefficient on the ratio of bad loans over loans behaves similarly, with a significance that lasts up until 2011. The global financial crisis seems to favor initially a pooling of the clientele with respect to their credit rating, with the difference between firms with an average rating and firms with a bad rating narrowing in 2009. However, average- and bad-rating firms diverge from good-rating firms from then on, reaching their joint maximum distance from zero at the end of the sample. The maturity of debt plays a role mainly before the crisis, and guarantees on loans remain a significant determinant of supply throughout the sample. The results for substitutes to bank lending are consistent with the benchmark estimation.

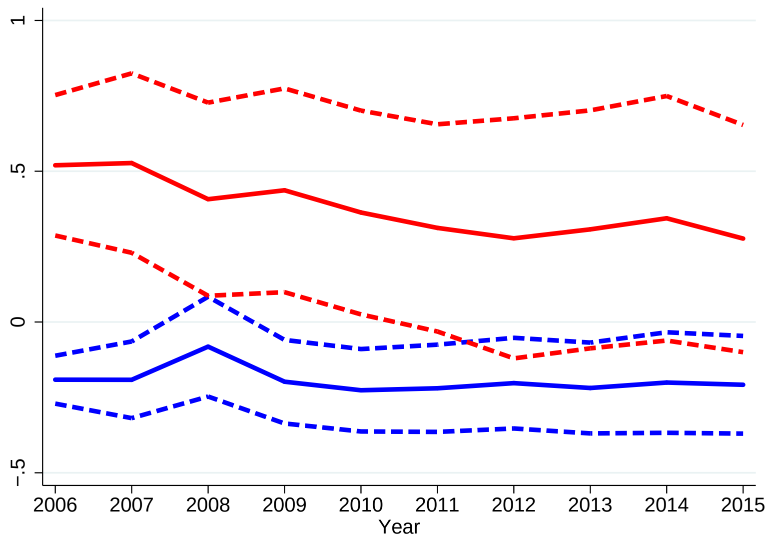


Figure 12: Time varying estimates for the predicted loan margin on the demand (in solid blue) and on the supply (in solid red). Dashed lines indicate the 95% confidence interval of the estimates for each year.

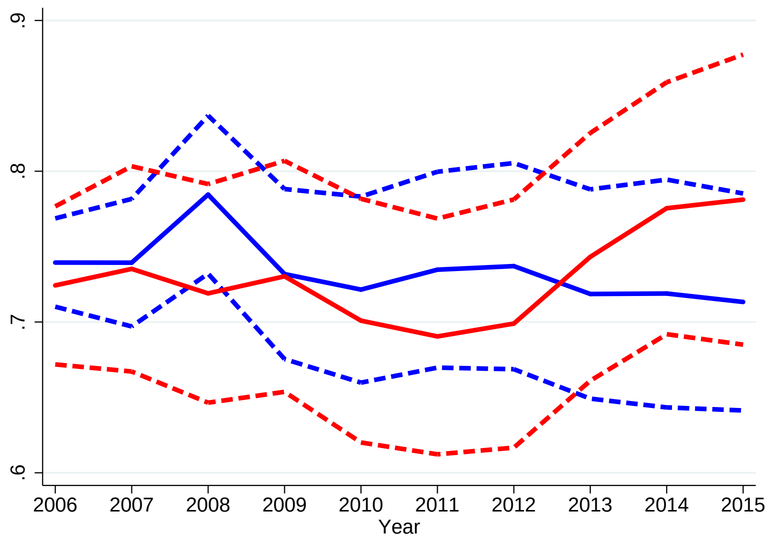


Figure 13: Time varying estimates for firms' assets on the demand (in solid blue) and on the supply (in solid red). Dashed lines indicate the 95% confidence interval of the estimates for each year.

