The impact of credit substitution between banks on investment

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Abstract

This paper estimates the elasticity of substitution across banks using matched bank-firm data. It also finds that credit supply shocks have significant effects on firms' investments in industries with a lower substitutability. In these industries, where firms find it difficult to acquire funding and obtain better credit conditions from other banks, a 10 per cent increase in credit supply increases firms' investment rate by 2 per cent. The effect of lenders substitutability on investment offsets that of bank specialization, thus highlighting that the risks of excessive bank concentration in specific industries may be alleviated by substituting lenders. Overall, the evidence suggests that considering the demand side, i.e. the heterogeneous effects of the elasticity of substitution in credit markets, is crucial for a better understanding of the bank lending channel.

Keywords: banks, credit, substitution, investment

JEL Classification: G21, D22, E22

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1 Introduction

This paper estimates the elasticity of substitution across banks and it examines how the quantitative impact of credit supply shocks on firms investment is shaped by this elasticity. This substitutability may be important given that a large body of research offers evidence that switching banks is costly and has consequences for firm borrowing and on real outcomes. Moreover, analyses on the effects of credit shocks typically consider specific events such as the Financial Crisis (Carvalho et al. (2015); Chodorow-Reich (2014); Jiménez et al. (2017)), forced switches induced by banks' branch closures (Bonfim et al. (2021); Liaudinskas and Grigaitė (2021)) or the failure of the main bank (Goncharenko et al. (2022)). By focusing on specific episodes, these analyses do not take into account how the effects are influenced by the substitutability across lenders, because when a major shock occurs switching across banks may be very difficult, such as in a credit crisis that involves many banks. However, this evidence leaves open the question of what the effects are in other periods. For example, in normal times substituting across lenders is easier than in a banking crisis, but the degree of substitution may also decrease because of other counteracting forces such as the process of consolidation in the banking industry that reduces the number of banks over time. Therefore, the ability of firms to substitute banks may influence the overall effect of credit constraints on firms investments, but its role is not easily predictable in absence of major shocks.

To address this issue, I estimate the elasticity of substitution between lenders, as a general measure of the degree of substitutability in credit markets. I find that the effects of credit supply shocks on firm investments depend on this this elasticity. Specifically, by exploiting the high heterogeneity of the elasticity across industries, the analysis reveals that credit supply shocks have a significant effect on firms' investment only in industries with lower elasticity. Thus, while previous evidence has found average effects of credit supply shocks on firms investments, this work highlights that this effect derives from a specific channel, the heterogeneous degree of substitutability across banks.

I estimate the elasticity of substitution across lenders using matched bank-firm data on loans and on interest rates in Italy. Italy offers an ideal setting because Italian companies largely rely on bank credit rather than other firms of external financing (such as bonds, etc. . .). Moreover, the wide coverage of the Italian credit register allows the inclusion of data on loans and interest rates of many small firms, for which bank credit is more relevant and switching costs are typically high.

I derive the estimating equation from a constant elasticity of substitution (CES) function that is flexible enough to be directly mapped onto microeconomic data. The empirical methodology adopted allows for the correct identification of the elasticity parameter using matched bank-firm data. Reverse causality is addressed by instrumenting the change in the interest rates with credit supply shocks, which are given by the bank-time fixed effects. Furthermore, the estimating equation includes firm-time fixed effects, which allow for the accounting of any unobserved features of the firm, such as other forms of external financing, firm rating, etc...

It is worth noting that for the estimation of these fixed effects I resort to the methodology of Amiti and Weinstein (2018) (AW shocks, hereafter) to prevent the estimation bias brought about by the existence of new lending relationships, which would result from employing a basic OLS. This is particularly important because during a crisis credit relationships are very likely to be interrupted, while new ones are more likely to be formed in other periods. By using the AW shocks estimator, the correct estimates of the elasticity of substitution that incorporates all types of credit relationships can be obtained (continuing, originating and terminating loans). The presence of such biases in the estimation can be substantial, as shown in subsection 6.3.

The baseline results show that the elasticity of substitution across banks is about 2.3. Note that σ, the elasticity of substitution across banks with respect to the gross interest rate r_t, is approximately the same as the semi-elasticity with respects to the net interest rate $r_t/R_{c,t}$ This means that if one bank increases its interest rate by 100 basis points relative to all other banks in the same area, the firm decreases its borrowing by 2.3% from this bank relative to all other banks in the same area.

I find that the elasticity of substitution is heterogeneous across firm and bank characteristics and in particular it increases for bigger and older firms. The evidence with respect to firm rating, bank size and the length of the credit relationship is more mixed, in line with the opposing predictions of the literature on each of these variables. The model used to derive the estimating equation can be easily adapted to include various features, such as a different definition of the aggregate interest rate, moral hazard and collateral. In the robustness checks I use these extended specifications and the magnitude of the estimated elasticities is similar to that of the baseline, except for two relevant exceptions: *a)* when the estimates are made on bank groups, the elasticity is sensibly smaller than the baseline because within-group switches are not taken into account; *b)* the estimated elasticity is higher for relationship lending because these loans (term and overdraft loans) may affect the overall financial condition of the firm to a greater extent than transaction loans (advances against receivables).

The elasticity of substitution is found to be important in determining firm investment decisions, as it alters the overall impact of credit constraints. Specifically, investment is affected by credit supply shocks only in firms that are in industries with the lowest elasticity of substitution. This finding can be explained by the fact that firms in these industries find it more difficult to switch across lenders, thus hampering the possibility to obtain more credit or better credit conditions. In this way, their investment decisions are significantly affected by credit supply shocks: a 10% increase (decrease) in credit supply to firms in these industries raises (decreases) the investment rate by about 2%. Additionally, augmenting the empirical model with measures of bank specialization does not change the results, as the effect of bank substitutability offsets that of bank specialization. Finally, the magnitude of this differential effect is larger for investments in tangible assets and in manufacturing firms.

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 outlined by Dwarkasing et al. (2016), the existence of the BLC relies 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 from 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 banks shocks can explain firm outcomes (see, for example Carvalho et al. (2015), Jiménez et al. (2012) and Bottero et al. (2020) 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 a similar vein, Altavilla et al. (2022) estimate the elasticity of substitution across lenders using European data focusing on a specific period (the Covid-19). The present paper is similar because the elasticity is estimated using matched bank firm data on loans and on the interest rates. Nevertheless, it differs because their paper does not compute the effects on firm outcomes, while in the present work I calculate how the effects of credit supply shocks on investment are mediated by the estimated elasticity of substitution.

