Does credit substitution between banks shape the effects of financial frictions on firm investment?

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Abstract

The ease for a borrower to switch banks plays a central role in assessing the impact of financial shocks on the real economy, but the measurement of this ability is a very difficult empirical task. Using matched bank-firm data, this work estimates a wide distribution of the elasticity of substitution between banks taking into account firm industry, size class, and credit score. Firms' ability to substitute credit between lenders, given by this elasticity, shapes the impact of financial shocks on investments. Companies with lower elasticity are more susceptible to a lending cut. These firms reduce investments significantly, as they experience a more severe decline in credit and a higher rise in interest rates. The effect of the elasticity of substitution on investment depends on how firms adjust to reduced lending. Firms relying only on existing bank relationships (intensive margin) cut investment only if their elasticity is very low (below the first quartile). The impact is broader—affecting firms with elasticity below the median—when they also adjust through the extensive margin (e.g., adding or dropping bank relationships). Overall, the evidence provided suggests that a better understanding of the bank lending channel requires taking into account the diverse implications of the elasticity of substitution in credit markets.

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1 Introduction

This paper estimates the elasticity of substitution between banks and examines how the quantitative impact of credit supply shocks on firms' investment is shaped by this elasticity. This substitutability may be important: when a firm faces a lending cut from some of its banks, whether due to changes in credit policy or other kinds of supply shocks, a substantial share of the adjustment in borrower firms occurs through the reallocation of credit across remaining or newly added lenders. The ease of reallocating credit among lenders, given by the elasticity of substitution between banks, shapes the severity of the effects of credit shocks on real outcomes.

A large body of research offers evidence that switching banks is costly and has consequences for firm borrowing and on real outcomes. These studies focus on specific episodes of major shocks, after which switching between banks can be very difficult, such as the Financial Crisis ([17], [19]; [42]), forced switches induced by bank branch closures ([12]; [45]) or failure of the main bank ([33]). However, by focusing on specific and extreme events, this evidence leaves open the question of what the effects are in other periods when reallocation across other lenders is easier. Indeed, switching lenders is simpler during normal times than during a banking crisis, although other pressures can also significantly reduce the ease of switching over time. For example, the process of consolidation in the banking industry gradually reduces the number of banks. Alternatively, the connection established between the bank and the company can induce the borrower to turn more favorably to lenders with whom it has already established a credit relationship than others. Therefore, the ease of credit reallocation among lenders, both existing and new, after a credit shock is a critical but also an overlooked margin of adjustment. In this sense, this paper estimates the elasticity of substitution between banks, using a model-derived estimating equation that takes into account any unobserved demand and supply factor. Moreover, this substitution affects the overall effect of credit constraints on firm outcomes and primarily investments.

To address this issue, this paper provides three empirical results. First, we estimate the elasticity of substitution between lenders and use it as a general measure of the degree of substitutability in credit markets. Specifically, a wide distribution of estimated elasticities is obtained between firms by taking advantage of their characteristics (industry, firm size class, and credit score). Secondly, by exploiting the heterogeneity in the estimated elasticities, we show that credit supply shocks have a significant effect on investment only for firms with lower elasticity. Finally, we show that the effects of credit supply shocks on investment depend on the intensive/extensive margin of lending.

For the first argument, we use matched bank-firm data on loans and interest rates in Italy to estimate the elasticity of substitution between lenders. Because Italian businesses mostly rely on bank credit rather than alternative sources of external funding (such as bonds, etc.), Italy provides an optimal environment. Furthermore, the Italian credit register's extensive coverage makes it possible to include information on loans and interest rates for a large number of small businesses, for which bank credit is more important and switching costs are usually considerable.

The estimating equation is derived from the minimization of lending costs, subject to an output constraint that is given as a CES function. We show that this plan is flexible enough to achieve a credit demand equation that can be directly mapped onto microeconomic data. As for identification, the change in the relative interest rate is instrumented with credit supply shocks, which in turn are given by the bank-time fixed effects of a preliminary regression. Furthermore, the estimating equation includes firm-time fixed effects, which account of any unobserved features of the firm, such as other forms of external financing, firm credit score, etc.

It should be noted that for the estimation of these fixed effects, we resort to the methodology of [4] (AW estimator, hereafter) to prevent the estimation bias which occurs when there are new or terminating lending relationships and the fixed effects are estimated with OLS. This is particularly important because in every period credit relationships are not only maintained ongoing from the previous period, but they are also terminated or created, and this extensive margin dimension involves many firms not only at the occurrence of major events, but also during normal times. Therefore, using the AW estimator allows one to correctly estimate these fixed effects and in this way also the elasticity of substitution between lenders. We estimate a wide distribution of the elasticity of substitution by taking into account the fact that this elasticity may depend on various characteristics of the firm, such as industry, size and credit score.

The main result of the paper is to show that the elasticity of substitution is important in determining firm investment decisions, as it alters the overall impact of credit constraints. Specifically, credit supply shocks have an impact on investment in businesses with lower elasticity of substitution. To understand this finding, consider the businesses that have the most difficulty changing banks, also in terms of a lower ability to obtain more credit or better credit conditions. Then, these companies invest only when they benefit from an expansion in credit supply, ceteris paribus also other factors (cash flow, etc.). Thus, while previous evidence focused on the average effects of credit supply shocks on firms' investments, this work highlights that this impact derives from a specific channel, the heterogeneous degree of substitutability between banks. To show this point, we first estimate the bank-time fixed effects and the elasticity of substitution by leaving out for each firm its industry, its size, and its credit score bin. In this way, we obtain a wide distribution of the estimated elasticities across firms. Then we estimate the weighted average credit supply shock at the firm level on investment: a 10% increase (decrease) in credit supply to firms with a lower elasticity of substitution (decreases) the investment rate by approximately 1.8%. This result holds after controlling for a host of relevant variables (including bank specialization), and it survives to various robust checks.

Lastly, extensive and/or intensive margins of lending also contribute to shape the differential impact of the elasticity of substitution on investment. When examining firms that make adjustments only on the intensive margin (that is, using only ongoing credit relationships with banks), the effect is restricted to firms with an elasticity that is in the first quartile of the distribution. Differently, considering firms that use adjustments not only with ongoing relationships, but on the extensive margin, for example by starting a line of credit with a new bank, or firms that have terminated a credit relationship, the effect of a credit shock on investment spreads to firms with elasticity in the first two quartiles of the distribution. The rationale behind this "narrower" finding for firms that adjust only on the intensive margin is asymmetric information. In fact, these businesses have fewer barriers to improving loan conditions because of their ongoing relationships with their lenders. If one bank increases the interest rate, they are better able to substitute credit of the more expensive bank by expanding borrowing from other lenders rather than switching to a new bank, for a given elasticity of substitution. Differently, if the firm wants to raise funds by turning to a new bank, it would face higher initial costs, especially because it is not known to the new lender. Then, this last set of results thus highlights the importance of the margins of lending in shaping the effects of the bank lending channel.

1.1 Related Literature

This paper contributes to two main strands of the literature. The first contribution is related to the line of research on the bank-lending channel (BLC, henceforth). As described in [31], the existence of the BLC is based on two assumptions: a) the inability of banks to alter their portfolio of assets and liabilities to insulate the shock; b) the inability of firms to substitute the lending cut from affected banks for other loans extended by other banks or for other types of financing.

While a large literature on the BLC has focused on the first channel, using supply side explanations, where the heterogeneous exposure of firms to bank shocks can explain firm outcomes (see, for example [17], [41] and [14] just to mention few of them), this paper is related to the second assumption, as it shows that also the demand side heterogeneity, namely the elasticity of substitution across lenders, is relevant for understanding the effects of credit supply shocks on firms' investment.

In general, this literature does not consider how these effects can be mitigated (or exacerbated) by demand-side characteristics. Differently, here we provide estimates of the elasticity of substitution, which is heterogeneous across a variety of firm characteristics, and we show how this matters for firms' investment. In other terms, the results suggest that the ease of substitution between banks, typically unobserved by the econometrician, affects economic activity.

To my knowledge, very few works so far have gauged the ease of substituting banks using this measure of elasticity: [36] has introduced the concept of the elasticity of substitution in credit markets, and [2] have estimated the elasticity of substitution between lenders using European data focused on a specific period (Covid-19). The present paper is very related to this second work, because the elasticity is estimated using matched bank-firm data on loans and on the interest rates. However, it differs in two important respects. First, their paper does not compute the effects on firm outcomes, while in the present work, we calculate how the effects of credit supply shocks on investment are mediated by the estimated elasticity of substitution. Second, their paper does not make any differentiation between the intensive and extensive margin of lending, while this aspect here is very relevant in the estimation of the elasticity of substitution and of the effects on investments, as is described in detail in section 3.

Another contribution in this vein of the literature is to highlight how the heterogeneity of demand shapes the effects of bank shocks on real economic activity. A large number of papers have measured the effects of bank shocks on firm outcomes, but they mostly focus on specific periods or on supply side features. As for the first issue, various works (just to mention a few of them, for example, see: [30], [19], [20], [6]) exploit specific events, such as the Financial crisis. Despite these works are very insightful, the ability of firms to substitute between lenders is limited after major shocks, so it is not explicitly derived.[1] However, since the estimated elasticity here is a valid measure of the ease of substituting lenders also in periods outside of specific episodes, it makes sense to calculate how it shapes the impact of bank shocks on investment in a banking crisis as well as in a normal period.

Finally, with regard to the first point of the BLC literature, the inability of banks to alter their portfolio of assets and liabilities to insulate the shock, a recent literature has highlighted the role of bank specialization, where banks specialized in some activities lend more to firms that produce more intensively in those activities (industry or export markets, for example). To take this point into account, in the estimation of the investment equation, a measure of bank specialization à la ([48]) is added as a control variable, but it is not significant, while the mitigating role of the elasticity of substitution survives.

The paper is also related to the line of research focused on estimating credit demand. Some works have used surveys in banks ([28]) and find an inverse relationship between interest rates and loan demand. However, by using aggregate or bank-level data, they ignore the large heterogeneity between firms, which allows them to also explore substitutability between banks. Very few studies in this literature have estimated credit demand using micro-data on firms in developed countries. [24] find a semi-elasticity to the interest rate of -1.45 in the credit demand equation (they used only the first year of each firm's main line of credit to avoid the need to model the dynamics of firm-bank relationships). The present work is related to that paper because it uses matched bank-firm data of the same country, but it differs because the limitations they apply to the data are not necessary for this work. Indeed, my methodology allows one to use data by all lenders and all the years (not only the first) of the bank-firm lending relationship.

The remainder of the paper is structured as follows. Section 2 describes the data sources and provides a discussion on sample selection due to the assumption of the structure of the credit market. In Section 3 the model, the estimating equation, and the adopted identification method are presented. Section 4 reports the results on the validity of the instrumental variables and presents initial estimates of the

[1] An exception is [34] who show that loan originations to small firms in the US have a statistically insignificant impact on employment during the Great Recession and in normal times. Unlike the current work, in their study, bank substitution is not directly measured.

elasticity of substitution, while Section 5 shows empirically how the effects of credit supply shocks on the investment rate depend on this elasticity. Section 6 provides a series of robustness checks on the estimate of the elasticity. Conclusions are presented in Section 7.

2 Data

The paper uses various sources of data from Italy. Since Italian companies - different from those in the US - are highly reliant on bank credit, we use matched bank firm data on loans from the Credit Registry (CR, henceforth) of the Bank of Italy. Bank-firm data on interest rates (including gross fees and commissions) are from the Taxia survey of the Bank of Italy, covering almost all banks operating in the country. Joining the two registries allows to have data on both loans (granted and used) and interest rates by bank-firm in each quarter.[2]

The second source is the Company Account Data service (CADS, henceforth), which collects yearly data on the balance sheets and income statements of limited liability firms and joint stock companies in Italy. For the purpose of this work, the CADS dataset provides data on investments, capital and also a measure of the firm's credit score. The score is known by banks and they use it to screen borrowers (actual and potential).[3] Capital is derived using the perpetual inventory method.

Finally, firm size is measured by the number of employees, which is from the social security archives (INPS, henceforth).

The dataset is built in various steps, described as follows. In the first step, we select non-financial firms with at least one employee between 2006 and 2015. Having at least one employee it is more likely that the firm has an actual economic activity. In a second step, we merge the selected firms to the CR archives, which report the loan amounts a firm borrows from each bank. Third, we merge the resulting dataset with the Taxia survey, which reports the interest rates for each bank-firm pair.[4] After the merge, we keep only matched observations where we observe both the loan amount and the interest rate (this step is essential to my estimation methodology, as discussed in the next section). Fourth, we merge the result of the previous selections with CADS to obtain capital, investment, the credit score variables, and finally, we merge it with INPS again to obtain employment. Fifth, we remove singletons iteratively using the reghdfe command developed by [23] to correctly estimate bank-time and firm-time fixed effects. Sixth, since we impose monopolistic competition in local credit markets, we remove the more concentrated ones

[2] In the main analyses we use data summing all types of loans that a firm has borrowed from a bank. However, in subsection 6 we perform a robustness check to differentiate loans between types: term, overdraft loans, and loans backed by receivables.

[3] The credit score is the Z-score computed using various balance sheet indicators (assets, rate of return, debts, etc.) using the methodology described in [3]. The variable is categorical with natural numbers ranging from 1 to 9, where higher values indicate a higher probability of default. In this work, the variable has been recoded so that lower numbers denote the worst firms, and the highest values the best firms.

[4] Note that all financial intermediaries (named henceforth simply as banks or lenders, for sake simplicity) have to report to the CR loan amounts if the overall outstanding of a borrower exceeds 30 thousands euros to the bank; differently, in Taxia the corresponding reporting duty is for loans of at least 75 thousands euros. Given the two different limits, we apply the upper limit of all loans exceeding 75 thousand euros on CR credit data.

from the dataset. For this purpose, we consider the commuting zone (the local area defined by commuting patterns with a size that typically involves few towns) as the local credit market. Note that commuting zones are much narrower territorial units than what other works using Italian data do: [35], [24] and [51] consider as a measure of the local credit market wider territorial units (provinces).[5] To exclude very concentrated local credit markets, we keep only on firms located in commuting zones with an average HHI$\leq$0.25, considering areas with a higher threshold as concentrated markets where collusion between banks may occur (for a wider discussion on monopolistic competition and the choice of these thresholds, see Section A in the Appendix). With this selection, we drop 50 commuting zones from the dataset out of a total of 611, as showed in figure 1. Finally, we keep only firms that have been present in at least two consecutive years to avoid the sporadic presence of firms that may influence the analysis.

At the end of all these steps, we remain with a dataset of 7,408,049 observations, with 96,902 firms and 209 banks. Note that the final dataset has both companies that in a given year and quarter have a credit relationship with one single bank and those borrowing from multiple banks. However, in the main estimates we carry out the analysis mainly with multiple bank firms, following the methodology most commonly used with bank firm data and first developed by [43]. We also include single-bank companies in a robustness check to confirm the main results.

3 Empirical specification

In this section, we show that the empirical equation of credit demand derives from a model in which firms have a "love of variety" and there is monopolistic competition between banks in the lending market. Imposing both these assumptions in the Dixit and Stiglitz framework allows one to interpret the elasticity of demand to the interest rate as the elasticity of substitution.