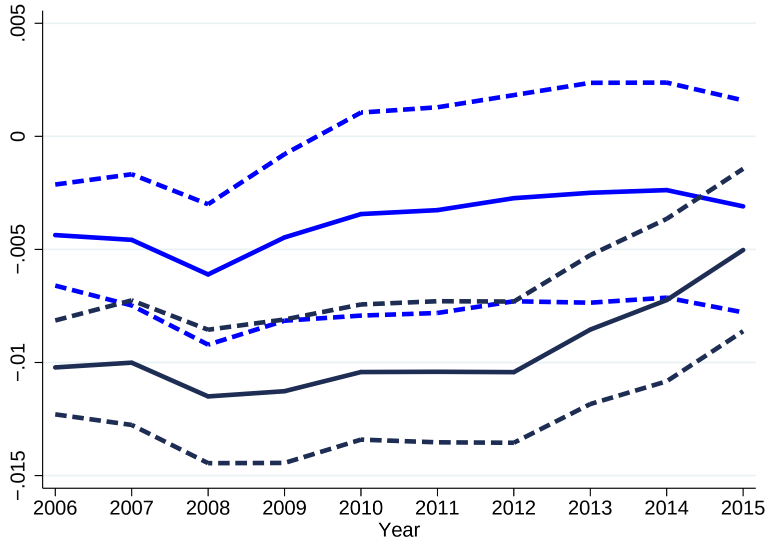


Figure 14: Time varying estimates for the alternatives to bank credit in the demand function, that is, firms' ratio of cash-flow over sales (in solid blue) and firms' ratio of trade debt over assets and on the supply (in solid navy). Dashed lines indicate the 95% confidence interval of the estimates for each year.

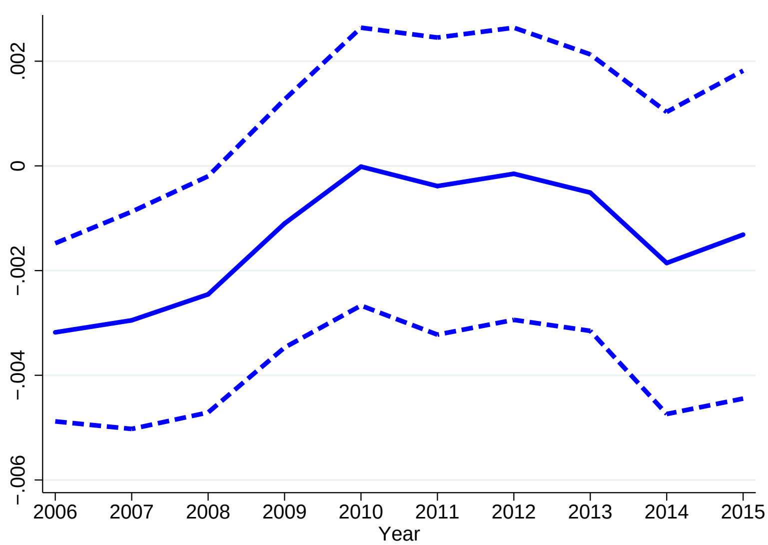


Figure 15: Time varying estimates for the percentage of short-maturity credit (in solid blue). Dashed lines indicate the 95% confidence interval of the estimates for each year.

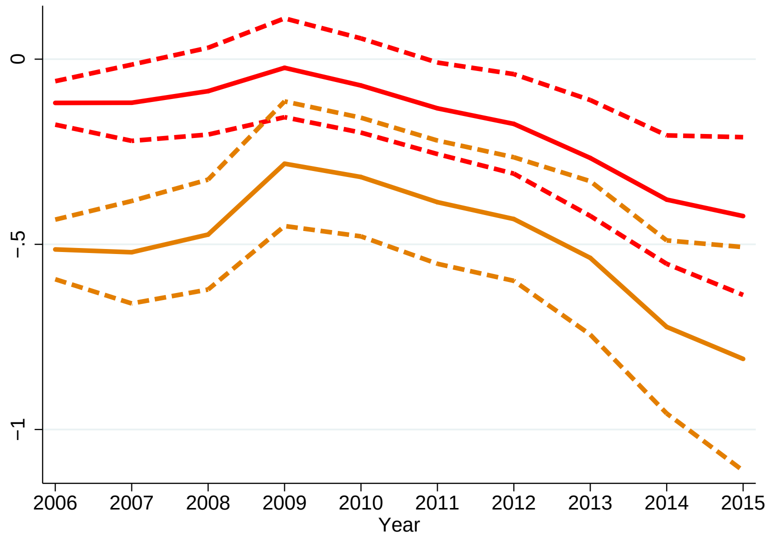


Figure 16: Time varying estimates for firms' rating, that is, the dummy for average rating (in solid red) and the dummy for bad rating (in dark orange). Dashed lines indicate the 95% confidence interval of the estimates for each year.