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 has 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 few of them, see for example: Duchin et al. (2010), Chodorow-Reich (2014), Cingano et al. (2016), Beck et al. (2021)) exploit specific events, such as the Financial crisis. Despite these works are very insightful, the ability of firms to switch across lenders is limited after major shocks, so it is not explicitly derived.[1] However, since the estimated elasticity here is a valid measure also in periods out 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.

With regard to bank characteristics, note that a relevant contribution in this strand of literature is that on bank specialization developed by (Paravisini et al. (2023)), where banks specialized in some activities lend more to firms that produce more intensively in those activities (export markets in that case). In this work, I add their measure of specialization with that of bank substitution, and the horse race estimation on investment reveals that while the mitigating role of substitution survives, that of specialization disappears.

[1] An exception is Greenstone et al. (2020) 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. However, also in their work banks switching is not directly measured. Moreover, in the current work I use a sample with many SME's and the results I obtain are very robust to controlling for size.

In general, this literature does not consider how these effects can be mitigated (or exacerbated) by the relevant demand side characteristic (the degree of substitutability of lenders). Differently, here I provide estimates that the estimated elasticity of substitution, which is heterogeneous across industries, matters for firms' investment. In other terms, these results suggest that switching costs, typically unobserved by the econometrician, affect firm activity.

The paper is also related to the line of research focusing on estimating credit demand. Some works have used surveys on banks (Del Giovane et al. (2018)) and they find an inverse relationship between interest rates and loan demand.[2] However, by using aggregate or bank-level data they ignore the large heterogeneity across firms, which allows exploring also the substitutability across banks. Very few studies in this literature has estimated credit demand using micro data on firms in developed countries. Crawford et al. (2018) find a semi-elasticity to the interest rate of -1.45 in the credit demand equation. They use 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 enables to use data by all lenders and all the years (not only the first) of the bank-firm lending relationship.

The rest of the paper is structured as follow. Section 2 describes the data sources period of analysis and it provides a reasoned discussion on the sample selection due to the credit market structure assumption. In section 3 the model, the estimating equation and the identification method adopted are presented. Section 4 reports the main results of the estimates of the 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. The conclusions are in Section 7.

2 Data

Since Italian companies – differently from the ones in the US – are strongly reliant on bank credit, I 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 of fees and commissions) are from the Taxia survey of the Bank of Italy, covering almost all banks operating in the country. Data on both loans and on interest rates include overdraft loans, term loans, loans backed by receivables.[3]

The second source is the Company Account Data service (CADS, henceforth) which collects yearly

[2] For example, Del Giovane et al. (2018), using the Euro-system Bank lending survey to Italian banks, find a negative coefficient of the semi-elasticity of the interest rate spread on the loans in the credit demand equation and with a magnitude of about 2.29 in absolute value.

[3] In the ensuing analysis I use the data at bank-firm level summing all types of loans. Nevertheless, in the subsection 6.3 I run a robustness check differentiating loans between relationship lending (overdraft and term loans) and transaction lending (loans backed by receivables) and the main results are confirmed.

data on the balance sheets and income statements of limited liability firms in Italy. To the purpose of this work, the CADS dataset provides a measure of the firm credit rating, data on investment and capital. The credit rating is used by banks to screen borrowers (actual and potential).[4] Investment and capital are computed on fixed tangible assets; capital is derived through the perpetual inventory method. Finally, in some estimates I consider firm size, measured by the number of employees. This measure derives from the social security archives (INPS, henceforth).

The dataset is built in various steps, described as follows. In the first step I select non-financial limited liability firms with at least one employee between 2006 and 2015.[5] Indeed, firms with at least one employee – in the INPS archives – are more likely to have an actual economic activity. In a second step, I merge the selected firms to the CR archives, which report the loan amounts a firm borrows from each bank. Third, I merge the resulting dataset with the Taxia survey, which reports the interest rates for each bank-firm pair.[6] Fourth, I reduce the dataset by excluding companies that have single bank relationship in each quarter (see section 3 below), following the methodology first developed by Khwaja and Mian (2008).[7] Fifth, I merge the outcome of the previous selections with CADS to obtain balance sheet data and with INPS again to obtain employment levels.[8] Sixth, I remove singletons iteratively using the reghdfe command developed by Correia (2017). Finally, I remove from the dataset the observations of commuting zones where credit markets are more concentrated (see the next subsection). At the end of all these steps, I remain with a dataset of 5,036,614 observations, with 114,987 firms and 210 banks.

2.1 Market structure

In this subsection I discuss the assumption of monopolistic competition, which rules out strategic interaction across lenders. Imposing this assumption implies to exclude from the dataset the local credit markets with a higher banks concentration. By imposing this assumption, the local credit markets with a higher concentration of banks are excluded from the dataset.

There is a wide consensus in the literature of the existence of market power in lending markets (Carletti (2008)), and one of the main causes is the presence of switching costs for both customers and lenders. [9]. The theoretical predictions are confirmed by a wide empirical evidence which is consistent

[4] The variable is categorical with natural numbers ranging from 1 to 9, where higher values indicate a greater probability of default. In this work the variable has been re-coded so that lower numbers denote the worst firms, and the highest values the best firms.

[5] Indeed, only limited liability firms have a tax code that can be used for matching across data archives.

[6] Note that all financial intermediaries (named henceforth simply as banks, 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 reporting duty is for loans of at least 75 thousands euros. Given the two different limits, I apply the upper limit of all loans exceeding 75 thousands euros also on credit data from CR.

[7] Note that the main analysis uses bank data, not bank groups. This choice allows to limit the loss of firms; indeed, if I were to use bank groups I would lose all firms that have a single-bank group lender. In any case, in the robustness checks I repeat the main estimates using bank groups and single bank firms.

[8] In the main estimates, since they do not involve CADS data, I keep also unmatched observations.