The assumption of monopolistic competition was discussed in the previous section. Regarding the assumption of love of variety, firms prefer not to be captured by one bank because having multiple relationships mitigates switching costs ([46]), which are relevant in credit markets ([44]). Multiple relationships also allow borrowers to reduce the risk of an unexpected credit dry-up by their main bank ([38]; [29]; [25]). Even though a relevant share of firms in Italy borrows from only one bank, the focus in the main analysis is only on multi lending firms.[6]

To derive credit demand, we outline a simple model that captures the essential elements of credit markets and that can easily be transformed into an estimating equation. Firm f chooses the optimal loan amount $L_{b,f,t}$ to demand to the bank b at time t to minimize the cost of borrowing ($\sum_{b=1}^{B} r_{b,f,t} L_{b,f,t}$) given by the interest rate $r_{b,f,t}$, and subject to the constraint of the output produced from the borrowed capital. This is modeled as a constant elasticity of substitution (CES) function where firms express love

[5] In Italy there are 611 commuting zones and 110 provinces, these last ones correspond to NUTS level 3 according to the Eurostat definition of territorial units.

[6] In section 6 we repeat the analysis extending the dataset to single-bank firms, and the main results are confirmed.

of variety across banks:

$$y_{f,t} = \left(\sum_{b=1}^{B} \varphi_{b,f,t} L_{b,f,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

In equation (1) σ is the elasticity of substitution ($\sigma > 1$) and $\varphi_{b,f,t}$ is an unobservable idiosyncratic factor of appeal for bank b by firm f, similar to [37]. Equation (1) implies that there is an implicit imperfect substitution in the production function between the funds provided by different banks. This formulation is coherent with the idea that banks provide different financial services or provide financing with different productivity levels.[7]

From the cost minimization plan, the following credit demand equation in logs is derived:

$$\ln L_{b,f,t} = -\sigma \ln r_{b,f,t} + \sigma \ln R_t + \sigma \ln \varphi_{b,f,t} + \ln y_{f,t} \tag{2}$$

where $R_t = [\sum_{b=1} \varphi_{b,t} (\frac{r_{b,f,t}}{\varphi_{b,t}})^{1-\sigma}]^{\frac{1}{1-\sigma}}$ is the aggregate interest rate. In order to derive an estimating equation from (2), note that the last term on the right hand side ($\ln y_{f,t}$) is a firm-time variable:

$$a_{f,t} = \ln y_{f,t} \tag{3}$$

Since $\ln(r_{b,f,t})$ and $\ln(R_t)$ in equation 2 have the same coefficient σ, they may be considered as a unique variable. Letting $\sigma \ln \varphi_{b,f,t}$ be in the error term, equation (2) becomes:

$$\ln L_{b,f,t} = -\sigma \ln \left(\frac{r_{b,f,t}}{R_t} \right) + a_{f,t} + u_{b,f,t} \tag{4}$$

Taking first differences,[8] we obtain the main equation of interest:

$$\Delta \ln(L_{b,f,t}) = -\sigma \Delta \ln \left(\frac{r_{b,f,t}}{R_t} \right) + \Delta a_{f,t} + u_{b,f,t} \tag{5}$$

In order to estimate equation (5) we need to define in the empirical specification three variables: the dependent variable, the relative interest rate and the demand shifter. First, the specification of the dependent variable in the logarithmic change ($\Delta \ln(L_{b,f,t})$). By specifying the dependent variable with the natural log of 1 + credit, the dependent variable captures both the intensive margin (how much a firm borrows from banks with continuing relationships) and also the extensive margin (how much a firm borrows from a new lender in t or how much it borrowed from a loan that ended in the corresponding quarter of the previous year, $t-4$).[9] Since this is a demand equation, the change in credit is made on

[7] For example, the firm selects an individual bank to finance each intermediate entering into the production of final output, or firm output is composed of a continuum of tasks and banks have heterogeneous productivity levels in financing each task.

[8] we use first differences because, as explained in the next subsection (3.1), the instrumental variable is in first differences.

[9] In unreported estimates (omitted for sake of brevity) we test the results using an alternative specification of the dependent variable $\Delta \ln(L_{b,f,t})$.

the change of used credit.

Second, the aggregate interest rate is given by a weighted average of the interest rates applied by all lending banks in the previous year: $R_t = \sum_{b=1} w'_{b,f,t-4} r_{b,f,t}$, where:

$$w'_{b,t-4} = \frac{L_{b,f,t-4}}{\sum_{b'=1} L_{b,f,t-4}} \tag{6}$$

where again, $t-4$ indicates the corresponding quarter of the previous year. In other terms, R_t is the aggregate interest rate applied by all lending banks b' at time t. Note that following a rigorous solution of the cost minimization plan, as described in equation 1, the aggregate interest rate R_t should be defined by the banks from which the firm actually borrows ($R_{f,t}$). However, this definition of the aggregate rate would imply considering an excessively narrow set of banks, so that the aggregate rate would misrepresent the true reference rate that may applicable to a given firm.[10] Hence, without loss of generality, one can assume that the aggregate interest rate is defined by all banks lending to firms that share with firm f the same industry, the same size bin, and the same credit score bin. Using the average cost of lending to firms similar to firm f (by industry, size, and credit score) allows one to better consider the appropriate average interest rate of reference to the firm. Moreover, to reduce any reverse causality bias, in equation (6) we define banks in summation by b', which is a leave-out form that considers all other banks different from bank b at time $t-4$. In this way, $w'_{b,t-4}$ is simply the ratio of bank loans b at time $t-4$, to the total of loans of all other lending banks b' in the same period. Then, the aggregate rate is $R_{k,t}$:

$$R_{k,t} = \sum_{b=1} w'_{b,f,t-4} r_{b,f,t} \tag{7}$$

where the subscript k denotes the triplet industry j, size bin s and credit score bin n.

Finally, $\Delta\alpha_{f,t}$ is the change in the loan demand shifter, which is independent of the interest rate. It is determined empirically by a firm-time fixed effect, which is the result of a preliminary estimation, useful also for identification, as explained in the next subsection.

3.1 Identification

Reverse causality of the relative interest rate in equation (5) is addressed using 2SLS and the instrumental variable is a credit supply shock measured with the bank-time fixed effect. Indeed, with bank-firm data one can disentangle the firm-borrowing and the bank-lending channels by estimating the following equation:

$$D_{b,f,t} = \alpha_{f,t} + \beta_{b,t} + \epsilon_{b,f,t} \tag{8}$$

[10] Indeed, in the dataset there are many small or medium sized firms which typically borrow only from a few banks: the average firm size is 37.5 employees and each firm borrows from 3.4 banks on average in each quarter.

where $D_{b,f,t}$ is the percentage growth rate of lending, $\alpha_{f,t}$ is the firm-time fixed effect, $\beta_{f,t}$ is the bank-time fixed effect and $\epsilon_{b,f,t}$ is a random error term. Equation 8 is estimated using the credit granted because this measure provides a better measure of the supply of credit.

Following [43], a large literature has evolved estimating equation 7 on a sample of firms borrowing from more than one bank. In the ensuing analysis, this approach is followed here by restricting the analysis to firms borrowing from at least two banks. Borrowing from multiple banks is quite common in Italy, especially for limited liability firms ([15] and [54]).[11] In this multiple-bank framework, the fixed effect of firm-time $\alpha_{f,t}$ fully controls for observed and unobserved heterogeneity at firm and time level (aka the "firm-borrowing channel"). The "bank-lending channel" is captured by $\beta_{b,t}$, which represents a credit supply shock, fully accounted by credit quantity because it is independent of any change in the interest rates.[12] Then, the estimated credit supply shock ($\hat{\beta}_{b,t}$) is a suitable candidate for the instrumental variable of the interest rate change in the estimation of equation (5).[13] Nevertheless, since this is a data built variable, two adjustments may be necessary: the choice of the correct estimator and a correction to take away any possibility of endogeneity in the bank-time fixed effect.

As for the first point, note that estimating equation (8) with simple OLS has been the subject of criticism by [4] because it does not take into account new lending. To solve this problem they develop a new estimator, which we denote here as the "AW estimator", which consists of the estimation of equation (7) where $D_{b,f,t}$ is defined as a percentage change [$D_{b,f,t} = \frac{L_{b,f,t}-L_{b,f,t-4}}{L_{b,f,t-4}}$]. In the last case, the termination of loans is not a problem because $D_{b,f,t}$ is defined ($D_{b,f,t}$=-1). Differently, for new lending relationships, the solution is to estimate equation (8) with WLS (with the weight given by $L_{b,f,t-4}$) and where the first firm and the first bank have been dropped from the estimation: $\ddot{\alpha}_{f,t} = \alpha_{f,t} - \alpha_{1,t}$ and $\ddot{\beta}_{f,t} = \beta_{f,t} - \beta_{1,t}$. The AW estimator decomposes credit growth rate $D_{b,f,t}$ into three components: a credit demand shock ($\alpha^{AW}_{f,t}$), a credit supply shock ($\beta^{AW}_{b,t}$) and the sum of common firm and bank shocks ($\epsilon^{AW}_{b,f,t}$).[14] Since the size of the AW estimators are relative to the omitted firm of the omitted bank, the three components ($\alpha^{AW}_{f,t}$, $\beta^{AW}_{b,t}$ and $\epsilon^{AW}_{b,f,t}$) are produced as deviations from the time-specific medians.[15] we apply this procedure and use the estimated credit supply shock $\beta^{AW}_{b,t}$ as the instrumental variable for the change in the relative interest rate in equation (5). Moreover, we use the estimated change in the firm-time effect $\Delta\alpha^{AW}_{f,t}$ as a measure of $\Delta\alpha_{f,t}$ in the same equation.[16]

Secondly, note that the estimated bank-time fixed effect ($\hat{\beta}^{AW}_{b,t}$), implicitly assumes that the credit

[11] With this assumption we exclude from the dataset single-bank firms which, as noted by [27], are typically smaller, more prone to credit constraints. For this reason, in a robustness check (subsection 6), we check that the main results can also be confirmed by expanding the analysis to single-bank firms.

[12] Graphically, this could be represented as a shift of a vertical credit supply curve, where the interest rate is on the vertical axis.

[13] For a similar use of the bank-time and of the firm-time fixed effects using matched bank-firm data see [1].

[14] Estimating equation (7) implies also leaving any factor affecting both the lender and the borrower (such as non-random matching) into the error term $\epsilon_{b,f,t}$. However, [4] show that any of these factors can be decomposed into a bank-time fixed effect and a firm-time fixed effect. This implies that any of these unobserved factors collapses into $\alpha_{f,t}$ and $\beta_{b,t}$.

[15] For more details see section B in the Appendix.

[16] In a robustness check (Section 6) we repeat the estimates using bank-time and firm-time fixed effects estimated with OLS.

supply policy of each bank is invariant to the characteristics of the firm. However, this variability is likely to be present in the definition of bank credit policy, and thus it may affect the exogeneity assumption of the instrument. In order to remove any influence of firm characteristics on the credit supply variable, following [22], we estimate the bank-time fixed effect by excluding for each firm its industry, its size and its credit score bin, similarly to equation (7).[17] This leave-out version of the bank-time fixed effect, denoted as $\beta^{AW}_{b,k,t}$, creates a measure of changes in the supply to all other firms to which the bank b lends. Obtaining $\beta^{AW}_{b,k,t}$ implies estimating the equation (8) leaving out one element k at a time from the dataset (nine years, four quarters, 30 industries, four size bins and four credit score bins), which means estimating 17,280 coefficients.

Finally, note that an advantage of this identification methodology is that it can be applied to any period without having to use an exogenous event, such as a bank-specific shock. Indeed, in the ensuing analysis, this approach will be used in the whole period (2006-2015), where there has been the Financial crisis and the Sovereign debt crisis, as well as periods of slow recovery of the economy.

4 Results

This section reports the descriptive statistics and estimates of the model described in section 3. First, we show some preliminary statistics (Section 4.1), then Subsection 4.2 shows the validation exercise of the instrumental variable. The baseline estimates of the model are given in subsection 4.3.

4.1 Preliminary statistics

The dataset on the main estimates (with multi-bank firms) includes 7,058,659 observations, with 96,902 firms and 209 banks. In every quarter, there are on average 60,972.9 firms and 180.5 banks; on average each firm borrows from 3.4 banks and each bank lends to 1,393.1 firms. The summary statistics, described in detail in panel A of table 1 in the Appendix, show that each firm has on average 37.3 employees, an average outstanding debt of about 774,816 euros and it pays an interest rate of 5.1%.

4.2 Validation of the instrumental variable

Before moving to the estimates of the model outlined above, it may be appropriate to perform a validation exercise of the instrumental variable, the credit supply shock $\beta^{AW}_{b,k,t}$ estimated from equation 8 with the AW estimator as outlined in 3.1. If this variable is a valid instrument, it should correlate significantly with some of the variables used in the literature with matched bank-firm data to identify credit supply. Some articles have used the percentage of interbank funding of banks to identify the banks most affected

[17] This "leave-one-out" approach for generating the bank-industry-size-credit score supply shock measure follows the one suggested in [13] and it has been implemented, for instance, in [32]. For a discussion on matching between banks and firms riskiness see [18]

Table 1: descriptive statistics

	variable	Obs.	Mean	Std. Dev.	Min	Max
	Panel a: multiple bank firms					
Bank-firm-year-quarter variables	$L_{b,f}$ (credit granted)	7,058,659	774,816	1,099,265	0	9,100,000
	$N_{b,f}$ (credit used)	7,050,914	462,550	767,976	0	6,397,323
	$r_{b,f}$	7,058,659	5.1	5.6	0.0	51.6
	$\Delta\ln(L_{b,f})$	7,058,659	0.2	6.0	-16.0	16.0
	$\Delta\ln(N_{b,f})$	7,040,082	0.2	5.7	-15.6	15.7
	$\Delta\ln(r_{b,f})$	7,058,659	0.1	0.9	-3.8	4.0
	$\Delta\ln(R_k)$	7,058,659	0.0	0.1	-2.3	2.0
Firm-year-quarter variables	$\alpha^{AW}_{f,t}$	6,940,557	0.02	0.17	-0.43	0.86
	$\alpha^{AW}_{f,t-1}$	6,937,532	0.03	0.17	-0.40	0.94
Firm-year variables	$Employees_{f,t-1}$	429,269	37.3	167.7	1.1	30,792.3
	$Creditscore_{f,t-1}$	430,176	5.0	1.8	1.0	9.0
	$Age_{f,t-1}$	423,548	23.4	13.3	0.0	162.0
	$Investment\ rate_{f,t-1}$	416,471	0.2	0.4	0.0	3.7
	$Investment\ rate_{f,t}$ (tangibles) f,t-1	416,356	0.2	0.3	0.0	3.3
Bank-year-quarter variable	$\beta^{AW}_{b,k,t}$	1,453	0.01	0.06	-0.14	0.40
Bank-year variables	$IBKratio_{b,t}$	1,452	0.3	0.3	0.0	1.0
	$FOR\ ratio_{b,t}$	1,452	0.1	0.2	0.0	1.0
	$Tier\ 1\ ratio_{b,t}$	1,364	147,313	467,669	0.18	3,820,300
	$Tot\ cap.\ ratio_{b,t}$	1,364	159,247	501,770	0.36	4,381,900