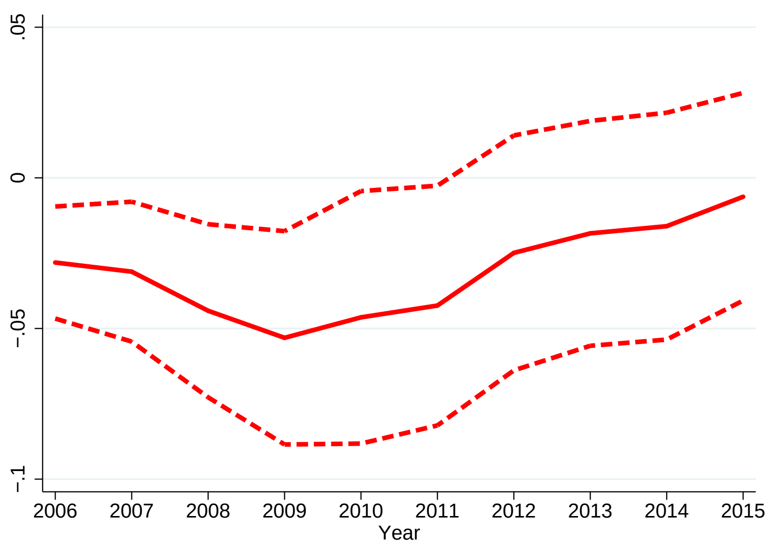


Figure 17: Time varying estimates for banks' ratio of bad loans over total loans (in solid red). Dashed lines indicate the 95% confidence interval of the estimates for each year.

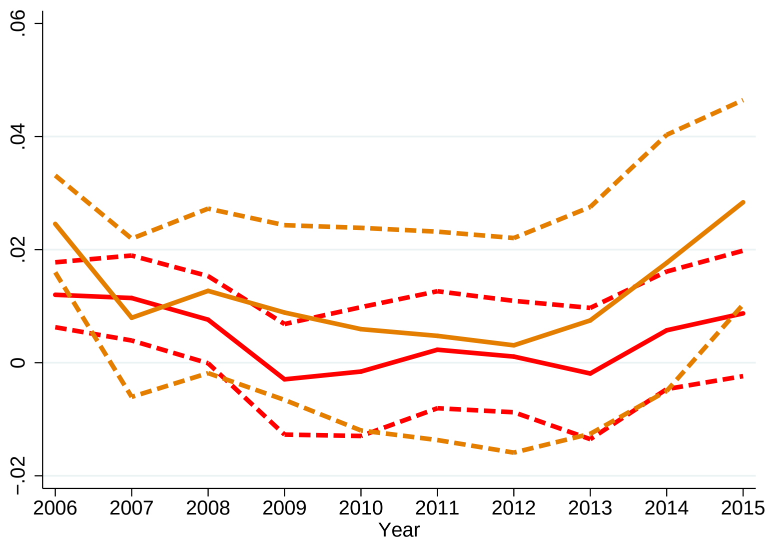


Figure 18: Time varying estimates for banks' interbank ratio (in solid red) and banks' Tier 1 capital ratio (in dark orange). Dashed lines indicate the 95% confidence interval of the estimates for each year.