[9] Indeed, on the bank side asymmetric information induces banks to devote resources to screen new customers. On the other side, also firms incur costs with a new lender, to signal their creditworthiness (such as re-assessing the value of collateral or the validity of investment projects) or because of "menu costs" (for example, fees charged to close or open a bank account). Then, switching banks is costly also for borrowers because of the fixed costs of setting a new relationship

with the finding of market power in banking markets. More specifically, Claessens and Laeven (2004) 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, I follow Benetton and Fantino (2021), who measure competition in local credit markets in Italy using the Herfindahl-Hirschman Index (henceforth, HHI) computed on the outstanding amounts of loans.[10] I compute the HHI in each commuting zone every year and then I take the average across 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.[11]

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 from the analysis the commuting zones with higher concentration. Unfortunately, there is no general agreement on which threshold of the HHI defines the level of market concentration.[12] Given the variety of the values suggested, I keep only the commuting zones with an average HHI$\leq$0.25, considering areas with a greater threshold as concentrated markets where collusion among banks may take place: in this way, I discard from the dataset 45 commuting zones out of 611, and the dataset has 5,036,614 observations. In a robustness check (subsection 6.3) I repeat the main estimates using a restricted sample of commuting zones with HHI$\leq$0.18 or HHI$\leq$0.15 and the main results are confirmed. Finally, note that by imposing only an upper bound to the HHI, I keep markets with very low levels of concentration. Nevertheless, 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 (Benvenuti and Prete (2019)).

After restricting the dataset so that coordination among banks is less likely, I 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:[13] panel c of figure A.1 in the online Appendix shows that there

with a lender and because they might lose the value of an established one. Thus, the presence of switching costs gives banks market power, due to a "lock-in" effect with their borrowers.

[10] Differently from the concentration ratios, the HHI encompasses the whole distribution of loans extended in the market and it is not influenced by the arbitrary choice of the number of players considered. The HHI represents correctly credit competition in local credit markets: panel a and panel b of figure A.1 in the online 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 Pagano (1993) and Sapienza (2002)).

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

[12] Analyzing local credit markets, Degryse and Ongena (2008) 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 as "moderately concentrated". Besanko et al. (2013) considers that here is monopolistic competition in the market if the HHI falls between 0.21 and 0.40.

[13] Nevertheless, note that some coordination may take place as banks respond to monetary policy shocks or due to the lending practices which may be standardized across banks.

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 the informational rent extraction is reduced in more competitive areas.

3 Empirical specification

In this section, I show that the empirical equation of credit demand derives from a model *à la* Dixit and Stiglitz, where firms have "love of variety" and there is monopolistic competition among 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 has already been discussed in the previous section. As regards love of variety, firms prefer not be captured by only one bank because, as already mentioned in the literature review in Section 1, having multiple relationships allows firms to reduce the switching costs, which derive from information monopoly of only one bank and to the risk of an unexpected credit dry up by the single lender (Degryse et al. (2011)). 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.[14]

To derive credit demand, I outline a simple model that captures the essential elements of credit markets and that can be easily be transformed into an estimating equation.[15] Firm f chooses the optimal loan amount $L_{b,f,t}$ demanded to bank b at time t in order 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 borrowed capital. This is modeled as a constant elasticity of substitution (CES) function where firms express love 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 Hottman et al. (2016). 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.[16]

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

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

[14] In section 6.3 I repeat the analysis extending the dataset to single-bank firms, and the main results are confirmed.
[15] The model is sufficiently general in order to be easily transformed into an estimating equation. Nevertheless, it can be extended to consider various loan characteristics (maturity, duration, etc...).
[16] 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.

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,[17] I 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) I 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 log change ($\Delta \ln(L_{b,f,t})$) should capture only the intensive margin (how much a firm borrows from continuing loans). However, in the empirical analysis I include 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 $t-1$), by specifying the dependent variable with the natural log of 1 + credit.[18]

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

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

In other terms, R_t is the aggregate interest rate applied by all lending banks b' at time t. In order to reduce reverse causality, in equation (6) I define banks in the summation by b', which is a leave-out form, that considers all other banks different from bank b at time $t-1$. In this way, $w'_{b,t-1}$ is simply the ratio of loans of bank b at time $t-1$, over the total of loans by all the other lending banks b' in the same period.

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 ($R_{f,t}$). Nevertheless, one can assume, without loss of generality, that the aggregate interest rate is defined by all banks operating in the local area where the firm is located. In support of this assumption, note that I observe only actual lending (and not potential). Then, defining the aggregate rate only among banks actually lending to firm f might mis-represent the aggregate cost of lending in the area. This bias might

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

[18] In the robustness checks (see subsection 6.3) I test the results using an alternative specification of the dependent variable $\Delta \ln(L_{b,f,t})$.

be very relevant for SME's, which are very relevant in the dataset, inasmuch as they typically borrow only from few banks.[19] Indeed, various works have highlighted that especially small businesses are highly dependent on local credit markets because of the local nature of the soft information necessary for credit decisions (Petersen and Rajan (1994);Guiso et al. (2004) Degryse and Ongena (2005); Then, defining the aggregate rate at firm level ($R_{f,t}$) would imply to consider an excessively narrow set of banks, so that the aggregate rate would mis-represents the actual cost of lending in the area.[20]

In order to reduce the bias from this assumption as much as possible, I consider that the local area is the commuting zone, that is the local area defined by commuting patterns with a size that typically involves few towns. Note that commuting zones are much narrower territorial units than what other works using Italian data do: Guiso et al. (2013), Crawford et al. (2018) and Presbitero et al. (2014) consider as a measure of the local credit market wider territorial units (provinces).[21] Then, the aggregate rate is $R_{c,t}$, where the subscript c denotes the commuting zone. In any case, in order to partially overcome the limits of this assumption, in the robustness checks section I repeat the estimates where the aggregate interest rate is defined over the loans to the firm ($R_{f,t}$) as well as to firms in the same region ($R_{r,t}$)[22], industry ($R_{s,t}$), region-industry ($R_{r,s,t}$), province ($R_{p,t}$), size bin ($R_{size,t}$) and credit rating bin ($R_{rat,t}$).

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

3.1 Identification

Reverse causality 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:

$$D_{b,f,t} = \alpha_{f,t} + \beta_{b,t} + \epsilon_{b,f,t} \tag{7}$$

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. Following Khwaja and Mian (2008), a large literature has evolved estimating equation 7 on a sample of firms borrowing from more than one bank. In the ensuing analysis I follow this approach by restricting the analysis to firms borrowing from at least two banks.

[19] The average firm size is 34.4 employees. Each firm borrows from 2.6 banks on average in each quarter.

[20] In equation 5 there is the implicit assumption that the loan contracts have already been determined. Actually, this is the outcome of a process in which firms decides how much to borrow from the subset of offering banks. In turn, this subset is determined by the banks to which firm f has requested a loan and that the request has not been declined. While I do not observe application to all banks, by defining the area very narrowly, such as the commuting zone, I greatly reduce the bias stemming from this assumption.

[21] 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.

[22] Regions are larger administrative units than the provinces. They correspond to NUTS level 2 in the Eurostat nomenclature.