	Panel b: all dataset					
Bank-firm-year-quarter variables	$L_{b,f}$ (credit granted)	7,408,049	762,315	1,092,168	0	9,100,000
	$N_{b,f}$ (credit used)	7,399,983	452,583	761,717	0	6,397,323
	$r_{b,f}$	7,408,049	5.2	5.7	0.0	51.6
	$\Delta\ln(L_{b,f})$	7,408,049	0.1	6.0	-16.0	16.0
	$\Delta\ln(N_{b,f})$	7,388,602	0.2	5.7	-15.6	15.7
	$\Delta\ln(r_{b,f})$	7,408,049	0.1	1.0	-3.8	4.0
	$\Delta\ln(R_k)$	7,408,049	0.0	0.1	-2.3	2.0
Firm-year-quarter variables	$\alpha^{AW}_{f,t}$	7,278,743	0.02	0.17	-0.43	0.86
	$\alpha^{AW}_{f,t-1}$	7,275,163	0.03	0.17	-0.40	0.94
Firm-year variables	$Employees_{f,t-1}$	511,649	37.5	198.5	1.1	30,792.3
	$Credit\ score_{f,t-1}$	512,869	5.2	1.9	1.0	9.0
	$Age_{f,t-1}$	504,871	23.3	13.3	0.0	162.0
	$Investment\ rate_{f,t}$	497,139	0.2	0.4	0.0	3.7
	$Investment\ rate_{f,t}$ (tangibles)	497,052	0.2	0.3	0.0	3.3
Bank-year-quarter variable	$\beta^{AW}_{b,k,t}$	1,458	0.01	0.06	-0.14	0.40
Bank-year variables	$IBKratio_{b,t}$	1,458	0.3	0.3	0.0	1.0
	$Foreign\ ratio_{b,t}$	1,458	0.1	0.2	0.0	1.0
	$Tier\ 1\ ratio_{b,t}$	1,369	149,159	470,418	0.18	3,820,300
	$Tot\ cap.\ ratio_{b,t}$	1,369	161,501	505,515	0.36	4,381,900

by the interbank freeze that followed the collapse of Lehman Brothers in 2008 ([20]; [39]). Other works have used the percentage of foreign funding to examine the effects of the credit crunch, which affected banks after the outbreak of the Financial Crisis ([49]). The results, in columns 1 and 2 of table 2, show that both of these regressors are significant and have the expected correct negative sign. Indeed, a higher interbank (IBK) ratio implies a contraction of the credit supply as expected of about 0.021% (column 1); similarly, the estimated coefficient on the foreign funding ratio (Foreign ratio) shows that the contraction of the credit supply would be 0.019% (column 2). Both these results are robust to the inclusion of time fixed effects, which may take into account of unobserved quarter specific shocks affecting the economy, and of bank fixed effects, which include any unobserved heterogeneity at bank level, such as management practices, size, etc. The remaining columns (3 and 4) of table 2 repeat the exercise using two relevant measures of bank capital (Tier 1 ratio and Total capital ratio). Only the coefficients of the last variable is significant (column 4), but the magnitude of the correlation is substantially null.[18]

Table 2: validation of the instrumental variable I

	(1)	(2)	(3)	(4)
$IBKratio_{b,t}$	-0.021**			
	[0.011]			
$Foreign\ ratio_{b,t}$		-0.019**		
		[0.005]		
$Tier\ 1\ ratio_{b,t}$			0.000	
			[0.000]	
$Tot\ cap.\ ratio_{b,t}$				-0.000*
				[0.000]
Constant	0.032***	0.033**	0.033***	0.033***
	[0.012]	[0.013]	[0.005]	[0.005]
Observations	1,447	1,447	1,358	1,358
Adj.R-squared	0.155	0.155	0.162	0.163
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
# Banks	207	207	196	196

The table reports the OLS estimates of the instrumental variable $\beta^{AW}_{b,t}$. The dependent variable is the percentage change of loans explained by bank fixed effects estimated with the AW estimator. Data are collapsed by bank-year. IBK ratio is the ratio of interbank deposits over total bank funding. Foreign ratio is the ratio of foreign deposits (of households and of financial intermediaries) over total bank funding. All variable definitions are in Table A1. Fixed effects are included ("Yes"). The estimation period is 2007-2015. All data are trimmed at 1% at both tails. Heteroskedastic robust standard errors, clustered at the bank level, are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Another concern for the validity of the instrument is whether the bank-time fixed effect represents only shocks to credit supply or whether it is also contaminated by demand factors that are in the estimated interest rate. To check this point empirically, we regress the estimated bank-time fixed effect on the log change in bank average interest rate, and we use the firm-time fixed effect as instrument to overcome reverse causality (see section C in the Appendix for a more detailed description of the procedure). Finding that the bank-time fixed effect does not depend on the change of the interest rate allows one to conclude that it is good for identifying credit supply shocks as it is not affected by demand. Estimates are reported

[18] Indeed, the available empirical evidence is not conclusive on whether these ratios affect credit supply.

in table A2. In columns 1 and 2, where the instrumental variable is the firm-time fixed effect estimated with the AW procedure ($\hat{\alpha}_{f,t}^{AW}$), the bank-time fixed effects is not significantly correlated with the average interest rate at bank level ($\Delta r_{b,t}$), although the instrument is weak. In columns 3 and 4, where the instrument is the weighted average at k level of the growth rate of lending ($\hat{L}_{b,k,t}$), again the effects are not significant. Finally, in columns 5 and 6, where the instrument is the weighted growth rate by k ($x_{k,t}$: see the definition in the Appendix C), we obtain similar results on the average interest rate and the instrument is not weak. Overall, the evidence in this table shows that the bank-time fixed effect correctly identifies true credit supply shocks.

Finally, a third concern is whether credit supply shocks are fully captured by the bank-time fixed effects or if they instead are to be differentiated with respect to some firm characteristic. For example, a bank might apply different interest rates to borrowers depending on firm size or their credit score. This point has already been discussed in the subsection 3.1 to motivate the leave-out version of the instrumental variable ($\beta_{b,k,t}^{AW}$).

4.3 Elasticity estimates

This subsection shows the estimates of the elasticity of substitution using the entire dataset. The estimate of σ is made using equation (5), where the parameter of interest σ is the elasticity of loans to the interest rate defined relative to the aggregate interest rate $R_{k,t}$. In order to minimize the identification problems, all estimates of the elasticity of substitution include various fixed effects: to take into account business cycle shocks at the local or industry level (commuting zone&time and industry&time fixed effects, respectively), of firm characteristics (size class, age class, credit score) and by type of loan (continuing, terminating, and new). Moreover, to take into account any correlation between unobserved bank characteristics that may affect lending to businesses (such as bank specialization or competition in local credit markets), in the estimation of the elasticity of substitution, standard errors are clustered at the bank and commuting zone level.

The estimates of the elasticity of substitution are reported in Table 3 and were made on the dataset of multiple lending firms, to follow most of the literature. Column 1 is estimated using all firms and shows that the elasticity is negative and significant, with a magnitude of -3.4. Moreover, the estimated change in the credit demand shifter ($\Delta\alpha_{f,t}^{AW}$) has a significant and positive effect, in line with the prediction of equation 5. The sign of the instrumental variable in the first stage ($\beta_{b,k,t}^{AW}$) is negative (-0.33), which is consistent with the fact that a positive shock in credit supply implies a change along the demand curve that reduces the price of credit. The estimated coefficient of σ implies that an increase of 1% in the lending price is associated with a reduction of 3.4% in the demand for loans. Finally, the instrument is not weak: the statistic for the F test is 562.2.

In addition to the estimates on all the dataset, the analysis considers different cases depending on whether a company, in a given quarter, has started or terminated a credit relationship with a lender (in comparison with the corresponding quarter of the previous year) or if the firm has maintained the relationships with the same lenders. This differentiation allows to highlight the relevance of the intensive and of extensive margin.

It is not straightforward to separate the two margins of lending because most firms in the data maintain credit relationships with some banks over many periods, but at the same time, they also start and/or terminate relationships with other lenders. Therefore, to examine the effects of the extensive margin, we consider three different cases: first, we exclude firms that have terminated a credit relationship with at least one bank in a given period; in the second case, we exclude firms that have started a new relationship with at least a new lender in a period. Finally, we consider firms that adjust lending only on the intensive margin, that is, with the pool of banks with which they have an ongoing concern, without starting or terminating other credit relationships. Note that in both the first two cases, firms not only use the extensive margin but also may adjust along the intensive one. Therefore, the first case considers only firms that have both continuing and/or terminating relationships with lenders, and the results are showed in column 2. Note that this is a quite general case as it encompasses almost the entire dataset, since in each quarter most firms start at least a new credit relationship. Not surprisingly, the estimated σ is almost identical in magnitude to that of column 1.

In columns 3 we repeat the estimate excluding firms that started a credit relationship with a new bank. (or in other terms, we analyze firms that have continuing and/or terminating relationships with lenders). Also this case involves most of the observations, and again the estimated coefficient of the elasticity of substitution is quite similar (although slightly higher in absolute value) to that of the previous case.

Finally, in columns 4 we analyze firms that adjust only at the intensive margin, meaning that these firms keep the same borrowers of the previous corresponding period (since we are using quarterly data and first differences, the previous period is the same quarter of the previous year). This case involves only 55% of the firms and only one fifth of all observations. The estimated elasticity is still negative and significant, as expected, but the magnitude of the coefficient is (in absolute value) much lower than that of column 1. This means that when there are no new or terminating relationships, the change in borrowing between lenders is less reactive to interest rate changes.

The lower magnitude, in absolute value of the estimated σ in column 4 compared to that in column 2 or 3 can be explained by the presence of asymmetric information. In fact, consider the case of a firm that has continued relationships with more banks. For a given increase in the relative interest rate set by one bank, the firm may plausibly react by substituting credit from that bank to increase borrowing from other banks, or it can start new credit relationships. If it uses banks with ongoing concerns, these lenders have better knowledge of the firm than a new borrower. Moreover, the borrower firm does not have to pay the switching costs of starting a new relationship. Therefore, it is easier to substitute credit between

Table 3: Elasticity of substitution by type of loan

	(1)	(2)	(3)	(4)
	all dataset	excluding firms with ending relationships	excluding firms with new relationships	intensive margin
		2nd stage		
$\Delta \ln \frac{r_{b,f,t}}{R_{k,t}}$	-3.381***	-3.381***	-3.475***	-2.355***
	[0.154]	[0.161]	[0.163]	[0.183]
$\Delta\alpha^{AW}_{f,t}$	0.314***	0.311***	0.306***	0.314***
	[0.011]	[0.011]	[0.011]	[0.013]
		1st stage		
$\Delta\beta^{AW}_{b,t}$	-0.332***	-0.318***	-0.355***	-0.324***
	[0.014]	[0.014]	[0.015]	[0.018]
F-test	562.2	495.4	568.2	331.3
Observations	5,588,335	5,389,476	5,419,918	1,144,413
# Firms	82,610	82,406	82,522	45,271
# Banks	208	208	208	205

The table reports the 2SLS estimates of credit demand. The dependent variable is the natural log change of used loans. $\Delta \ln \frac{r_{b,f,t}}{R_{k,t}}$ is the relative interest rate. $\Delta\alpha^{AW}_{f,t}$ is the firm-time FE's estimated with the AW estimator. $\Delta\beta^{AW}_{b,k,t}$ is the instrumental variable, the bank-time FE's estimated with the AW estimator. The first two rows report the second stage estimates; the first stage estimates of the instrumental variable are in the third row. The variable definitions are in table A1. All estimates include fixed effects at commuting zone&time, industry&time, size class, age class, credit score class and by type of loan (continuing, new or terminating). The estimation period is 2007-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed at 1% at both tails. Heteroskedastic robust standard errors, clustered at the bank and commuting zone level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

a pool of lenders to which the company is already known rather than having to switch to a new bank. [19]

In contrast, if a borrower switches to a new bank, since it does not have a reputation with the new lender, a larger total decline in borrowed credit is expected. As a result, when a lender raises the interest rate, the overall credit reduction is smaller in an ongoing relationship than it is in a new one, and consequently also the change in investment of a lower magnitude.

It is also easier to replace the lending cut from the pool of other lending banks if a firm has terminated a credit relationship with one lender. Indeed, as can be seen in column 3, the amount of σ is higher in absolute value than that of column 4, because termination of a relationship exacerbates the overall decrease in credit.

In general, this discussion suggests that the elasticity of substitution varies with the presence (or lack) of new and/or terminating lenders.

5 Effects on investment

In this section, we analyze whether and how much the elasticity of substitution shapes the overall effects of financial shocks on firms' investment. Numerous studies have showed that these shocks have an impact on firms' investments (see, for example, [20]) or other real economic outcomes (see, for example, [19] for employment). However, this literature does not differentiate between companies according to their ability to switch lenders in order to bypass credit restrictions. By looking at how businesses that face a credit supply shock are impacted differently by the elasticity of substitution between banks, the article provides the first analysis in this approach.

In order to analyze this point, the analysis proceeds in two steps. First, we estimate the elasticity of substitution adapting the empirical model used in section 4.3: leaving out for each firm its industry j, its size bin s and its credit score bin n. For each triplet $k = \{j, s, n\}$, the estimates use the appropriate $\hat{\beta}^{AW}_{b,k,t}$ and to remove any source of simultaneity, they are run the two years before the reference year. Considering four size bins, four credit score bins, 30 industries and 7 years,[20] implies the estimation of 3,360 elasticities, each denoted as $\sigma_{k,t}$. None of the estimated elasticities is different from zero and they vary (in absolute value) between a minimum of 1.68 and a maximum of 7.35, with an average value of 4.20.[21].

As a second step, we estimate an investment equation, as explained in detail in the next subsection.

[19] The fundamental models of relationship lending (e.g. [55]; [52]) and also a more recent evidence (see for example [11]) show that a bank gains more knowledge about the borrower's characteristics than other banks do when it extends a loan to a business.

[20] In order to reduce calculations and to a have a sufficient differentiation by industry for the estimation by industry, we regroup 2 digit industries (classified with the NACE Rev. 2 nomenclature) into 30 homogeneous industry groups. Using the past two years means that the analysis period is 2009 to 2015.

[21] Appendix D reports more details on the estimations of the elasticities $\sigma_{k,t}$, and it also shows the improvement in the stability of the estimates, leaving out firm industry, its size bin and its credit score bin.