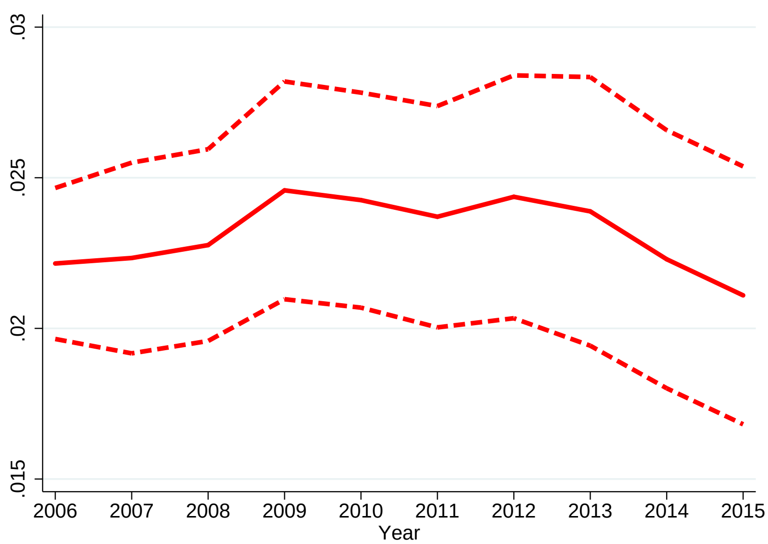


Figure 19: Time varying estimates for the percentage of guaranteed credit (in solid red). Dashed lines indicate the 95% confidence interval of the estimates for each year.

Bootstrap evidence

Our estimation imposes as little structure on the data as we deem necessary for the purpose of estimating a measure of credit rationing. Hence, our method is eminently reduced-form and therefore our estimates are conditional upon our sample and in particular upon the distribution of characteristics across observations in our sample. We try to encompass as large a portion of the Italian market for term loans as possible. However, despite our best efforts our estimates may still be just the result of the special composition of our sample, which may well change in the future in case different developments occur. Thus, we try to control for the biases that the composition of our sample may entail by considering a bootstrap procedure. In particular, we set-up a bootstrap for the maximum-likelihood estimation of our second-stage system of equations. Table 7 reports the bootstrap results for the key covariates, and Figure 20 and Figure 21 report the distribution for our estimates for the semi-elasticities of demand and supply to the interest rate as they result from the bootstrap procedure. The bootstrap estimates coincide in magnitude with our benchmark, and the statistical significance is substantially higher. This is evident also by the distribution of the semi-elasticities' estimates. Hence, our benchmark estimation appears to be robust to variations in the composition of our sample, at least to the extent that such variations are random.

Table 7: Robustness. Bootstrap results

	(1)
	Bootstrap
Demand	
Loan margin	-0.290 ***
	(0.008)
Cash-flow/Sales	-0.003 ***
	(0.000)
Trade debt/Assets	-0.010 ***
	(0.000)
Short maturity	-0.001 ***
	(0.000)
Firm assets	0.711 ***
	(0.003)
Supply	
Loan margin	0.478 ***
	(0.014)
Average rating	-0.187 ***
	(0.005)
Bad rating	-0.515 ***
	(0.009)
Bad loans/Loans	-0.027 ***
	(0.001)
Interbank/Assets	0.004 ***
	(0.000)
Tier 1 capital	0.010 ***
	(0.001)
Collateralization	0.024 ***
	(0.000)
Firm assets	0.749 ***
	(0.003)
Log-likelihood	-7848774.3
Observations	5231134

Notes: The model includes dummies for firms' sector, firms' macroarea, banks' ID, and quarter. Statistical significance is represented by $*$ for $p < 0.05$, $**$ for $p < 0.01$, and $***$ for $p < 0.001$. Standard errors are clustered at the firms' sector times banks' type level in each iteration, and computed over 100 bootstrap iterations. Each iteration is computed over half od the sample, that is, 2615567 observations.