Borrowing from multiple banks is quite common in Italy, especially for limited liability firms (Buono and Formai (2018); Sette and Gobbi (2015)) because it allows to mitigate the switching costs (Ongena and Smith (2000)), which are relevant in credit markets because of asymmetric information (Kim et al. (2003)), and they also reduce the risk of an unexpected credit dry up by its main bank (Degryse et al. (2011)).[23]

In this multiple-banks framework, the firm-time fixed effect $\alpha_{f,t}$ fully controls for firms observed and unobserved heterogeneity at firm and time level (aka "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.[24] The estimated $\hat{\beta}_{b,t}$ is the instrumental variable for the interest rate change in the estimation of equation 5.[25]

Estimating 7 with simple OLS has been subject to criticism by Amiti and Weinstein (2018) because it does not take into account of new lending. To solve this problem they develop a new estimator, that I denote here as the "AW estimator", which consists of estimating equation 7 where $D_{b,f,t}$ is defined as a percentage change [$D_{b,f,t} = \frac{L_{b,f,t}-L_{b,f,t-1}}{L_{b,f,t-1}}$]. In this last case, terminating loans are 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 7 with WLS (with the weight given by $L_{b,f,t-1}$) 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 ($\epsilon^{AW}_{b,f,t}$).[26] 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. [27] I 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, I use the estimated change in the firm-time effect $\Delta\alpha^{AW}_{f,t}$ as a measure of $\Delta\alpha_{f,t}$ in equation 5.[28]

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 on the whole period (2006-2015) where there have been the Financial crisis and the Sovereign debt crisis as well as periods of slow recovery of the economy.

[23] Note that with this assumption I exclude from the dataset many single-bank firms which, as noted by Degryse et al. (2019), are typically smaller, more prone to credit constraints and they might represent a relevant share of the overall population of firms, thus limiting the external validity of the empirical exercise. For this reason, in a robustness (subsection 6.3) I check that the main results can be also confirmed by expanding the analysis to single bank firms.

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

[25] For a similar use of the bank-time and of the firm-time fixed effects using matched bank-firm data see Alfaro et al. (2020).

[26] 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, Amiti and Weinstein (2018) 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 $\beta_{b,t}$.

[27] For more details see section A in the online Appendix.

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

4 Results

This section reports the descriptive statistics and the estimates of the model outlined in section 3. First I show some preliminary statistics (subsection 4.1), then subsection 4.2 shows the validation exercise of the instrumental variable. The baseline estimates of the model are in subsection 4.3. Finally, subsection 4.4 reports additional results where the baseline model is estimated in sub-samples to consider specific firm or bank characteristics that may affect the elasticity.

4.1 Preliminary statistics

The dataset includes 5,036,614 observations, with 114,987 firms and 210 banks. In every quarter, there are on average 53,289.9 firms and 167.2 banks; on average each firm borrows from 2.4 banks and each bank lends to 1,080.3 firms. The summary statistics, described in detail in panel A of table 1 in the online Appendix, show that each firm has on average 36.4 employees, an average outstanding debt of about 451,350.7 euros and it pays an interest rate of 5.21%. Finally, a preliminary look at the data reveals that there is an inverse relationship between the growth rate of loans and the growth rate of the interest rate (figure A.2 in the online Appendix).

4.2 Validation of the instrumental variable

Before moving to the estimates of the model outlined above, it may be appropriate to make a validation exercise of the instrumental variable, the credit supply shock $\beta_{b,t}$ estimated from equation 7 with the AW estimator. If this instrument is valid, then it should correlate significantly with some of the variables used in the literature with matched bank firm data to identify credit supply. Some papers have used the percentage of interbank funding of banks in order to identify banks most affected by the interbank freeze which followed the collapse of Lehman Brothers in 2008 (Cingano et al. (2016); Iyer et al. (2014)). Other works have used the percentage foreign funding to examine the effects of the credit crunch, which affected banks after the outbreak of the Financial Crisis (Paravisini et al. (2015)). The results, in columns 1 and 2 of table 2, show that both these regressors are significant and have the correct expected negative sign. Indeed, a higher interbank (IBK) ratio implies a contraction of credit supply as expected of about 0.041% (column 1); similarly, the estimated coefficient on the foreign funding ratio (Foreign ratio) shows that the contraction of credit supply would be of 0.038% (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). The coefficients of both these variables are significant, but the magnitude of the effect on credit supply shocks is substantially null.[29]

Another concern for the validity of the instrument is whether the bank-time fixed effects represent only shocks to credit supply, or if they are also contaminated by demand factors that are in the estimated interest rate. To check this point empirically, I regress the estimated bank-time fixed effect on the log change in bank average interest rate and I use the firm-time fixed effect as instrument to overcome reverse causality (see B in the online 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. The estimates are reported in table A2. In columns 1 and 2, where the instrumental variable is the firm-time fixed effect estimated with the AW procedure ($\hat{\alpha}^{AW}_{f,t}$), the bank-time fixed effects is not significantly correlated with the bank-average interest rate ($\Delta r_{b,t}$), even though the instrument is weak. In columns 3 and 4, where the instrument is the weighted growth rate by industry ($x_{s,t}$: see the definition in the online Appendix B) as suggested by Altavilla et al. (2022), I obtain similar results on the average interest rate and the instrument is not weak. Overall, the evidence of 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, consider the case of a bank applying different interest rates to various borrower firms depending on their size. To show this point, I regress the candidate instrumental variable $\hat{\beta}^{AW}_{b,t}$ on the fixed effects of a relevant firm characteristic interacted with the residual of equation 7 ($\hat{\epsilon}^{AW}_{b,t}$). The idea is to test whether the instrument depends on any non-random matching between banks and firms, captured by $\hat{\epsilon}^{AW}_{b,t}$, which is shaped by some observable firm characteristics; these are rating, size and age. Figure A.3 in the online Appendix shows that the coefficients are not significant, thus further validating the instrumental variable.

4.3 Baseline estimates

In this subsection I describe the results of the estimates of the main equation of interest, equation 5, where the parameter of interest is the elasticity of loans to the interest rate defined in relative terms with respect to the aggregate interest rate defined at commuting zone level ($R_{c,t}$).[30]

Column 1 of table 3 shows that the estimated elasticity in the simple specification is negative and significant, with a magnitude of -4.2. The sign of the instrumental variable in the first stage ($\beta^{AW}_{b,t}$) is negative (-0.10), which is coherent with the fact that a positive credit supply shock implies a move along the demand equation that reduces credit price. Moreover, the instrument is not weak: the F test statistic is 36.7. In column 2 I add the change in the credit demand shifter in the estimation ($\Delta\alpha^{AW}_{f,t}$), which has

[29] The available empirical evidence is not conclusive on whether they affect credit supply.