5.1 Estimates on the investment rate

Since investment data are available only by firm year, we define the credit supply shock, the bank-time fixed effect of Amiti and Weinstein at the same level. In practice, first we take the weighted average of the credit supply shock between banks at firm-quarter level, so that the aggregate idiosyncratic bank supply shock hitting a firm f at quarter t is:

$$Bk\ Shock_{f,t} = \sum_{b=1} (w_{bf,t-4} \hat{\beta}^{AW}_{b,k,t}) \tag{9}$$

where $w_{b,f,t-4}$ is the weight of loans from bank b to firm f in the same quarter of the previous year t. Then, we take the yearly average of $Bk\ Shock_{f,t}$ of equation (9). The investment rate (defined as the investment of the firm in year t over capital in the previous year $t-1$ is estimated on the credit supply shocks that hit firm f at time t defined as the yearly average of equation (9) interacted with a dummy of whether its industry is in one of the four bins defined by the quartiles of the estimated elasticity of substitution.

$$I_{f,t} = \sum_{\iota=1}^{4} \gamma_\iota (Bk\ Shock_{f,t}) \times \mathbf{1}(\iota) + \gamma_\zeta (Bk\ Shock_{f,t}) \times\ S^k_{f,t} + \delta X_{f,t} + \gamma_{j,t} + \gamma_f + \gamma_\lambda + \nu_{f,t} \tag{10}$$

where $\iota (= 1, 2, 3, 4)$ is the bin indicator of the distribution by quartile values of the estimated elasticities of substitution per k and year ($\hat{\sigma}_{k,t}$). Moreover, following a recent and growing literature that has highlighted the presence of a comparative advantage in lending by banks specialized in lending towards specific industries or markets ([40] and [48]), we add a measure of bank specialization by industry to the empirical model to capture the effect due to the information advantage that may derive from a relative specialization of the bank in the industry of the firm. Whether bank specialization matters in a context of substituting lenders is relevant also from a policy perspective. If the comparative advantage of specialized lenders is particularly strong in a given industry, firms in that industry are less likely to substitute specialized lenders with other banks, so that substitution across lenders is less relevant for the external financing of firm investment. To test this point empirically, we add an interaction of $Bk\ Shock_{f,t}$ with a measure of bank specialization by industry per firm and year ($S^j_{f,t}$), that is derived by adapting that of [48] to this empirical model (for more details on the construction of the measure of specialization $S^j_{f,t}$, see section E in the Appendix).

Equation 10 also includes firm-year controls $X_{f,t-1}$ that may be relevant: firm size (proxied by the log number of employees), firm age (years) and the credit score in the previous year. Moreover, following [4][22] $X_{f,t}$ also includes firm covariates that may affect the financing choices of investment: cash flow

[22] See in their paper table 2, page 558.

(over capital), the mean loan to assets ratio and the bonds to assets ratio. In addition to these, two other variables can affect investment financing: the logarithmic change in the collateral ([5]) and the residual duration of the credit relationship. Finally, equation 10 also includes fixed effects that absorb any unobserved factor that may influence firms' investments: at industry-year ($\gamma_{j,t}$) to capture industry specific shocks,[23] at firm level (γ_f) to consider unobserved variable (such as managerial skills), and by type of credit relationship (γ_λ).[24]

The estimates run only from 2009, because we lose two years in the estimation of the elasticity of substitutions, as explained in the previous subsection. Finally, we drop all firms that never make any investment throughout the period (about 24.8%); after applying this filter, still 12% of observations report zero investment, so we apply the inverse hyperbolic sine transformation to the investment rate.

The results are in table 4. In column 1, we estimate the model on the credit supply shock, the various controls $X_{f,t}$, and the fixed effects $\gamma_{j,t}$, γ_f, and γ_λ. The effect on the credit supply shock is significant and positive as expected. This is the usual quantity effect found also in the large literature using matched bank-firm data: a one percent increase of credit supply rises the investment rate by 0.06%.

In order to take into account the role of banks substitution, in column 2 we repeat the estimate that interacts the bank shock with the bin dummies defined by the quartile values of the estimated elasticities: $\hat{\sigma}_{\iota,t}$, as in equation (10). The effect of a credit supply shock on investments is positive and significant only in the first and in the second bin, that is, only for firms with a lower elasticity of substitution.[25] To get a sense of the magnitude of this specification, a 1% growth of the shock of the credit supply to the firms in the first bin increases the investment rate by 0.18% and by 0.17% to the ones in the second bin.

In column 3 we exclude firms that have ended a credit relationship, which means dropping only 1.9% of the firms. The remaining firms are those which have continued credit relationships with banks and also with at least one new bank in the quarter. In this case, the credit supply shock is significant for the first and second bins, but the magnitude of both coefficients is slightly lower than those estimated in column 2.

In column 4 we repeat the estimation, by dropping firms with new relationships. This case, which excludes only 0.9% of the firms in the dataset, considers businesses that have continued credit relationships with banks and also have terminated (at least one) with another bank in the year. Again, credit shocks affect investments only of firms in the first and second bins, with an equal magnitude between the first and second coefficients.

Column 5 shows the estimate of equation (10) using firms that had only adjustments on the intensive

[23] This variable is obtained by aggregating at industry-year level the estimated firm-time fixed effects ($\alpha^{AW}_{f,t}$).

[24] The fixed effects γ_λ are obtained by averaging at firm-year level the types of relationship at bank-firm indicator (continuing, new or terminating). The resulting set of fixed effects considers all possible cases depending on the type of credit relationship a firm has with banks: *i*) only continuing; *ii*) only new; *iii*) only ending; *iv*) continuing and new; *v*) continuing and ending; *vi*) new and ending; *vii*) continuing, ending, and new.

[25] Note that this result is not obvious, because the empirical evidence is not conclusive on two opposing views. On the one hand, *market power hypothesis* argues that firms with a lower elasticity of substitution ($|\sigma|$) may face a stronger market power of banks, which leads to tighter financial constraints ([26]). On the other hand, according to *information hypothesis* a less competitive lending market is associated with a higher credit availability because a greater market power induces banks to engage in relationship lending that reduces information asymmetry with the borrower firms ([50]).

margin, that is, using only firms with continued credit relationships with banks between the current year and the previous year. As already seen in table 3, there is a sensible drop in observations, with a drop of about 62% of firms with respect to the whole dataset. In this case, credit shocks affect investments significantly only of firms with the lowest elasticity of substitution, which means only of firms in the first bin and not also of the ones in the second bin.

As already explained in subsection4.3, this different result for 'continued' firms can be explained by the fact that the continuing nature of the relationship with the bank facilitates a reduction in asymmetric information with the lender ([9]). Thus, access to credit for these companies is easier, independently of the bank policy (e.g., whether to expand or contract credit supply). In other terms, even in the absence of a credit supply shock, 'continued' firms have more easily access to credit than other companies (such as those dealing with a new lender or those facing the end of a credit relationship). Then, only companies with the lowest elasticity need an expansion of credit supply to significantly increase investments.

Finally, note that in all columns the effect of the credit supply shock due to bank specialization is not significant.

In general, these estimates show that only firms that have greater difficulty moving credit between banks increase investment after a credit supply shock. The limiting effect of elasticity is especially relevant for firms that have only continuing relationships with banks.

5.2 Effects through firm debt and interest rates

In order to better understand how the effects of credit supply shocks on investment are shaped by the distribution of the estimated elasticities of substitution, we examine whether there is also any effect on firm total debt and on firm average interest rate, when banks cut (or expand) lending. To clarify this point, consider, for example, total debt (a similar reasoning applies also to firm average interest rate): if firms were able to offset the fall in lending from one bank by increasing borrowing from other lenders, then there should be no seizable effect on firm total debt. Conversely, if a business is less able to substitute banks in presence of that shock, then its total debt should decrease to some extent.

To verify this prediction empirically means testing whether credit supply shocks have a relevant impact on total debt (or on the average interest rate) on firms with a lower elasticity of substitution. In practice, analogously to the previous estimation, we regress the total debt (or the average interest rate) of a firm f on the credit supply shock hitting the firm in year t and on the interactions of the dummy of the four bins defined by the quartiles of $\hat{\sigma}_{k,t}$. The regressions include the same set of controls and fixed effects as before.

The estimates are reported in Table 5. The first dependent variable is the total credit of the used by the firm. The overall effect is significant (column 1). When considering the interaction with the bins of the estimated $\hat{\sigma}_{k,t}$ (column 2), the effect is positive and significant for firms in all bins of the elasticity of

Table 4: investment rate regressions using estimated σ's - baseline

	(1)	(2)	(3)	(4)	(5)
	all firms	all firms	excluding firms with ending relationships	excluding firms with new relationships	intensive margin
$Bank\ Shock_{f,t}$	0.058**				
	[0.027]				
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\text{bin}=1)$		0.176***	0.162***	0.187***	0.157*
		[0.042]	[0.043]	[0.043]	[0.083]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\text{bin}=2)$		0.167***	0.166***	0.187***	-0.017
		[0.042]	[0.043]	[0.042]	[0.082]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\text{bin}=3)$		0.019	0.003	0.019	0.053
		[0.034]	[0.035]	[0.034]	[0.070]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\text{bin}=4)$		0.007	-0.002	0.013	-0.079
		[0.031]	[0.032]	[0.031]	[0.060]
$(Bank\ Shock_{f,t})\times(Specialization_{t-1})$	0.020	0.010	0.022	-0.007	0.060
	[0.128]	[0.129]	[0.131]	[0.133]	[0.262]
$\ln(Employees_{f,t-1})$	-0.056***	-0.056***	-0.058***	-0.055***	-0.050***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.008]
$Age_{f,t}$	0.008***	0.008**	0.007**	0.008**	0.036***
	[0.003]	[0.003]	[0.004]	[0.004]	[0.003]
$Credit\ Score_{f,t-1}$	0.020***	0.020***	0.020***	0.020***	0.015***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.000***	0.000***	0.000**	0.000***	0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$(Bank\ Shock_{f,t})\times(LAR_f)$	0.022	0.025	0.035	0.007	-0.012
	[0.070]	[0.070]	[0.075]	[0.071]	[0.132]
$(Bank\ Shock_{f,t})\times(BAR_f)$	-0.117	-0.110	-0.072	-0.103	-0.050
	[0.189]	[0.189]	[0.192]	[0.191]	[0.330]
$\Delta\ln(collateral)_{f,t}$	0.005***	0.005***	0.005***	0.005***	0.006***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Residual\ duration_{f,t-1}$	-0.001***	-0.001***	-0.001***	-0.001***	-0.001*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Industry\&year$	0.317***	0.315***	0.322***	0.320***	0.167
	[0.059]	[0.059]	[0.060]	[0.059]	[0.140]
Observations	345,100	345,100	336,467	338,820	76,778
#Firms	66,491	66,491	65,245	65,917	24,776
Adj. R2	0.173	0.173	0.173	0.173	0.181

The table reports the estimates of the investment rate. The dependent variable is the investment rate (ratio between investment in tangible and intangible assets at time t and the corresponding capital in $t-1$) expressed in the inverse hyperbolic sine transformation. The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In the other columns this is interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009). LAR_f is the mean loans-to-assets ratio of firm f defined as the average ratio of loans to assets over the sample period. BAR_f is the mean bonds-to-assets ratio, similarly defined. $Industry\&year$ is the median of credit demand shocks ($\alpha^{AW}_{f,t}$) across firms by industry and year. The variable definitions are in table A1. All estimates include fixed effects for the firm, year and type of credit relationship. The estimation period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed at 1% at both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

substitution. However, the magnitude decreases with the $\hat{\sigma}$ bin. This is even more evident in column 3, where the analysis is limited to firms that have only ongoing relationships with banks: in this case, the coefficient in the first bin (σ bin = 1) is almost double of the corresponding coefficient in column 2. For firms with continuing or new banks, the effect on total credit is large for firms in the first two bins, and then it decreases by almost a half in the fourth bin (column 4). Similar results are obtained in column 5 where the firms have continuing or ending relationships.

In columns 6 to 10 we test the effects of credit supply shocks on the average interest rate. In general, the average borrowing cost decreases as expected (column 6). Differentiating between bins (columns 7 to 10), the average interest rate decreases significantly for all firms in the first three bins of $\hat{\sigma}$, but the magnitude is greater (in absolute value) in the first two bins. In particular, in column 8, where we consider firms having credit relationships only with continuing banks, the effect on the first bin is again almost double (in absolute value) to the corresponding effect in column 7. As for the fourth bin, the effect of the credit supply shock is barely significant for firms having credit relationships with continuing banks, as well as new or ending ones. (columns 9 and 10).

Table 5: estimates on firm total loans and average interest rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
dep. vars.:	ln(bank debtf,t)					ln(rf,t)				
	all firms	all firms	excluding firms with ending relationships	excluding firms with new relationships	intensive margin	all firms	all firms	excluding firms with ending relationships	excluding firms with new relationships	intensive margin
$Bank\ Shock_{f,t}$	0.622***					-0.634***				
	[0.157]					[0.044]				
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin= 1)		0.840***	1.028***	0.809***	1.448***		-1.345***	-1.414***	-1.422***	-2.157***
		[0.178]	[0.141]	[0.171]	[0.143]		[0.056]	[0.053]	[0.055]	[0.074]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin= 2)		0.880***	1.143***	0.818***	0.642***		-1.550***	-1.558***	-1.594***	-1.582***
		[0.196]	[0.154]	[0.188]	[0.156]		[0.061]	[0.058]	[0.060]	[0.081]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin= 3)		0.634***	0.655***	0.665***	0.551***		-0.520***	-0.550***	-0.555***	-0.633***
		[0.168]	[0.142]	[0.162]	[0.148]		[0.051]	[0.049]	[0.050]	[0.076]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin= 4)		0.415**	0.522***	0.422**	0.441***		-0.038	-0.083*	-0.070	-0.325***
		[0.179]	[0.144]	[0.168]	[0.149]		[0.049]	[0.047]	[0.048]	[0.068]
$(Bank\ Shock_{f,t})\times(Specialization_{t-1})$	0.790	0.804	0.064	0.904*	-0.222	-0.396**	-0.391*	-0.528***	-0.362*	-0.078
	[0.496]	[0.498]	[0.416]	[0.479]	[0.549]	[0.193]	[0.200]	[0.202]	[0.193]	[0.342]
$\ln(Employees_{f,t-1})$	0.417***	0.417***	0.386***	0.416***	0.271***	-0.035***	-0.034***	-0.049***	-0.032***	-0.053***
	[0.013]	[0.013]	[0.010]	[0.013]	[0.018]	[0.004]	[0.004]	[0.004]	[0.004]	[0.008]
$Age_{f,t-1}$	0.031***	0.031***	0.036***	0.026***	0.011***	0.045***	0.045***	0.049***	0.046***	0.061***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.004]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
$Credit\ Score_{f,t-1}$	-0.103***	-0.104***	-0.091***	-0.101***	-0.065***	-0.011***	-0.010***	-0.008***	-0.010***	-0.002*
	[0.003]	[0.003]	[0.002]	[0.002]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	-0.000	-0.000	-0.000	-0.000	-0.000**	-0.000***	-0.000***	-0.000***	-0.000*	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$(Bank\ Shock_{f,t})\times(LAR_f)$	-1.045***	-1.023***	-1.461***	-1.048***	-1.093***	-0.393***	-0.456***	-0.441***	-0.371***	0.073
	[0.355]	[0.356]	[0.300]	[0.337]	[0.328]	[0.110]	[0.111]	[0.101]	[0.108]	[0.137]
$(Bank\ Shock_{f,t})\times(BAR_f)$	-1.048	-0.996	-0.574	-0.613	1.282*	0.050	-0.093	-0.030	-0.132	0.313
	[1.026]	[1.025]	[0.789]	[0.992]	[0.776]	[0.277]	[0.274]	[0.267]	[0.262]	[0.378]
$\Delta\ln(collateral)_{f,t}$	0.014***	0.014***	0.011***	0.013***	0.011***	0.000	0.000	-0.000	0.000	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Residual\ duration_{f,t-1}$	-0.015***	-0.015***	-0.015***	-0.015***	-0.006***	0.002***	0.002***	0.001***	0.001***	-0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
$Industry\&year$	1.635***	1.608***	1.172***	1.571***	0.822***	-2.848***	-2.766***	-2.876***	-2.773***	-2.647***
	[0.222]	[0.222]	[0.178]	[0.214]	[0.252]	[0.089]	[0.088]	[0.087]	[0.088]	[0.137]
Observations	347,142	347,142	338,468	340,765	77,236	347,142	347,142	338,468	340,765	77,236
# Firms	66,617	66,617	65,368	66,039	24,880	66,617	66,617	65,368	66,039	24,880
Adj. R2	0.775	0.775	0.815	0.789	0.884	0.606	0.608	0.621	0.614	0.776

The table reports the estimates of the natural log of total loans (columns 1 to 5) and of the natural log of the weighted average interest rate (columns 5 to 10). The main explanatory variable is the credit supply shock at the firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In the other columns this is interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g.: 2007 and 2008 for the year 2009). LAR_f is the mean loan-to-asset ratio of the firm f defined as the average loan-to-asset ratio over the sample period. BAR_f is the mean bond-to-asset ratio, similarly defined. $Industry\&year$ is the mean of credit demand shocks ($\alpha^{AW}_{f,t}$) between firms by industry and year. The variable definitions are given in table A1. All estimates include fixed effects for the firm, year and type of credit relationship. The estimation period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed to 1% in both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Taken together, the estimates presented in this subsection show that the effect on investment (of credit supply shocks to firms with lower elasticity of substitution) derives from a greater change in firm total debt and in the average interest rate. In other terms, the firms most affected by a change in lending supply are the ones less able to offset these changes by turning to other banks.