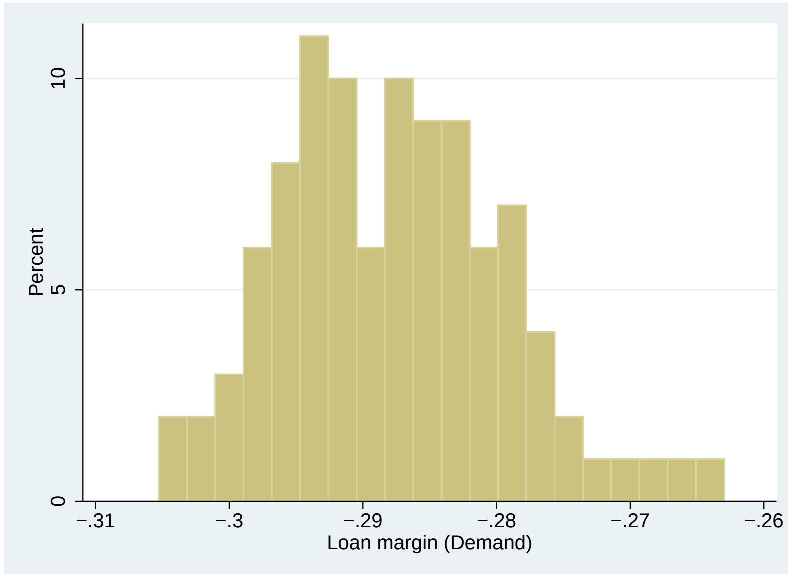


Figure 20: Distribution of the bootstrap estimates for the semi-elasticity of the demand function to the loan margin.

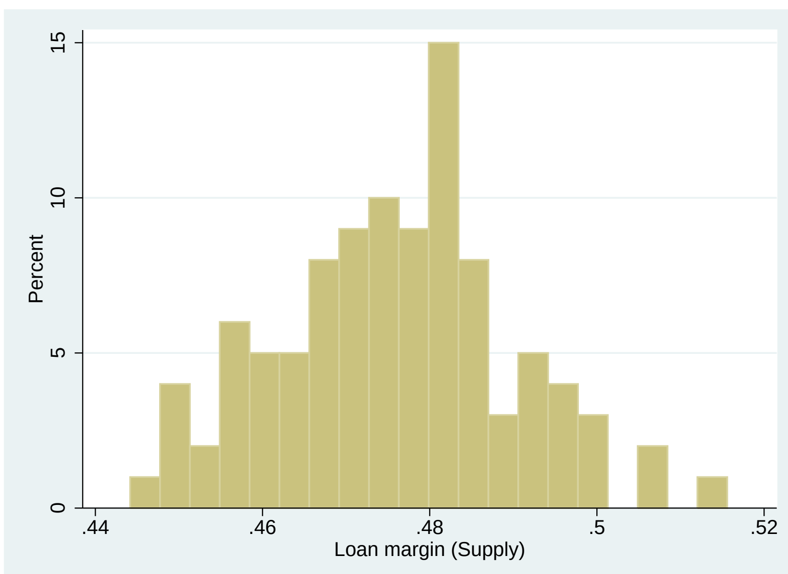


Figure 21: Distribution of the bootstrap estimates for the semi-elasticity of the supply function to the loan margin.

Clustering schemes

There are several potential dimensions of correlation in the residuals of our estimation. Hence, we make sure that our results do not depend on the clustering strategy we adopt for our benchmark specification. Table 8 reports the p-values that correspond to each key covariate for different clustering variables. In particular, we report clusters by firms' sector in column 1, by banks' type in column 2, by time in column 3, and by firms' sector, banks' type, and time in column 4. Finally, we report the case of no clustering in column 5. In none of these cases we find any sensitivity of our results to the clusters we use.

Table 8: Robustness. Clustering variable

	(0) Benchmark	**(1) Sector**	**(2) Type**	**(3) Date**	**(4) Sector/Type/Date**
Demand					
Loan margin	0.000	0.000	0.000	0.000	0.000
Cash-flow/Sales	0.000	0.000	0.000	0.000	0.000
Trade debt/Assets	0.000	0.000	0.000	0.000	0.000
Short maturity	0.063	0.203	0.001	0.000	0.000
Firm assets	0.000	0.000	0.000	0.000	0.000
Supply					
Loan margin	0.000	0.001	0.000	0.000	0.000
Average rating	0.000	0.000	0.000	0.000	0.000
Bad rating	0.000	0.000	0.000	0.000	0.000
Bad loans/Loans	0.000	0.000	0.000	0.000	0.000
Interbank/Assets	0.036	0.063	0.145	0.000	0.000
Tier 1 capital	0.000	0.000	0.113	0.000	0.000
Collateralization	0.000	0.000	0.000	0.000	0.000
Firm assets	0.000	0.000	0.000	0.000	0.000
Number of clusters	110	22	5	38	4180

Notes: All models include dummies for firms' sector, firms' macroarea, banks' ID, and quarter. The entries correspond to the p-values associated to each coefficient for each specification.