[30] The results of the estimates using the aggregate rate defined at firm level ($R_{f,t}$), at province level ($R_{p,t}$), etc... are in the section of the robustness checks (see section 6).

a significant and positive effect, in line with the prediction of equation 5; also in this case, the estimated elasticity is negative and significant. Despite this empirical specification is the one that most closely reflects equation 5, I test the empirical model in order to include other unobserved factors. In column 3, I repeat the last estimate adding time fixed effects, in order to capture any unobserved time shock that may affect demand: the previous results are confirmed, but the magnitude of the coefficient of interest changes to -2.8. Finally, in column 4 I add industry-time and commuting zone-time fixed effects in order to include any unobserved changes at industry or at commuting zone level in each quarter. Also in this last case, the previous results are confirmed: the elasticity is negative and significant, with a magnitude of about -2.3; the instrument is valid: the coefficient of $\beta_{b,t}^{AW}$ is negative and significant and the F test is quite large (242.2).

Among the various estimates of the baseline model, I choose the last specification (column 4) as a reference for the additional empirical exercises in ensuing part of the paper, as this is the most demanding with respect to various unobserved factors that may affect the elasticity due to omitted variable bias.

4.4 Elasticity of substitution by firm characteristics

In the empirical analysis conducted in the previous subsection I estimated the value of the coefficient on the interest rate change of the credit demand equation. In the simple model of section 3 this coefficient is the elasticity to the interest rate. Moreover, as discussed above, assuming monopolistic competition and love of variety, this coefficient can also be interpreted as the elasticity of substitution. In order to further convince the reader that this interpretation is correct in the case at hand, I calculate the elasticity of substitution differentiating firms with respect some firm relevant characteristics for which bank substitutability should vary substantially. This analysis might at first glance look redundant, inasmuch as in the baseline regression I have already included the firm-time variable $\alpha_{f,t}$, which captures most of the unobserved firm time variant characteristics (such as managerial practices or specific investment projects, etc...). Nevertheless, I consider three specific variables that may affect the ability/difficulty of companies to switch across lenders, and thus the elasticity of substitution: size, age and credit rating. The aim is to check whether the data confirm the predictions of the theory on how substitutability is affected by each of these variables. In practice, I first compute the elasticity using the methodology in subsection 3 for deciles of each of the three variables just mentioned above and then comment the results with respect to what is expected by the literature.[31]

With regard to firm size, it is well known that SME's typically face tighter credit constraints, as highlighted by a wide literature (see for example, Beck and Demirguc-Kunt (2006)), due to the ability

[31] Theoretically, the analysis by firm characteristics can be modeled by considering that each group k of the population of firms has its own elasticity σ_k and the output function of each group k is: $y_{f,k,t} = \left(\sum_{b=1}^{B} \varphi_{b,t} L_{b,f,t}^{\frac{\sigma_k - 1}{\sigma_k}} \right)^{\frac{\sigma_k}{\sigma_k - 1}}$. Assuming that banks do not take into account these firm characteristics when setting the interest rate, and thus they do not price discriminate across groups, the corresponding demand is $\Delta \ln(L_{b,f,t}) = -\sigma_k \Delta \ln \left(\frac{r_{b,f,t}}{R_t} \right) + \Delta a_{f,t} + u_{b,f,t}$.

to provide a limited amount of collateral or insufficient internal financing. SME's may overcome these limits by relying on established relationships with their lenders, who benefit from tacit knowledge of the firm. However, since building tacit knowledge is costly, relationship lending may hinder the probability of switching lenders. I repeat the previous analysis estimating the elasticity using deciles of firm size (given by the number of employees). The estimates reported in figure 2 show that the elasticity increases almost monotonically with size, and there is a sharp peak with the last decile of largest firms, implying that these companies are extremely more sensitive to credit conditions than other firms.

Secondly, I estimate the elasticity of substitution using deciles of firm age. Even though banks play a critical role in financing young businesses in the economy, because of their ability to engage in relationship banking (Berger et al. (2005)), younger firms, similarly to SME's, typically face tight credit constraints. Therefore, their ability to switch across banks is relevant in alleviating these constraints. The estimates corroborate this idea. Indeed, the estimated elasticities increase, almost monotonically, with firm age (see figure 2).

Finally, I analyze the elasticity with respect to firm rating (this is given by the z-score variable, re-coded such that a higher value denotes a better rating). Again, I estimate the elasticity, using the baseline model as outlined in table 3 for each of the nine values of the rating variable. Figure 2 shows that the elasticity is very high for firms with the lowest rating. Since they are very sensible to interest rate changes, they are more likely to switch across banks. The elasticity drops by about half for firms in the other deciles and there is not a monotonic pattern. Note that the elasticity of substitution drops to the lowest values for best firms (with rating equal to 9). This last result can be interpreted as the ability of banks to retain the best borrowers in their lending portfolio.[32].

Overall, the analysis above reveals that the estimated elasticities increase with at least two firms characteristics (size and age) that allow firms to switch more easily across lenders, thus it supports the interpretation of the elasticity as that of substitution.[33]

5 Effects on investment

In the previous subsection I showed how the elasticity of substitution varies with some relevant bank/firm characteristics: firm credit rating, firm size, firm age, bank size and length of relationship. In this section, I address another relevant question, whether and how the elasticity of substitution alters the overall effects of credit constraints on firms. With this aim, I test the effects of the credit supply shocks on corporate investment. A large literature has showed that credit supply shocks affect firms' investments (see for example Cingano et al. (2016)) or other real economic outcomes (see for example Chodorow-Reich (2014) for employment). Nevertheless, this literature does not differentiate firms according to their ability to

[32] For a discussion on matching between banks and firms riskiness see Chang et al. (2021)

[33] In the online Appendix (section C) I also analyze the elasticity of substitution by bank size and by the length of the bank-firm relationship.

overcome credit constraints by switching across lenders. In this sense, the paper provides the first analysis by considering how the elasticity of substitution across banks has a differential impact on investment by firms that receive a credit supply shock. In order to show this result, I exploit the heterogeneity of the elasticity of substitution across industries, and not by any of the variables analyzed above (size, age, etc...). Indeed, considering for example the credit rating, it is not clear whether credit supply or demand shocks vary independently of the elasticity of credit rating, thus impairing the validity of the identification in estimating the elasticity of substitution.