6 Robustness checks

This section reports various robustness checks of the estimates on the investment rate.

Single-bank firms. First, we repeat the analysis by adding single-bank firms to the dataset. These firms are typically smaller and more opaque, thus one would expect the effects of credit shocks on investment to be significant for all firms, regardless of their elasticity of substitution. This is not the case. The significant effects of the credit supply shocks are relevant for firms in the two lower bins of the elasticity of substitution, except the case of continuing banks in which the credit shock is significant only for firms in the first bin.[26] see table 6). Thus, after including single bank firms to the dataset, the main results are confirmed.

Less concentrated markets. Second, the analysis is restricted to less concentrated markets. To this end, the dataset is limited to commuting zones with an HHI index less than or equal to 0.18 (see table 7 in panel a) and even more restrictive to 0.15 (panel b).[27] The estimates show that the main results are confirmed in both cases.

Tangible fixed assets. Third, table 8 contains estimates when the investment rate is built using only tangible fixed assets in the definition of capital and investment. The results are quite similar to the main ones, but the magnitude of the significant coefficients is smaller than in the main results, indicating that there is a considerable additional effect on intangible fixed assets, which have been included in the main analysis.

Loan types. Fourth, in table A3 the estimates are repeated using loan types. In columns 1 and 2 we use term loans, which are typically used for medium- or long-term projects, like investments. In column 1, the coefficient of the bank shock is significant at 5% in the first bin and only at 10% in the second bin; differently, when considering only continuing relationships, no bank shock is significant, thus suggesting that all the relevant impact of credit supply shocks derives from the extensive margin, that is to say, it involves firms which have started or terminated a term loan with a bank. In successive columns, we repeat the exercise using overdraft loans (columns 3 and 4) and accounts on receivables (columns 5 and 6). In both cases, there are no significant effects only on the first two bins of the σ distributions. This is not surprising, as these loans are typically used to finance short-term needs and not investment projects.

[26] The descriptive statistics for this wider dataset (see panel a of table 1) reveal that for most of the variables the mean and standard deviation are similar to multi-bank firms.

[27] In the first case 102 out of 611 commuting zones are excluded, while with the more stringent assumption 146 zones are dropped from the data. For more details see section A in the Appendix.

Table 6: investment rate regressions including single-bank firms

	(1)	(2)	(3)	(4)	(5)
	all firms	all firms	excluding firms with ending relationships	excluding firms with new relationships	intensive margin
$Bank\ Shock_{f,t}$	0.046**				
	[0.021]				
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin$=1)$		0.135***	0.129***	0.160***	0.117*
		[0.034]	[0.036]	[0.035]	[0.067]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin$=2)$		0.116***	0.117***	0.136***	-0.053
		[0.033]	[0.035]	[0.034]	[0.061]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin$=3)$		0.011	0.014	0.017	-0.009
		[0.028]	[0.029]	[0.028]	[0.051]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin$=4)$		0.011	0.021	0.018	-0.068
		[0.025]	[0.027]	[0.025]	[0.047]
$(Bank\ Shock_{f,t})\times(Specialization_{t-1})$	-0.008	-0.017	0.007	-0.052	0.027
	[0.112]	[0.113]	[0.117]	[0.116]	[0.207]
$\ln(Employees_{f,t-1})$	-0.057***	-0.057***	-0.058***	-0.055***	-0.050***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.007]
$Age_{f,t-1}$	0.015**	0.014**	0.014**	0.015**	0.034***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.003]
$Credit\ Score_{f,t-1}$	0.020***	0.020***	0.020***	0.020***	0.016***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.000***	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$(Bank\ Shock_{f,t})\times(LAR_f)$	0.051	0.056	0.028	0.039	0.037
	[0.059]	[0.059]	[0.062]	[0.060]	[0.106]
$(Bank\ Shock_{f,t})\times(BAR_f)$	-0.209	-0.208	-0.163	-0.214	0.048
	[0.151]	[0.151]	[0.159]	[0.154]	[0.254]
$\Delta\ln(collateral)_{f,t}$	0.005***	0.005***	0.005***	0.005***	0.006***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Residual\ duration_{f,t-1}$	-0.001***	-0.001***	-0.001***	-0.001***	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Industry\&year$	0.286***	0.284***	0.296***	0.297***	0.197*
	[0.054]	[0.054]	[0.055]	[0.054]	[0.118]
Observations	416,535	416,535	396,843	404,015	103,188
# Firms	78,077	78,077	75,977	77,300	32,548
Adj. R2	0.17	0.17	0.171	0.169	0.176

The table reports the estimates of the investment rate, where the dataset includes firms financed by only one bank. The dependent variable is the investment rate (ratio between investment in tangible and intangible assets at time t and the corresponding capital in $t-1$) expressed in the inverse hyperbolic sine transformation. The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In the other columns this is interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009). LAR_f is the mean loans-to-assets ratio of firm f defined as the average ratio of loans to assets over the sample period. BAR_f is the mean bonds-to-assets ratio, similarly defined. $Industry\&year$ is the median of credit demand shocks ($\alpha^{AW}_{f,t}$) across firms by industry and year. The variable definitions are in table A1. All estimates include fixed effects for the firm, year and type of credit relationship. The estimation period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed at 1% at both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Sensitivity analyses. Finally, we run various sensitivity analyses, by dropping (one at a time) year, firm industry, the size bin, and the credit score bin from the dataset. Starting with sensitivity by year, A4 shows that in all columns only the coefficients of the first and second bins are significant. Note that when the year 2011 (or the year 2012) is dropped from the dataset, the magnitude is particularly greater for the first bin only. These are the years of the sovereign debt crisis in which a credit crunch affected the Italian economy. Although in normal years firms can switch banks relatively easily to negotiate better terms, during a credit crunch, as in the sovereign debt crisis of 2011 and 2012, even a positive shock might not provide the same incremental benefits because firms cannot substitute banks easily.

In table A5 we report in each row the sensitivity by dropping one industry at a time and the main results are confirmed: credit supply shocks are significant only for firms in the first two bins. In tables A6 and A7 the estimates are repeated dropping one size bin or one credit score bin at a time; again, the estimated coefficients are significant only for firms with lower elasticity of substitution in all columns.

Overall, all robustness checks confirm the main result of section (5) that credit supply shocks have a positive and significant effect on the investment rate, but the effect depends on the level of the elasticity substitution between lenders: the overall quantity effect on investments derives only from firms with lowest elasticity. Therefore, estimating the elasticity of substitution is important for a better understanding of the heterogeneous reaction of investment to credit constraints on firms.

Table 7: investment rate regressions in less concentrated markets

Panel a: commuting zones with HHI≤0.18					
	(1)	(2)	(3)	(4)	(5)
	all firms	all firms	excluding firms with ending relationships	excluding firms with new relationships	intensive margin
$Bank\ Shock_{f,t}$	0.061**				
	[0.027]				
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma \text{ bin}=1)$		0.182***	0.169***	0.194***	0.169**
		[0.042]	[0.044]	[0.043]	[0.084]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma \text{ bin}=2)$		0.170***	0.169***	0.190***	-0.014
		[0.042]	[0.043]	[0.042]	[0.083]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma \text{ bin}=3)$		0.021	0.006	0.021	0.053
		[0.034]	[0.035]	[0.035]	[0.071]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma \text{ bin}=4)$		0.010	0.002	0.016	-0.080
		[0.031]	[0.033]	[0.031]	[0.061]
Controls	Yes	Yes	Yes	Yes	Yes
Observations	342,010	342,010	333,425	335,772	75,560
# Firms	65,877	65,877	64,638	65,307	24,433
Adj. R2	0.173	0.173	0.173	0.173	0.181

Panel a: commuting zones with HHI≤0.15					
	(1)	(2)	(3)	(4)	(5)
	all firms	all firms	excluding firms with ending relationships	excluding firms with new relationships	intensive margin
$Bank\ Shock_{f,t}$	0.055**				
	[0.027]				
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma \text{ bin}=1)$		0.176***	0.163***	0.188***	0.165*
		[0.043]	[0.044]	[0.043]	[0.085]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma \text{ bin}=2)$		0.158***	0.157***	0.178***	-0.022
		[0.042]	[0.043]	[0.043]	[0.084]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma \text{ bin}=3)$		0.013	-0.002	0.014	0.048
		[0.035]	[0.036]	[0.035]	[0.072]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma \text{ bin}=4)$		0.006	-0.003	0.012	-0.083
		[0.032]	[0.033]	[0.032]	[0.062]
Controls	Yes	Yes	Yes	Yes	Yes
Observations	340,780	340,780	332,218	334,555	75,160
# Firms	65,617	65,617	64,381	65,048	24,315
Adj. R2	0.173	0.173	0.173	0.173	0.181

The table reports the estimates of the investment rate. Panel a uses a dataset with the HHI in each commuting zone is less or equal to 0.18, in panel b the threshold is set at 0.15. The dependent variable is the investment rate (ratio between investment in tangible and intangible assets at time t and the corresponding capital in $t-1$) expressed in the inverse hyperbolic sine transformation. The main explanatory variable in column 1 is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In the other columns this is interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009). Controls include $\ln(Employees_{f,t-1})$, $Age_{f,t-1}$, $Credit\ Score_{f,t-1}$, $Cash\ Flow_{f,t}/Capital_{f,t-1}$, $(Bank\ Shock_{f,t}) \times (LAR_f)$, $(Bank\ Shock_{f,t}) \times (BAR_f)$, $\Delta \ln(collateral)_{f,t}$, $Residual\ duration_{f,t-1}$, $Industry\&year$, as defined table A1. All estimates include fixed effects for the firm, year and type of credit relationship. The estimation period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed at 1% at both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: investment rate regressions using only tangible capital

	(1)	(2)	(3)	(4)	(5)
	all firms	all firms	excluding firms with ending relationships	excluding firms with new relationships	intensive margin
$Bank\ Shock_{f,t}$	0.046**				
	[0.021]				
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin= 1)		0.135***	0.129***	0.160***	0.117*
		[0.034]	[0.036]	[0.035]	[0.067]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin= 2)		0.116***	0.117***	0.136***	-0.053
		[0.033]	[0.035]	[0.034]	[0.061]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin= 3)		0.011	0.014	0.017	-0.009
		[0.028]	[0.029]	[0.028]	[0.051]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma$ bin= 4)		0.011	0.021	0.018	-0.068
		[0.025]	[0.027]	[0.025]	[0.047]
Controls	Yes	Yes	Yes	Yes	Yes
Observations	416,535	416,535	396,843	404,015	103,188
# Firms	78,077	78,077	75,977	77,300	32,548
Adj. R2	0.17	0.17	0.171	0.169	0.176

The table reports the estimates of the investment rate is calculated using only fixed tangible assets. The dependent variable is the investment rate (ratio between investment in tangible assets at time t and the corresponding capital in $t-1$) expressed in the inverse hyperbolic sine transformation. The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In the other columns this is interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009). Controls include $\ln(Employees_{f,t-1})$, $Age_{f,t-1}$, $Credit\ Score_{f,t-1}$, $Cash\ Flow_{f,t}/Capital_{f,t-1}$, $(Bank\ Shock_{f,t}) \times (LAR_f)$, $(Bank\ Shock_{f,t}) \times (BAR_f)$, $\Delta \ln(collateral)_{f,t}$, $Residual\ duration_{f,t-1}$, $Industry\&year$, as defined table A1. All estimates include fixed effects for the firm, year and type of credit relationship. The estimation period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed at 1% at both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

7 Conclusions

This paper estimates the elasticity of substitution between banks using matched bank-firm data on loans and interest rates and using a simple methodology that allows one to directly derive an estimating equation of credit demand from minimization of lending costs.

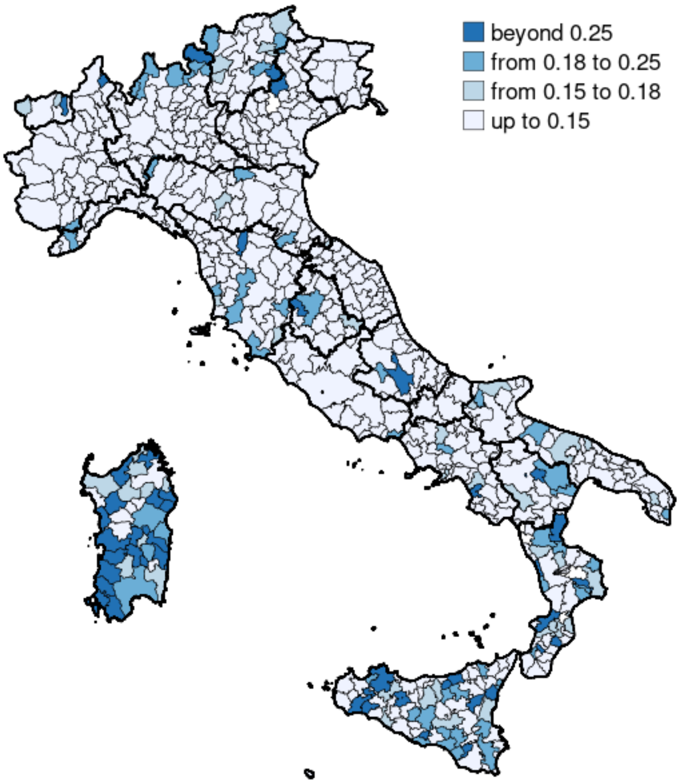
This elasticity is relevant, for the paper provides insight into two important contributions to the literature on the responsiveness of the real economy to financial shocks. First, by exploiting firm characteristics, such as industry, size, and credit score, the paper estimates a wide distribution of these elasticity. The paper shows that the distribution of this substitutability measure is relevant because it shapes the effect of credit shocks on firms' investments. Credit supply shocks increase the investment rate of firms, as found in the large literature so far, but the new first finding is that the effects are significant only for firms with the lowest elasticity of substitution. Therefore, the distribution of this elasticity on firms is important to understand the functioning of the bank lending channel and its effects on the real economy, which to the best of my knowledge has never been found before.