Reduced-form estimates

Table 9 reports the effect of each covariate on demand and supply considering also its effect on the interest rate, that is,

$$\frac{\mathrm{d}l^i_{bft}}{\mathrm{d}x} = \frac{\partial l^i_{bft}}{\partial x} + \frac{\partial l^i_{bft}}{\partial r_{bft}} \frac{\partial r_{bft}}{\partial x},$$

for every covariate x. In this way, we can see the actual reduced form of our model, that is, the effect that any exogenous variable has on the endogenous quantity term l_{bft} of each contract. Moreover, the last column of Table 9 presents the difference between the coefficients on the reduced form of the demand function and the reduced form of the supply function, which informs us on whether and to what extent a change in that exogenous variable reduces potential rationing of credit at the level of the single transaction. On the basis of these reduced-form representation, we see that substitutes of bank credit like the internal revenue and trade debt reduce credit rationing as they affect negatively more the demand than what they affect positively the supply through the interest rate. The risk profiles are not important determinants of quantity credit rationing, as the higher interest rate corresponds to higher supply which partially compensates for the direct negative effect on the quantity supplied. If anything, higher risk profiles reduce credit rationing due to the interest rate channel, which is an effect only our specification can isolate. Collateralization leads to a three-fold increase in supply and a mere 10% increase in the quantity demanded through the interest rate channel. In practice, as long as credit can be collateralized the intermediaries do not ration it at all. The lower demand and higher supply that due to shorter duration of contracts sum up to an almost nil credit rationing for short-term maturities. Access to interbank funding by the intermediary seems to increase credit rationing. This is due to the fact that, despite a higher availability of funds and therefore a higher supply at any given interest rate, the intermediary dumpens the interest rate so much that it more than compensates the direct increase in the supply. The reduced-form supply depends negatively on the interbank exposure, so an increase in the latter leads to an increase in the credit rationing. The same applies to the capital position of banks. The lower supply that derives from a lower interest rate compensates for an otherwise higher willing to lend by banks. However, the reduced-form supply increases in any case, although just as much as the reduced-form demand decreases. Overall, a higher Tier 1 capital ratio does not affect the quantity of credit rationing. The most straight-forward driver of credit rationing is the ratio of bad loans over loans that appears from banks' balance sheets. The direct effect on the quantity supplied by intermediaries more than compensates the interest rate channel and the overall effect on supply is higher than the overall effet on demnad. Thus, an increase in bad loans leads unambiguously to an increase in credit rationing. Size increases demand more than supply, so larger firms are likely to reflect more credit rationing than smaller firms, in absolute terms. This is again mainly due to the reduction in the interest rate, that lowers the credit that the banks find profitable to lend to large firms. Intersectoral differences focus primarily on the distinction between manufacturing firms and construction firms, where the latter are evidently more rationed than firms from any other sector. Credit rationing distributes geographically less in the South, whose negative supply and positive demand conditions reflect for the most part the level of the interest rates. Unobservable bank characteristics, as absorbed by bank fixed effects, contribute positively to credit rationing, as only as much as 4% of the intermediaries appear not to ration credit on the basis of these unobserved characteristics.

Table 9: Reduced-form coefficients

	(1) **Demand**	**(2)** **Supply**	**(3)** **Demand-Supply**
Cash-flow/Sales	-0.003***	0.000***	-0.004***
Trade debt/Assets	-0.010***	0.001***	-0.011***
Average rating	-0.095***	-0.031**	-0.064**
Bad rating	-0.196***	-0.191***	-0.005
Bad loans/Loans	-0.007***	-0.016***	0.009***
Interbank/Assets	0.005***	-0.004***	0.008***
Tier 1 capital	0.004***	0.004***	0.000*
Collateralization	0.001***	0.023***	-0.022***
Short maturity	-0.003***	0.003***	-0.007
Firm assets	0.782***	0.632***	0.150***

Notes: Statistical significance is represented by $*$ for one fourth of a standard deviation away from central estimates, $**$ for half a standard deviation, $***$ for one standard deviation.

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