In order to examine differential effects of the credit supply shocks that are solely due to the elasticity of substitution, I require a measure of differentiation among firms that has no effect on firm indebtedness and, therefore, also on their investments. Hence, as mentioned just above, I estimate the elasticity of substitution across industries. The elasticity may differ across industries because of the differences in technology or in market size. For instance, many services industries in the dataset are in highly non-tradable sectors.

To better show this point, I show that the two main variables that are used to estimate the elasticity ($\hat{\alpha}^{AW}_{f,t}$ and $\hat{\beta}^{AW}_{b,t}$) are correlated with the values of each of the variables above (firm credit rating, firm size, etc...), but not with firm industries. In other terms, I run regressions of $\hat{\alpha}^{AW}_{f,t}$ and of $\hat{\beta}^{AW}_{b,t}$ on the fixed effects of each characteristic.[34] Figure A.5 in the online Appendix shows that the estimated coefficients of the fixed effects of the credit rating have a non random pattern with respect to the dependent $\hat{\alpha}^{AW}_{f,t}$ (panel a) or with respect to $\hat{\beta}^{AW}_{b,t}$ (panel d). Differently, in panel b and panel e the coefficients on industry fixed effects have a random pattern, where industries are coded using an indexation that follows that of NACE Rev. 2. With regard to this last point, one may wonder that the indexation of industries hides an actual non-random pattern of sectors. Consequently, I repeat the previous exercise on industries using a measure of sector dependence on external finance: in this case the patterns of $\hat{\alpha}^{AW}_{f,t}$ ((panel c) and of $\hat{\beta}^{AW}_{b,t}$ ((panel f) are random.[35]

Since industries have a random pattern with respect to the firm-time and bank-time fixed effects, in the rest of this section I first estimate the elasticity of substitution by industries of economic activity and in the second step I regress the investment rate on the credit supply shocks interacted with dummies of industries defined by the quartile values of the estimated elasticities.

I estimate the elasticity of substitution by industry using the baseline model of section 4.3 and the data in the two years before the reference year. I regroup 2 digit industries (NACE Rev. 2 nomenclature) into 30 industries, in order to have a sufficient number of observations by industry and year. I keep only the estimated elasticities that are significantly different from zero; the average estimated elasticities by

[34] Each variable is split into 30 bins computed using percentiles so as to have a sufficient number of coefficients to evaluate the presence of non random patterns with the firm-time and bank-time fixed effects. The only exception is firm rating because this is a categorical variable that has 9 values.

[35] Differently when $\hat{\alpha}^{AW}_{f,t}$ and $\hat{\beta}^{AW}_{b,t}$ are regressed on the other characteristics that may affect the elasticity (firm size, firm age, bank size and the length of the relationship) a non-random pattern emerges: see figure A.5bis.

industry, which are summarized in table 4,[36] vary from a minimum value of 1.09 in other services to a maximum of 4.5 in the food industry.

5.1 Estimates on the investment rate

As a second step I estimate an investment equation. Note that since investment data are available only at firm-year level, I first need to define the credit supply shock, the Amiti and Weinstein bank-time fixed effect, at the same level. In practice, first I collapse the credit supply shock (the Amiti and Weinstein bank-time fixed effect) at firm-quarter level, so that the aggregate idiosyncratic bank supply shock hitting a firm f at quarter t is:

$$Bank\ Shock_{f,t} = \sum_{b=1} (w_{bf,t-1} \hat{\beta}^{AW}_{b,t}) \tag{8}$$

where $w_{b,f,t-1}$ is the weight of loans from bank b to firm f in the previous period $(t-1)$.[37] Then, I take the yearly average of the $Bank\ Shock_{f,t}$ of equation 8. The investment rate (investment at time t over capital at time $t-1$, both defined using fixed tangible assets[38]) is estimated on the credit supply shocks hitting firm f at time t as defined in equation 8, 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.

$$I_{f,t} = \sum_{\iota=1}^{4} \gamma_\iota (Bk\ Shock_{f,t}) \times \mathbf{1}(\iota) + \Gamma_5 X_{f,t} + \gamma_{j,t} + \gamma_f + \nu_{f,t} \tag{9}$$

where $\iota(= 1, 2, 3, 4)$ is the bin indicator of the distribution by quartile values of the estimated elasticities of substitution per industry and year ($\hat{\sigma}_{j,t}$). Equation 9 includes also firm-year controls $X_{f,t}$ that may be relevant: firm size (proxied by the log number of employees), firm age (years) and the credit rating in the previous year. Moreover, following Amiti and Weinstein (2018)[39] $X_{f,t}$ also includes firm covariates that may affect the financing choices of investment: cash flow (over capital), the mean loan to assets ratio and the bonds to assets ratio. Finally, equation 9 also includes fixed effects that absorb any unobserved factor at industry-year ($\gamma_{j,t}$) and at firm level (γ_f) affecting firms' investments. The estimates run only from 2009, because I lose two years in the estimation of the elasticity of substitution.[40]

The results are in table 5. In column 1, I estimate the model on the credit supply shock and the various controls $X_{f,t}$. The effect on the credit supply shock is significant and positive as expected. This is the usual quantity effect found also in a large literature using matched bank-firm data. In order to

[36] The details of each estimated elasticities are in tables A3.1 to A3.4 of the online Appendix.
[37] When dealing with quarterly data as in this case, the period $t-1$ refers to the same quarter of the previous year.
[38] 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.
[39] See in their paper table 2, page 558.
[40] I also estimate the parameters of interest by interacting the bank supply shock with the dummy ι and the elasticity of substitution: $I_{f,t} = \sum_{\iota=1}^{4} \gamma_\iota (Bk\ Shock_{f,t}) \times \mathbf{1}(\iota) \times \hat{\sigma}_{j,t} + \Gamma_5 X_{f,t} + \gamma_{j,t} + \gamma_f + \eta_{f,t}$. The estimates, unreported here for sake of brevity, confirm the results of the analysis in the paper.

take into account of the role of banks substitution, in column 2 I repeat the estimate interacting the bank shock with the bin dummies defined by the quartile values of the estimated elasticities $\hat{\sigma}_{j,t}$. The effect of a credit supply shock on investments is positive and significant only in the first bin, that is only for firms in industries with the lowest elasticity of substitution. [41]

Since 12.4% observations report zero investment, in column 3 I repeat the previous estimate applying the inverse hyperbolic sine transformation (ihst) to the dependent variable and the estimates are substantially unchanged: the effect is still significant only in the first bin. To get a sense of the magnitude with this specification, this estimate shows that with a one per cent increase (decrease) in the credit supply shock to firms in these industries, the investment rate rises (falls) by 0.2%.