Secondly, the differential effects on investments also depend on the extensive and the intensive margins of lending. If a bank cuts lending, firms reduce total borrowing (or suffer an increase in the interest rate) by less if they can substitute the loss of credit from that bank to other lenders with which they have an ongoing credit relationship. In this case, only firms with a very low elasticity of substitution (below the first quartile) need a credit supply expansion to increase investments. Differently, if a firm turns to a new bank (or if it suffers from the termination of a credit relationship), the effects of a lending cut on investments are relevant for a wider set of firms, namely businesses with an elasticity below the median.

These findings are also important for other reasons. First, they suggest that the elasticity of substitution is a reliable indicator of the ease of substituting and/or switching between lenders not only after specific episodes of financial distress, but also in other periods. This is especially relevant in the context of ongoing process of consolidation of the banking sector which reduces the number of banks over time in all advanced countries, and thus it may exacerbate the costs of switching lenders. Secondly, the elasticity of substitution is a reliable measure of the sensitivity of firms to changes in the cost of external funds, which can be particularly relevant in the current period of increased interest rates. Third, the paper provides a framework to assess the sensitivity of credit availability to changes in supply conditions for firms of different characteristics (industry, size, credit score, etc.). This could be relevant to evaluate the impact of supply shocks on the financial vulnerability of both firms and their lenders, with possible implications for systemic risk analyses and macroprudential policy decisions. For example, in the design of stress tests policy-makers might better identify clusters (of industries, size, etc.) that are more/less susceptible to substitution, which alleviates the negative effects of bank concentration.

Finally, the results of this study provide implications for future research. The estimates in the paper are based on data from Italy, where firms are highly dependent on bank credit. It would be interesting to expand the analysis to other advanced countries with a different structure of the banking sector. The heterogeneous response across firm characteristics could be considered for a deeper scrutiny of the responsiveness of the real economy to financial shocks.

Figure 1: Concentration in local credit markets



The figure shows the average HHI calculated on corporate loans in each commuting zone between 2005 and 2006. The thicker lines denote the borders of regions (NUTS level 2).

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Appendix

A Monopolisitic competition in local credit markets

In this section, we discuss the assumption of monopolistic competition, which rules out strategic interaction between lenders. we also discuss how to measure concentration in local credit markets.

There is a wide consensus in the literature on the existence of market power in lending markets ([16]), and one of the main causes is the presence of switching costs for both customers and lenders. [28]. The theoretical predictions are confirmed by a wide empirical evidence that is consistent with the finding of market power in banking markets. More specifically, [21] classify the banking system in Italy as that of various other advanced countries as monopolistically competitive. While much of the empirical literature has focused on country-level analyses, in order to assess the level of concentration in local markets, we need measures at the subnational level. To this purpose, we follow [7], who measure competition in local credit markets in Italy using the Herfindahl-Hirschman Index (henceforth, HHI) computed on outstanding amounts of loans.[29] we compute the HHI in each commuting zone in the years 2005 and 2006 and then we take the average across the two years, in order to avoid that single year events (e.g.: the entry of one bank that in a zone that exits in the following year) may affect the analysis.[30] Local credit markets in Italy are generally not very concentrated. The average value of the HHI is 0.13. However, there is a large heterogeneity as showed in figure 1: the HHI is in a range of values between 0.04 and 0.89. Therefore, it makes sense to drop the commuting zones with the highest concentration from the analysis. Unfortunately, there is no general agreement on which threshold of the HHI defines the level of market concentration.[31] Given the variety of the values suggested, we keep only the commuting zones with an average HHI$\leq$0.25, considering areas with a higher threshold as concentrated markets where collusion between banks may occur: this way, we discard 50 commuting zones of the data set out of 611, and the data set has 5,036,614 observations. In a robustness check (subsection 6) we repeat the main estimates using a restricted sample of commuting zones with HHI$\leq$0.18 or HHI$\leq$0.15 and the main results are confirmed.

[28] Indeed, on the bank side asymmetric information induces banks to devote resources to screen new customers. On the other hand, switching banks is costly also for borrower firms because of the fixed costs of setting a new relationship with a lender: to signal their creditworthiness, such as reassessing the value of collateral or the validity of investment projects, or due to 'menu costs' (for example, fees charged to close or open a bank account). Thus, the presence of switching costs gives banks market power, due to a 'lock-in' effect with their borrowers.

[29] Differently from the concentration ratios, the HHI encompasses the entire distribution of loans extended in the market and it is not influenced by the arbitrary choice of the number of players considered. The HHI correctly represents credit competition in local credit markets: panel a and panel b of Figure A1 in the Appendix show that the index is negatively correlated with lending and positively with the average interest rate, as predicted by the literature (see for example [47] and [53]).

[30] In a robustness check, not showed here for sake of brevity, we repeat the estimates using the HHI computed in one year before the initial period of the dataset (2005). All results are confirmed.

[31] Analyzing local credit markets, [26] cite as "widely accepted cut-offs" the values of 0.10 and 0.18 of the HHI, where a HHI$<$ 0.10 represents a competitive market and HHI$>$ 0.18 a concentrated market. In dealing with M&As of financial intermediaries, the Federal Reserve Board in the US refers to the Horizontal Merger Guidelines of the Department of Justice and of the Federal Trade Commission (https://www.justice.gov/atr/herfindahl-hirschman-index) where a market with an HHI between 0.15 and 0.25 is labeled 'moderately concentrated'. [10] considers that here there is monopolistic competition in the market if the HHI falls between 0.21 and 0.40.

Note that by imposing only an upper bound on the HHI, we keep markets with very low levels of concentration. However, assuming monopolistic competition in these local markets is still a reasonable assumption because even in very competitive environments local banks can impose informational barriers to outside competitors (e.g. national banks) whose practices are less based on relationship lending ([8]).

After restricting the dataset so that coordination among banks is less likely, we expect that in a monopolistically competitive setting there is enough observed heterogeneity of the lending conditions (most prominently, the interest rates) within each local market because banks do not have access to exactly the same information set of the borrower: panel c of figure A1 in the Appendix shows that there is enough heterogeneity in the interest rates within the commuting zones and that this heterogeneity is lower in markets with a higher HHI, which is consistent with the idea that informational rent extraction is reduced in more competitive areas.

B The Amiti and Weinstein estimator

In this section, we summarize the main features of the AW estimators of credit demand and supply shocks used in the paper. [4] develop a methodology to disentangle shocks in credit demand and credit supply using matched bank-firm data. Starting from the equation originally formulated by [43]:

$$D_{b,f,t} = \alpha_{f,t} + \beta_{b,t} + \epsilon_{b,f,t} \tag{B.1}$$

where $D_{b,f,t}$ is the percentage growth rate of lending, $\alpha_{f,t}$ is the firm-time fixed effect (firm borrowing channel), $\beta_{f,t}$ is the bank-time fixed effect (bank lending channel) and $\epsilon_{b,f,t}$ is a random error term. Typically, equation B.1 is estimated using OLS and restricting the analysis to observations with at least two connections for each bank or firm. The novel methodology of [4] implies that the estimation of the components of supply and demand is done by imposing an additional constraint that states that the changes in the growth of credit from banks to firms must add up to the overall, economy-wide change in credit growth. In other terms, this adding-up constraint ensures that estimates obtained from the micro-credit shocks are consistent with those of aggregate credit supply and demand in the economy. Adding this constraint implies that the total growth of bank b credit is a weighted sum of all the loans it extended to firms: $D^B_{b,t} = \sum_f D_{b,f,t} \frac{L_{b,f,t-1}}{\sum_f L_{b,f,t-1}}$. Similarly, firm f credit growth is a weighted sum of all the loans it borrowed by banks: $D^F_{f,t} = \sum_b D_{b,f,t} \frac{L_{b,f,t-1}}{\sum_b L_{b,f,t-1}}$.

Under a set of standard assumptions, [4]) retrieve $\alpha^{AW}_{f,t}$ and $\beta^{AW}_{b,t}$ by solving the following system of equations:

$$D^B_{b,t} = \beta^{AW}_{b,t} + \sum_f \phi_{f,b,t-1}\alpha^{AW}_{f,t} + \sum_f \phi_{f,b,t-1}\epsilon_{b,f,t} \tag{B.2}$$

$$D^F_{f,t} = \alpha^{AW}_{f,t} + \sum_b \theta_{f,b,t-1}\beta^{AW}_{b,t} + \sum_b \theta_{f,b,t-1}\epsilon_{b,f,t} \tag{B.3}$$

Equation (B.2) states that bank b credit growth is driven by bank-specific credit supply factors ($\beta^{AW}_{b,t}$), as well as a weighted average of changes in credit demand by all its borrowing firms ($\phi_{f,b,t-1} = \frac{L_{b,f,t-1}}{\sum_f L_{b,f,t-1}}$). Similarly, equation (B.3) shows that the total credit growth of firm f is based on its credit demand ($\alpha^{AW}_{f,t}$) and a weighted average of credit supply conditions in all banks lending to firm f ($\theta_{f,b,t-1} = \frac{L_{b,f,t-1}}{\sum_b L_{b,f,t-1}}$).

Since $\phi_{f,b,t-1}$ and $\theta_{f,b,t-1}$ are predetermined, the following moment conditions can be imposed: $\sum_f \phi_{f,b,t-1} \cdot E(\epsilon_{b,f,t}) = 0$ and $\sum_b \theta_{f,b,t-1} \cdot E(\epsilon_{b,f,t}) = 0$, respectively. Then, firm demand and bank supply shocks ($\alpha^{AW}_{f,t}$ and $\beta^{AW}_{b,t}$, respectively) can be estimated using these moment conditions in the following system of equations:

$$D^B_{b,t} = \beta^{AW}_{b,t} + \sum_f \phi_{f,b,t-1}\alpha^{AW}_{f,t} \tag{B.4}$$

$$D^F_{f,t} = \alpha^{AW}_{f,t} + \sum_b \theta_{f,b,t-1}\beta^{AW}_{b,t} \tag{B.5}$$

C Validation of Instrumental Variable

In this section, following [2] we describe the procedure to show that the instrumental variable (the estimated bank-time fixed effect) does not depend on demand components. The procedure is in two stages. In the first stage we obtain the bank-time fixed effects for each k by estimating the equation 8 with the AW estimator ($\hat{\beta}^{AW}_{b,k,t}$). In the second step, after collapsing the instrumental variable to bank-k-time level, we regress the estimated bank-time fixed effect ($E(\hat{\beta}^{AW}_{b,k,t})$) on the corresponding log change in the average interest rate ($\Delta \ln r_{b,k,t}$):

$$\hat{\beta}^{AW}_{b,k,t} = c + \rho \Delta \ln r_{b,k,t} + \epsilon_{b,k,t} \tag{C.1}$$

Because of reverse causality, $\Delta \ln r_{b,k,t}$ is instrumented with the average of the demand shifter measured with the AW procedure weighted at bank-k-time level ($\hat{\alpha}^{AW}_{f,k,t}$) or the weighted growth rate of lending by k-time, as suggested by [2]: $x_{k,t}$. In detail, $x_{k,t}$ is given by the product of bank b's growth rate of lending to the triplet k at time t and the exposure of the same bank to the same triplet in $t-1$:[32] $x_{b,k,t} = \sum_{k=1}(\frac{L_{-b,k,t}}{L_{-b,k,t-1}} - 1)\lambda_{b,k,t-1}$ where $L_{-b,k,t}$ is total lending to triplet k at time t (in leave-out form for bank b). The weight $\lambda_{b,k,t-1}$ is given by the bank b lending to triplet k relative to its total lending four quarters before time t: $\lambda_{b,k,t-1} = \frac{L_{b,k,t-1}}{L_{b,t-1}}$.

Finding that $\rho = 0$ implies that the estimated fixed effects of the bank time $\hat{\beta}^{AW}_{b,k,t}$ do not depend on the average interest rate that may contain any demand component. In this case, the instrumental variable correctly identifies the shock in the credit supply.

[32] we exploit variation across the triplet industry, size bin and credit score bin: the average growth rate of lending varies between -3.00% (in the triplet of Beverages & tobacco, 1 st size bin, 4th credit score bin, at the 4th quarter of year 2009) and 3.96% (in the triplet agriculture, 1st size bin and 4th credit score at the last quarter of 2010).

D The elasticity of substitution by firm characteristics

In this section, we show that the estimates of the elasticity of substitution vary with firm characteristics: industry, size, and credit score. Showing this allows us to understand the gain by leaving out each of these firm features in estimating the distribution of σ used in the paper.

Starting with the firm industry, figure A2 reports three types of estimates of the elasticity of substitution. Panel a reports the average of the estimates by industry: the elasticities show extreme variability, for two industries they reach abnormal values of -1103.6 (Beverages & tobacco) and 1100.9 (Transport & courier). This huge variation is reduced to a great extent when the estimates are repeated by leaving out each industry from the dataset (panel b); in this case, the average elasticity is 1.4, but the confidence intervals are still very large. Finally, in panel c the estimations also leave out from the analysis the size bin and the credit score bin; in this case, the estimated elasticity is very stable around the mean absolute value (4.20).

We repeat the previous exercise by estimating the elasticity of substitution with respect to the firm size, as showed in the figure A3. In this case the estimated by size bin (panel a) show a clear evidence of larger firms to a higher substitutability. This tendency is almost reversed when the elasticities are estimated by leaving out the firm size (panel b). In panel c, where the industry and the credit score bin are also left out of the estimation, the estimated parameters are very stable around the mean value (4.20).

Finally, repeating the exercise with respect to the credit score (in figure A4), shows similar results. Estimates by credit score have very large confidence intervals for lower score firms (panel a); the ones leaving out the score variable are much more precise but with a large coefficient (panel b). Finally, estimates leaving out also industry and the size bin (panel c) have the lowest variability, both by bin and across bins.

E Bank specialization

In this section, we show the construction of the comparative advantage measure of bank specialization by industry, adapting to that of [48], and then we show how to insert this measure into the firm's investment equation.

For the first point, we consider a measure of the comparative advantage of the bank b specific to the industry j. Define the portfolio share of lending of bank b towards the industry j by the lending of the bank towards to all its borrowing firms $f = 1, ..., F_j$ in the industry j (we.e., $L^j_{b,t} = \sum_{f \in F_j} L^j_{f,b,t}$) at time t, relative to the lending of the same bank b to all the industries ($L_{b,t} = \sum_{j=1}^{J} L^j_{b,t}$). [33]

[33] Note that $f \in F_j$ is a simplification of the notation, because it does not include all firms in the industry j, but only the subset of these firms that are borrowers of bank-b.

Formally this is given by the following:

$$S^j_{b,t} = \frac{L^j_{b,t}}{L_{b,t}} = \frac{\sum_{f \in F_j} L^j_{f,b,t}}{\sum_{j=1}^{J} L^j_{b,t}} \tag{E.1}$$

In the second step, to reconcile $S^j_{b,t}$, which is at bank-industry-year level, with data on investment, that are at firm-year level, we compute a weighted average of the previous measures of specialization at firm-year level (time subscript are reintroduced here):

$$S^j_{f,t} = \sum_{b \in f} w_{f,b,t-2} \cdot S^j_{b,t} \tag{E.2}$$

where $w_{f,b,t-2}$ is the weight of loans to firm f by each bank in $t-2$: $w_{f,b,t-2} = \sum_{b \in f} \frac{L_{f,b,t-2}}{L_{f,t-2}}$. $S^j_{f,t}$ is the measure of the intensity of bank specialization for each firm in each period t.