Alternatively, in column 4 I use the Poisson pseudo-likelihood estimator with multiple levels of fixed effects (ppmlhdfe) developed by Correia et al. (2020): the results in this last case are qualitatively similar, but the magnitude is much larger. Nevertheless, the main result of the previous columns is confirmed: credit supply shocks affect firms' investments only in industries with the lowest elasticity of substitution.

Since 2009 is a year in which the Financial Crisis was exerting its effects on credit markets in Italy, in columns 5 to 8 of table 5 I repeat the previous exercise using data from 2010 and the previous results are confirmed. In column 5 the overall effect of the bank shocks is slightly larger than the corresponding case that included the year 2009 in column 1. In the ensuing columns (6 to 8) again I find that the effect is significant only in the interacted variable in the first bin.

5.1.1 Robustness checks

In this subsection I show some robustness checks of the estimates on the investment rate.

First, I add measures of bank specialization by industry to the empirical model. The result described in the previous section is in line with the information hypothesis studies, according to which credit constraints are lessened by banks with a higher market power. To this aim, banks information advantage may derive from a relative specialization of the bank in the industry of activity of the firm. Indeed, a recent and growing literature has highlighted the presence of a comparative advantage in lending by banks specialized in lending towards specific industries or markets (Jiang and Li (2022) and Paravisini et al. (2023)). 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. At the opposite, if bank specialization is less relevant, the substitutability may be higher. To test this point

[41] Note that this result is not obvious, because the empirical evidence is not conclusive on two opposing views. On the one hand, the *market power hypothesis* argues that firms with a lower elasticity of substitution (σ) may face a stronger market power of the banks, thus leading to financial constraints (Degryse and Ongena (2008)). On the other hand, according to the *information hypothesis* a less competitive lending market is associated with a higher credit availability because greater market power induces banks to engage in relationship lending that reduces information asymmetry with the borrower firms (Petersen and Rajan (1995)).

empirically, I add interactions of $Bank\ Shock_{f,t}$ with a bin indicator of the quartile values ($\psi = 1, 2, 3, 4$) of the distribution of the bank specialization measure by industry per firm and year; in turn, the measure of bank specialization is derived by adapting that of Paravisini et al. (2023) to this empirical model (for more details see D in the online Appendix). The results are in table 6. Starting with column 1, where there is no measure of substitution, the investment rate increases with lending by specialized banks: indeed, the effect is not significant only for credit granted by less specialized banks ($\psi = 1$ and $\psi = 2$), a result in line with that of Paravisini et al. (2023). Adding the measures of the elasticity of substitution (column 2) changes the results remarkably: only the interacted measure of bank substitutability with the lowest value ($\iota = 1$) remains significant (as in 5), while the measures of bank specialization are not different from zero; the other columns in the table report similar results. Therefore, the results of table 6 imply that the effect of bank substitutability offsets that of bank specialization by industry. In other terms, taking the elasticity of substitution into account allows one to sensibly change the general result on bank specialization, found in other studies.

Second, I consider only less concentrated markets (see table A4.1 in the online Appendix), where the HHI index is limited to 0.18 (in panel a) and even more restrictive to 0.15 (panel b): the estimates show that the main result of table 5 is confirmed in both cases. Third, I add intangible assets to the definition of capital and of investment (table A4.2) and I obtain results that are qualitatively similar to main ones. Fourth, I estimate the investment rate equation by sectors, that is for manufacturing or services only: the effect (see table A4.3) derives from manufacturing, while the evidence for firms in services is less robust (at least with the linear model). Fifth, replicate the analysis, by adding to the estimation of σ fixed effects of rating, size and age (using quartiles for each variable) in order to remove as much omitted variable bias as possible from the estimates of the elasticity of substitution. The results (see columns 1 to 4 of table A4.4) show again that the credit supply shocks have a significant effects on investment only for firms in industries with the lower elasticity of substitution. Sixth, I replicate the analysis adding to the dataset single bank firms, which are typically smaller and more opaque. In this case, the estimates on this expanded dataset (see columns 5 to 8 of table A4.4) show that the significant effects of the credit supply shocks are relevant not only for firms in the lowest bins of the elasticity of substitution, but also for the other two bins, except for when $\iota = 4$, suggesting that switching costs are more relevant even if firms have a relatively greater elasticity of substitution. Again, bank specialization plays no role. [42] Seventh, I replicate the estimates by using an alternative measure of bank-specialization, by province. The main results (see table A4.5) are confirmed. Finally, I run a sensitivity analysis by dropping one industry at a time: figure A.6 shows that the estimated coefficients are quite stable for each industry dropped.

Overall, this evidence confirms that credit supply shocks have a positive and significant effect on the investment rate, a result that is in line with that of Amiti and Weinstein (2018) and of much if

[42] Note that in both these two cases, bank specialization plays no role in the horse race with the elasticity of substitution.

the literature using bank-firm data. After this general result, I provide new evidence on the role of the elasticity substitution across lenders: the overall quantity effect derives only from firms in industries with lowest elasticity. Therefore, estimating the elasticity of substitution is crucial for a better understanding of the heterogeneous reaction of investment to credit constraints on firms.

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 elasticity of substitution, I 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 effect on firm total debt. On the other hand, firm overall debt should decrease significantly if firms are less able to substitute banks. Empirically, I test whether credit supply shocks have a significant impact on total debt on firms with a lower elasticity of substitution. If this prediction is confirmed by the ensuing analysis, then the effects on investments showed in the previous subsection, are explained by the significant increase in total debt (or decrease in the average interest rate) due to low substitutability.

Empirically, I take the same set of firms of the previous exercise and I regress firm total debt and firm average interest rate on the credit supply shock hitting firm f at year t and on the interactions of the dummy of the four bins defined by quartiles of $\hat{\sigma}$. As before, I add the same set of controls (log of employees, firm age and firm credit rating, cash flow over capital, the mean loan to assets ratio, the bonds to assets ratio).