Plugging the previous expression (interacted with the $Bk\ Shock_{f,t}$) into the investment rate equation, gives the following:

$$I_{f,t} = \sum_{\iota=1}^{4} \gamma_\iota (Bk\ Shock_{f,t}) \times \mathbf{1}(\iota) + \gamma_\zeta (Bk\ Shock_{f,t}) \times S^j_{f,t} + \Gamma_5 X_{f,t} + \gamma_{j,t} + \gamma_f + \gamma_\lambda + \nu_{f,t} \tag{E.3}$$

Equation E.3 allows to test whether the effect of the bank shock is driven by the elasticity of substitution across banks (γ_ι) and/or the degree of banks specialization (γ_ψ).

Table A1: Variables description

Variable	Description	Frequency	Source[1]
Panel a: basic variables			
Loans	Outstanding loan amount (granted and used)	quarterly	CR
Collateral	Value of guarantee on loan	quarterly	CR
Interest rate	Interest rate	quarterly	Taxia
Employees	Number of employees	yearly	INPS
Investment	Firm investments	yearly	CADS
Capital[2]	Firm capital stock	yearly	CADS
Cash flow	Firm cash	yearly	CADS
Age	Firm age	yearly	CADS
Interbank funding	Sum of deposits from financial domestic and foreign intermediaries	yearly	SR
Foreign funding	Sum of deposits from foreign financial and retail intermediaries	yearly	SR
Bank assets	Bank total assets	yearly	SR
Tier 1 ratio	Ratio of a bank's core tier 1 capital to total risk-weighted assets[3]	yearly	SR
Total capital ratio	Ratio of a bank's core tier 1 capital plus core tier 2 capital to total r.w. assets[3]	yearly	SR
Judicial cases	Judicial cases: pending, ending and new cases at year start	yearly	Italian Ministry of Justice
Panel b: other derived variables			
Industry&year	median of credit demand shocks ($\alpha_{f,t}^{AW}$) between firms by industry and time	quarterly	CR
Residual duration	residual duration of a loan	quarterly	CR
LAR$_f$	mean loan-to-asset ratio [4]	yearly	CADS
BAR$_f$	mean bond-to-asset ratio [4]3	yearly	CADS
Credit score	Credit score variable [5]	yearly	CADS

(1): CR is the Credit Register; CADS is the Company Accounts dataset; SR is the Supervisory Reports dataset. (2): Capital is built using the perpetual inventory method with industry-year level depreciation rates coming from national accounts data. Both capital and investment are deflated using industry-year producer prices from national accounts data provided by the National Institute of Statistics (Istat). The starting value of capital $K_{i,0}$ is the first observation on firm book value, deflated using the industry investment deflator from T_i years before, where T_i is the average age of firm capital stock. (3): Core tier 1 capital includes equity and disclosed reserves. Core tier 2 capital includes undisclosed and revaluation reserves, general provisions, hybrid instruments and subordinated term debt. (4): LAR_f is the mean loan-to-asset ratio of the firm f defined as the average loan-to-asset ratio over the sample period. BAR_f is the mean bond-to-asset ratio, similarly defined. (5): Credit score is a categorical variable (with integer values from 1 to 9). It derives from the Z-score and it has been recoded so that higher values mean a better credit score (or a lower probability of default).

Table A2: Validation of the instrumental variable II

	(1)	(2)	(3)	(4)	(5)	(6)
Instrumental variable:	$\hat{\alpha}^{AW}_{f,t-1}$	$\hat{\alpha}^{AW}_{f,t-1}$	$\hat{L}_{b,k,t}$	$\hat{L}_{b,k,t}$	$x_{k,t}$	$x_{k,t}$
$\Delta r_{b,t}$	-0.00782	0.000628	0.709	0.00146	1.614	0.0384
	[0.0428]	[0.00187]	[3.822]	[0.00104]	[20.60]	[0.0253]
Constant	0.00991***		0.0167		0.0254	
	[0.00226]		[0.0354]		[0.188]	
Observations	1,052,349	1,052,203	1,052,200	1,052,054	1,051,673	1,051,529
F-test	373.2	30.39	33.01	197	0.484	27.86
Bank#time FE	No	Yes	No	Yes	No	Yes
# Banks	209	205	209	205	209	205

The table reports the 2SLS estimates, where the dependent variable is bank-time fixed effect estimated with the AW procedure ($\hat{\beta}^{AW}_{b,t}$). This is regressed on the natural log change of the interest rate (weighted average at k level, where k is bank, industry, size bin, and credit score bin) at time t: $\Delta r_{b,k,t}$. The instrumental variable is the firm-time fixed effect estimated with the AW procedure ($\hat{\alpha}^{AW}_{f,t}$) in columns 1 and 2, the growth rate of lending (weighted average at k level: $\hat{L}_{b,k,t}$) in columns 3 and 4 or the k-level growth rate ($x_{k,t}$) as defined in the Appendix (C) in columns 5 and 6. All variable definitions are in Table A1. and a constant Heteroskedastic robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Effects on investments by loan type

	Term loans		Overdraft loans		Accounts on receivables loans	
	(1)	(2)	(3)	(4)	(5)	(6)
	all firms	intensive margin	all firms	intensive margin	all firms	intensive margin
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma$ bin$= 1)$	0.119**	-0.142	0.012	0.239	-0.029	1.708**
	[0.049]	[0.106]	[0.111]	[0.205]	[0.340]	[0.796]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma$ bin$= 2)$	0.097*	-0.134	-0.005	-0.033	0.406	1.540*
	[0.052]	[0.111]	[0.119]	[0.186]	[0.382]	[0.894]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma$ bin$= 3)$	-0.002	-0.103	0.236**	0.329*	-0.021	1.582*
	[0.049]	[0.106]	[0.106]	[0.177]	[0.383]	[0.931]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\sigma$ bin$= 4)$	0.105	-0.156	0.173*	0.138	0.795*	2.145**
	[0.065]	[0.137]	[0.103]	[0.167]	[0.419]	[0.915]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,317	8,740	18,862	4,320	12,606	2,665
# Firms	17622	3407	5427	1544	3714	995
Adj. R2	0.195	0.211	0.183	0.214	0.182	0.205

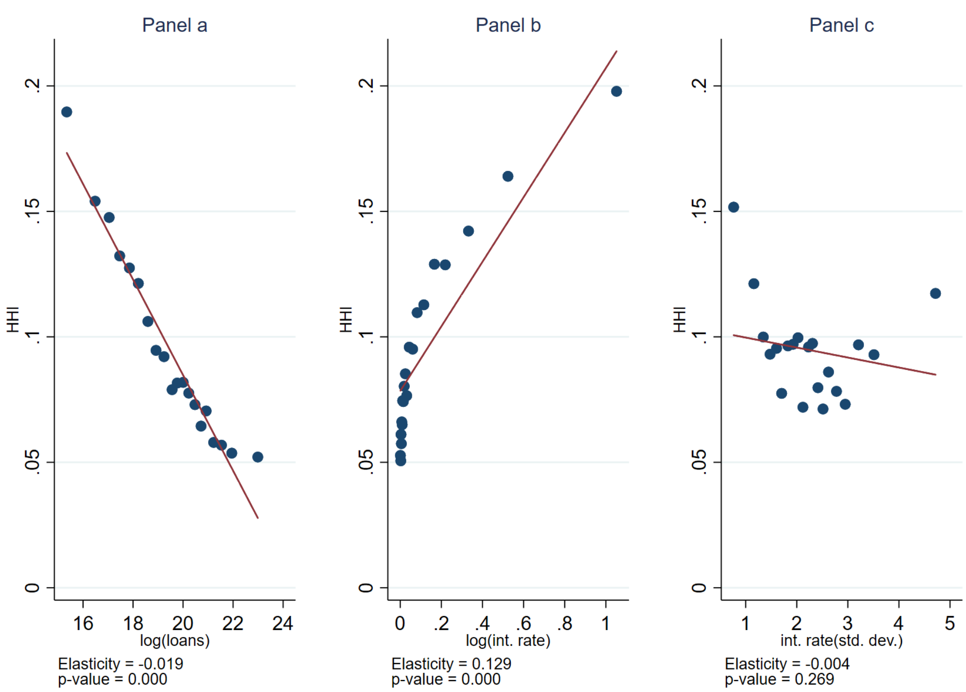
The table reports the estimates of the investment rate using different types of loans: term loans (columns 1 and 2), overdraft loans (columns 3 and 4) and accounts on receivables (columns 5 and 6). The dependent variable is the investment rate (ratio between investment in tangible and intangible assets at time t and the corresponding capital in $t-1$) expressed in the inverse hyperbolic sine transformation. The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009). The credit supply shock is calculated on each type of loans. Controls include $\ln(Employees_{f,t-1})$, $Age_{f,t-1}$, $Credit\ Score_{f,t-1}$, $Cash\ Flow_{f,t}/Capital_{f,t-1}$, $(Bank\ Shock_{f,t}) \times (LAR_f)$, $(Bank\ Shock_{f,t}) \times (BAR_f)$, $\Delta \ln(collateral)_{f,t}$, $Residual\ duration_{f,t-1}$, $Industry\&year$, as defined table A1. All estimates include fixed effects for the firm, year and type of credit relationship. The estimation period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed at 1% at both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: sensitivity by year

year dropped:	(1) 2009	(2) 2010	(3) 2011	(4) 2012	(5) 2013	(6) 2014	(7) 2015
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\text{ bin}=1)$	0.158***	0.152***	0.237***	0.197***	0.177***	0.153***	0.146***
	[0.049]	[0.049]	[0.062]	[0.046]	[0.044]	[0.043]	[0.043]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\text{ bin}=2)$	0.154***	0.153***	0.177***	0.220***	0.180***	0.162***	0.085*
	[0.050]	[0.049]	[0.044]	[0.049]	[0.046]	[0.043]	[0.048]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\text{ bin}=3)$	0.057	0.021	0.015	0.031	0.025	0.004	-0.032
	[0.051]	[0.036]	[0.036]	[0.036]	[0.038]	[0.036]	[0.038]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\text{ bin}=4)$	-0.089	-0.021	0.016	0.010	0.018	-0.002	0.012
	[0.056]	[0.034]	[0.033]	[0.033]	[0.033]	[0.033]	[0.033]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288,610	288,694	292,073	294,820	295,236	295,322	298,595
# Firms	62,201	62,333	65,284	65,248	65,374	63,748	63,999
Adj. R2	0.178	0.174	0.172	0.171	0.170	0.171	0.176

The table reports the estimates of the investment rate, where the dataset excludes one year at a time. The dependent variable is the investment rate (ratio between investment in tangible and intangible assets at time t and the corresponding capital in $t-1$) expressed in the inverse hyperbolic sine transformation. The main explanatory variable is the credit supply shock at the firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In the other columns this is interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009). Controls include $\ln(Employees_{f,t-1})$, $Age_{f,t-1}$, $Credit\ Score_{f,t-1}$, $Cash\ Flow_{f,t}/Capital_{f,t-1}$, $(Bank\ Shock_{f,t})\times(LAR_f)$, $(Bank\ Shock_{f,t})\times(BAR_f)$, $\Delta\ln(collateral)_{f,t}$, $Residual\ duration_{f,t-1}$, $Industry\&year$, as defined table A1. All estimates include fixed effects for the firm, year and type of credit relationship. The estimation period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed to 1% in both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A1: Correlations of HHI with credit and interest rates



Binned scatter correlations of the HHI and the log of loans (panel a), the average interest rate in logs (panel b) and the standard deviation of the interest rates within each commuting zone (panel c).

Table A5: sensitivity by industry

industry dropped	$(Bank\ Shock_{f,t})\times$ (σ bin= 1)	(σ bin= 2)	(σ bin= 3)	(σ bin= 4)	Observations	# Firms	Adj. R2
1	0.182***	0.169***	0.023	0.012	342,949	66,084	0.173
2	0.167***	0.159***	0.015	0.003	333,465	64,400	0.173
3	0.175***	0.168***	0.017	0.006	343,325	66,173	0.173
4	0.181***	0.178***	0.021	0.005	337,645	65,099	0.173
5	0.186***	0.168***	0.03	0.012	339,533	65,389	0.173
6	0.180***	0.183***	0.026	0.008	339,656	65,451	0.173
7	0.176***	0.166***	0.018	0.004	339,332	65,383	0.173
8	0.162***	0.158***	0.018	0.014	335,013	64,602	0.175
9	0.185***	0.163***	0.029	0.012	338,003	65,224	0.173
10	0.178***	0.163***	0.017	-0.001	332,739	64,249	0.174
11	0.187***	0.171***	0.018	0.01	335,822	64,743	0.173
12	0.174***	0.164***	0.017	0.006	339,828	65,557	0.174
13	0.185***	0.191***	0.017	0.001	307,258	59,344	0.177
14	0.170***	0.157***	0.014	0.004	334,761	64,551	0.171
15	0.158***	0.167***	0.034	0.019	322,885	62,299	0.174
16	0.177***	0.161***	0.022	0.007	341,409	65,780	0.173
17	0.170***	0.164***	0.018	0.004	337,723	65,077	0.173
18	0.177***	0.164***	0.025	0.01	336,674	64,821	0.173
19	0.180***	0.176***	0.016	0.003	340,290	65,560	0.173
20	0.154***	0.159***	0.004	0.01	308,882	59,230	0.179
21	0.157***	0.166***	-0.032	-0.003	276,716	53,842	0.178
22	0.162***	0.167***	0.018	0.008	332,439	63,845	0.173
23	0.185***	0.174***	0.029	0.01	333,462	64,161	0.173
24	0.179***	0.171***	0.02	0.006	338,744	65,080	0.172
25	0.196***	0.169***	0.03	0.014	338,012	64,992	0.163
26	0.175***	0.165***	0.017	0.009	340,617	65,470	0.173
27	0.173***	0.157***	0.006	-0.001	339,602	65,330	0.173
28	0.172***	0.160***	0.02	0.003	338,481	65,099	0.173
29	0.176***	0.155***	0.014	0.005	339,738	65,378	0.173
30	0.172***	0.164***	0.019	0.002	342,897	66,026	0.173

The table reports the estimates of the investment rate, where the dataset excludes one industry at a time. The dependent variable is the investment rate (ratio between investment in tangible and intangible assets at time t and the corresponding capital in $t-1$) expressed in the inverse hyperbolic sine transformation. The main explanatory variable is the credit supply shock at the firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In the other columns this is interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g.: 2007 and 2008 for the year 2009). The variable definitions are in table A1. All estimates include fixed effects for the firm, year, and type of credit relationship. The estimates period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed to 1% in both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

LAR_f is the mean loan-to-asset ratio of the firm f defined as the average loan-to-asset ratio over the sample period. BAR_f is the mean bond-to-asset ratio, similarly defined. $Industry\&year$ is the median of credit demand shocks ($\alpha^{AW}_{f,t}$) between firms by industry and year.

Table A6: sensitivity by size bin

size bin dropped:	(1) small	(2) small-medium	(3) medium-large	(4) large
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\ \text{bin}=1)$	0.145***	0.196***	0.195***	0.164***
	[0.047]	[0.048]	[0.049]	[0.053]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\ \text{bin}=2)$	0.203***	0.137***	0.178***	0.124**
	[0.047]	[0.048]	[0.049]	[0.052]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\ \text{bin}=3)$	-0.004	-0.012	0.014	0.06
	[0.038]	[0.042]	[0.039]	[0.041]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma\ \text{bin}=4)$	0.021	0.008	0.022	-0.008
	[0.035]	[0.036]	[0.038]	[0.036]
Controls	Yes	Yes	Yes	Yes
Observations	264,698	257,144	252,899	248,805
# Firms	52,093	53,554	52,831	50,651
Adj. R2	0.179	0.18	0.174	0.17

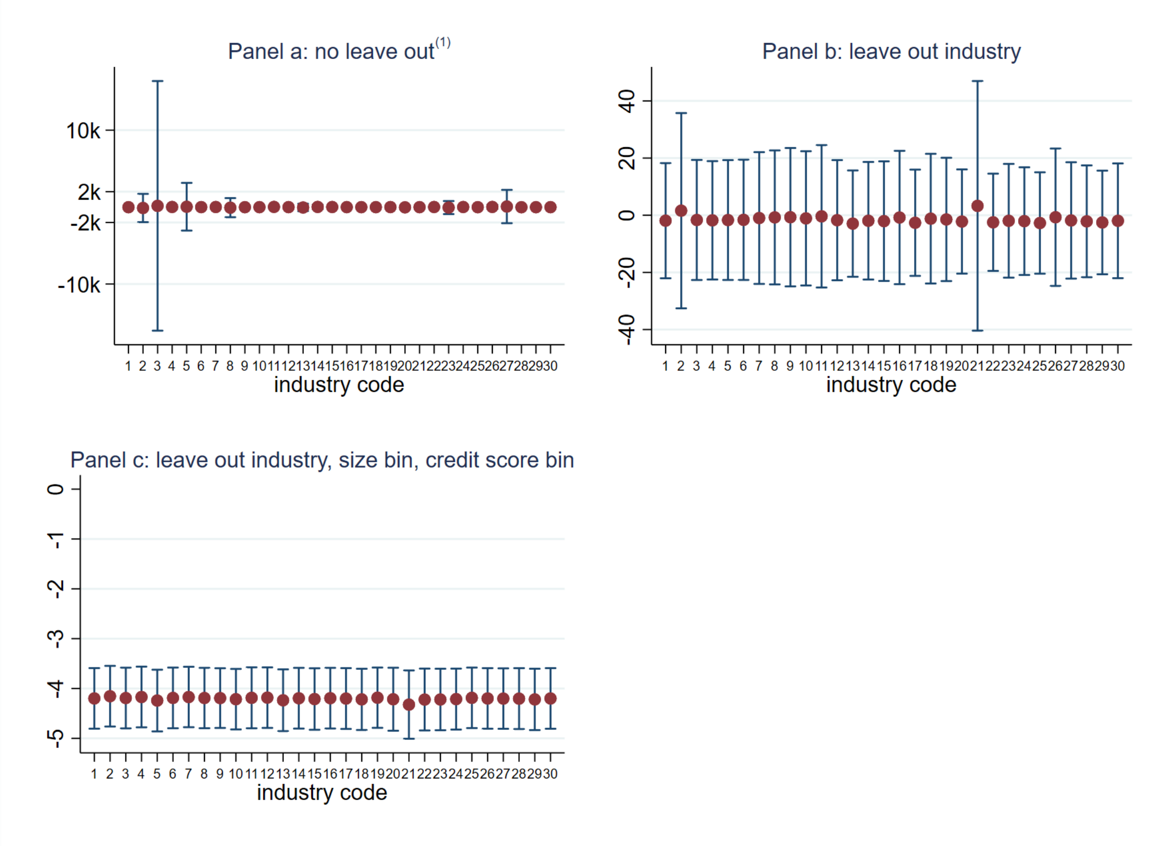
The table reports the estimates of the investment rate, where the dataset excludes one size bin at a time. The dependent variable is the investment rate (ratio between investment in tangible and intangible assets at time t and the corresponding capital in $t-1$) expressed in the inverse hyperbolic sine transformation. The main explanatory variable is the credit supply shock at the firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In the other columns this is interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g.: 2007 and 2008 for the year 2009). Controls include $\ln(Employees_{f,t-1})$, $Age_{f,t-1}$, $Credit\ Score_{f,t-1}$, $Cash\ Flow_{f,t}/Capital_{f,t-1}$, $(Bank\ Shock_{f,t})\times(LAR_f)$, $(Bank\ Shock_{f,t})\times(BAR_f)$, $\Delta\ln(collateral)_{f,t}$, $Residual\ duration_{f,t-1}$, $Industry\&year$, as defined table A1. All estimates include fixed effects for the firm, year and type of credit relationship. The estimates period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed to 1% in both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: sensitivity by credit score bin

credit score bin dropped:	(1) bad	(2) bad-medium	(3) medium-good	(4) good
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma \text{ bin}=1)$	0.190***	0.140***	0.124**	0.193***
	[0.052]	[0.047]	[0.052]	[0.049]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma \text{ bin}=2)$	0.108**	0.150***	0.195***	0.140***
	[0.053]	[0.046]	[0.049]	[0.050]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma \text{ bin}=3)$	0.022	-0.007	0.050	0.004
	[0.043]	[0.038]	[0.047]	[0.039]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\sigma \text{ bin}=4)$	0.024	0.016	0.015	-0.004
	[0.040]	[0.034]	[0.036]	[0.038]
Controls	Yes	Yes	Yes	Yes
Observations	206,673	274,402	253,001	282,744
# Firms	45,145	61,115	57,195	57,008
Adj. R2	0.184	0.176	0.172	0.174

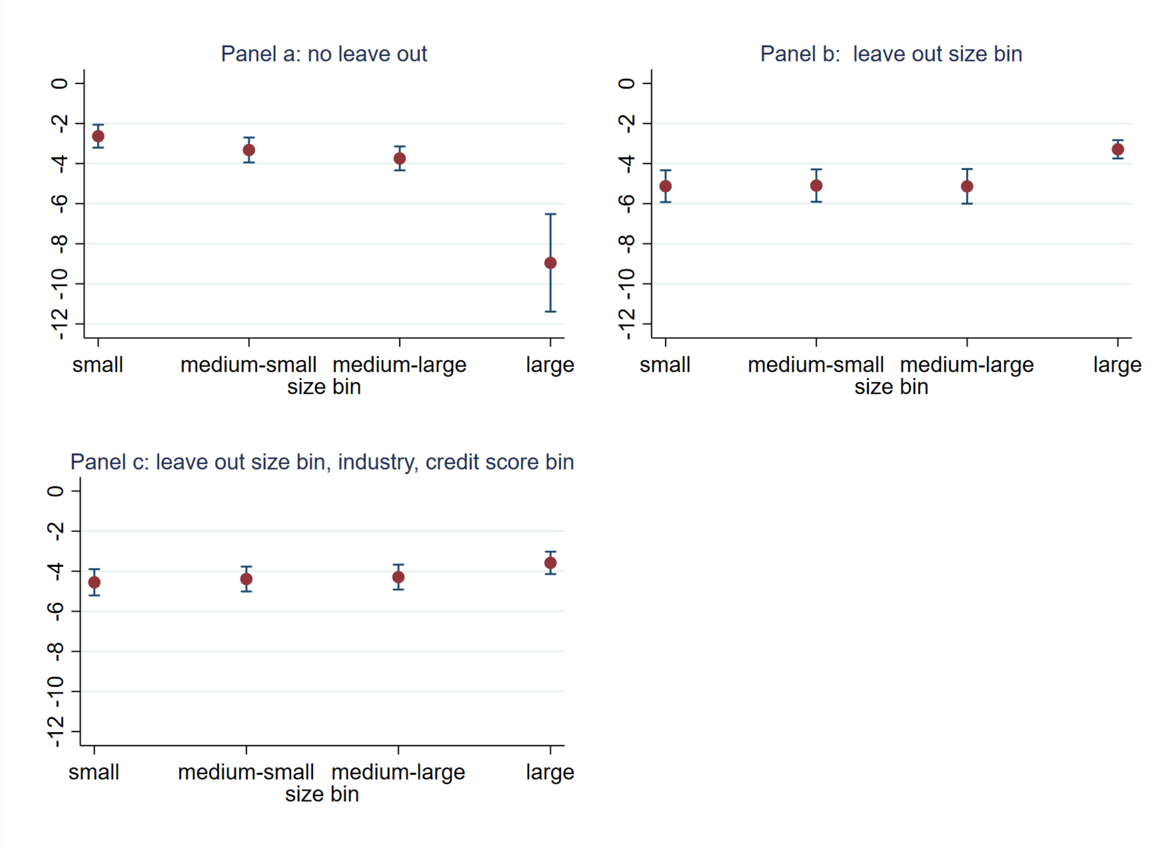
The table reports the estimates of the investment rate, where the dataset excludes one credit score bin at a time. The dependent variable is the investment rate (ratio between investment in tangible and intangible assets at time t and the corresponding capital in $t-1$) expressed in the inverse hyperbolic sine transformation. The main explanatory variable is the credit supply shock at the firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In the other columns this is interacted with dummy indicators of the four σ bins defined by the quartile values of the estimated σ by industry, size, credit score in the two years preceding the reference year (e.g.: 2007 and 2008 for the year 2009). LAR_f is the mean loan-to-asset ratio of the firm f defined as the average loan-to-asset ratio over the sample period. BAR_f is the mean bond-to-asset ratio, similarly defined. $Industry\&year$ is the median of credit demand shocks ($\alpha^{AW}_{f,t}$) between firms by industry and year. The variable definitions are in table A1. The variable definitions are in table A1. All estimates include fixed effects for the firm, year and type of credit relationship. The estimates period is 2009-2015 and the estimator is linear with large fixed effects (reghdfe). All data are trimmed to 1% in both tails. Heteroskedastic robust standard errors, clustered at the firm level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A2: Elasticity of substitution by industry



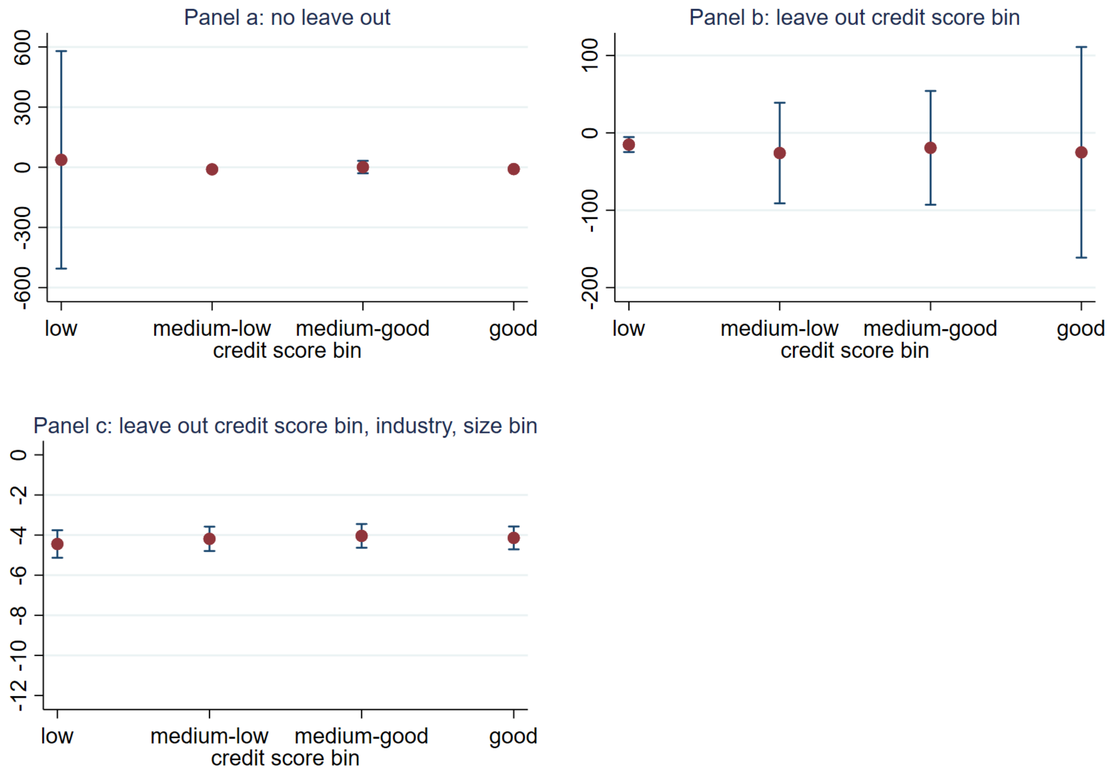
The figure reports three estimates of the elasticity of substitution by firm industry. The elasticities (red dots) and their confidence intervals at 99% (blue bars) are the averages across years. In panel (a) the elasticity is estimated by each industry j, in panel (b) it is estimated by leaving out industry j. In panel (c) it is estimated leaving out industry j, size bin s and credit score n. The industry codes are as follows: 1 is Agriculture & mining (NACE Rev. 2 codes 1 ,2 ,3 ,5 ,6 ,8 and 9), 2 is Food (code 10), 3 is Beverages & tobacco (11 and 12), 4 is Textiles (13), 5 is Apparel (14), 6 is Leather (15), 7 is Wood (16), 8 is Paper & print (17 and 18), 9 is Chemical & Pharma (19, 20 and 21), 10 is Rubber (22), 11 is Non metallic minerals (23), 12 is Basic metals (24), 13 is Metal products (25), 14 is Computer & electrical (26 and 27), 15 is Machinery (28), 16 is Motor & vehicles (29 and 30), 17 is Furniture (31), 18 is Other manufacturing (32 and 33), 19 is Utilities (35, 36, 37, 38 and 39), 20 is Construction (41, 42 and 43), 21 is Wholesale trade (45 and 46), 22 is Retail trade (47), 23 is Transport & courier (49, 50, 51, 52, 53), 24 is Hotels & restaurants (55, 56), 25 is Info & Communication (58, 59, 60, 61, 62 and 63), 26 is Real estate (68), 27 is Professional services (69, 70, 71, 72, 73, 74 and 75), 28 is Support services (77, 78, 79, 80, 81 and 82), 29 is Public services (84, 85, 86, 87 and 88), 30 is Other services (90, 91, 92, 93, 94, 95 and 96).

Figure A3: Elasticity of substitution by firm size bins



The figure reports three estimates of the elasticity of substitution by firm size bin, determined by quartiles of the number of employees per year. The elasticities (red dots) and their confidence intervals at 99% (blue bars) are the averages across years. In panel (a) the elasticity is estimated by each size bin s, in panel (b) it is estimated by leaving out size bin s. In panel (c) it is estimated leaving out industry j, size bin s and credit score n.

Figure A4: Elasticity of substitution by credit score bins



The figure reports three estimates of the elasticity of substitution by credit score bins of the borrower firm, determined by quartiles of the number of credit score per year. The elasticities (red dots) and their confidence intervals at 99% (blue bars) are the averages across years. In panel (a) the elasticity is estimated by each credit score bin n, in panel (b) it is estimated by leaving out credit score bin n. In panel (c) it is estimated leaving out industry j, size bin s and credit score n.