The estimates are reported in table 7. The first dependent variable is firm total financial debt, where this includes borrowing from banks and also debt from other financial sources (such as leasing and factoring). The overall effect is not significant (column 1), but when considering the interaction with the bins of the estimated σ (column 2), the effect is positive and significant only for firms in industries with the lowest elasticity of substitution. Moving to debt only from banks, the overall effect (column 3) is positive, but barely significant. Nevertheless, the effect on total bank debt derives only from firms in the first bin (column 4) and it is significant at 99%. Provided that the distribution of the elasticity of substitution determines firm total borrowing, it is not ex ante clear whether there are any effects on firm overall lending costs: in the last two columns I check whether the effects are also on the average interest rate. Column 5 shows that an expansion of credit supply lowers the average interest rate on loans, but column 6 shows that this reduction regards only firms in the first two bins (with the elasticity below the median); differently, companies with a higher elasticity do not have any significant change in the average interest rate.

Taken together, the estimates presented in this subsection show that the effect on investment (of credit supply shocks in industries with the lowest elasticity of substitution) derives from the 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 least able to offset these changes by turning to other banks.

6 Robustness checks on the elasticity of substitution

In this section, I present various robustness checks on the elasticity of substitution. First, I consider various definitions of the aggregate interest rate (6.1), and then I add a different specification of the estimating equation where the aggregate interest rate is absorbed by firm fixed effects (6.2). In the subsection 6.3 I repeat the estimates of the elasticity using various variants of the baselines model: adapted to moral hazard, considering relationship and transaction lending separately, using OLS bank-time and firm-time fixed effects, considering lenders at bank group level, using an alternative specification of the growth rate of lending, adding a measure of collateral, excluding moderately concentrated local credit markets and finally including single bank firms.

6.1 Different aggregate interest rate

As a first robustness check, I use the aggregate interest rate defined in various ways. The first is at firm level ($R_{f,t}$), where this is defined as a weighted average of all interest rates applied by all banks b' (in leave-out form, that is to say all other banks different from bank b) lending to firm f at time t and where the weight is given by the previous period percentage of loans to the firm (see equation 6). I also use the interest rate defined at industry level ($R_{j,t}$)[43], at regional level ($R_{r,t}$), at province level ($R_{p,t}$)[44], at regional-industry level ($R_{r,j,t}$), at size bin level ($R_{size,t}$) and at credit rating bin level ($R_{rat,t}$). Columns 1 to 7 of table 8 report the estimates using these aggregate interest rates: in each case, the estimated elasticities are negative and significant. The magnitude of the estimated elasticity varies from -3.2 in column 1 to -2.3 in all the other columns (from 2 to 7). With the exception of the estimate in column 1 (with $R_{f,t}$), the other values are very similar to that of the baseline estimate (-2.3), thus confirming that there might be a bias in letting the aggregate interest rate be defined only at firm level.

6.2 Single rate specification

Empirically, equation 5 can be estimated also by collapsing the aggregate interest rate $R_{c,t}$ into a commuting zone-time fixed effect, or into a industry-time fixed effect if the aggregate rate is $R_{j,t}$, etc... Consider the case in which $R_{f,t}$ is collapsed into a firm-time fixed effect, the empirical specification of the

[43] Industries in $R_{j,t}$ are defined at 1 digit using the NACE Rev. 2 nomenclature, except for manufacturing where they are defined at 2 digits.

[44] $R_{r,t}$ and $R_{p,t}$ are defined by averaging the interest rates by regions or by provinces. Regions correspond to NUTS level 2, using the Eurostat classification. Provinces are NUTS level 3. Overall, in Italy there are 20 regions and 110 provinces.

basic model becomes:

$$\Delta \ln(L_{b,f,t}) = -\sigma \Delta \ln(r_{b,f,t}) + \Delta a^*_{f,t} + \nu_{b,f,t} \tag{10}$$

where the change in the firm-time FE's now absorbs the change in the aggregate interest rate: $\Delta a^*_{f,t} = -\sigma\Delta \ln(R_{f,t}) + \Delta a_{f,t}$. The estimation of this specification implies adding firm-time fixed effects to the model and replacing the log of the interest rate on the rhs ($\Delta \ln(r_{b,f,t})$). The result of this estimate is in column 8 of table 8 and the magnitude in absolute value (2.2) is just slightly smaller (in absolute value) than the one of the baseline (2.3). Therefore, also in this case the main results of the baseline model are confirmed.[45]

6.3 Other robustness checks

In this section we report briefly the other robustness checks on the estimation of the elasticity of substitution, while I postpone all the details to the online Appendix. I first consider the case of moral hazard, where the firm plans to repay only a fraction of the lending costs μ_t, which is proxied by the degree of efficiency of local courts at province-year level: $\mu_{p,t}$ (the estimating equation is derived in section E of the online Appendix); the result of this estimation is in column 1 of table 9: the estimated elasticity is negative, significant and with a magnitude very close to that of the model without moral hazard.[46]

The second check is to estimate the elasticity of substitution for transaction lending and for relationship lending separately, where the latter includes term loans. [47] The results of these estimates, reported in columns 2 and 3 of table 9, show that the estimated elasticity of transaction loans is in absolute value greater in magnitude than that of relationship lending, confirming the view that the elasticity of substitution is larger for loans that are more likely to affect the overall financial situation of the firm.

Third, I repeat the estimate of the elasticity of substitution using OLS bank-time and firm-time fixed effect, which are used still by a large number of papers. The estimated elasticity (column 4) is, in absolute value, much larger than the one in the baseline (see column 4 of table 3), thus revealing that it is appropriate to use the Amiti and Weinstein estimator to remove the estimation bias.

Fourth , I repeat the main estimates using data of banks collapsed by bank groups to take into account of credit supply policy set at bank group level. The estimated elasticity (column 5) is in magnitude much smaller than the corresponding parameter of table 3 (2.3), because these estimates do not take into account changes across banks within bank groups.

[45] The estimates are very similar using alternatively only commuting zone-time, province-time FE's, industry-time FE's or region-time FE's. The results are unreported here for sake of brevity, but they are available under request.

[46] In unreported estimates I re-estimate the model including another dimension of asymmetric information, "soft information", that is known to the bank but not observed by the econometrician. Soft information is derived in the spirit of Crawford et al. (2018) and it is the residual of the estimate of the interest rate on bank-time fixed effects and firm rating. The results are very similar to those of table 9 and they are available under request.

[47] In order to distinguish these two types of loans, here I denote loans backed by receivables for transaction lending and term loans and overdraft loans for relationship lending. Note that this is not the only method. For example, Bolton et al. (2016) use physical distance, but here I have already restricted the local credit market to a very narrow area (commuting zone). Berger and Udell (1995) use the length of the relationship between the borrower and the lender (see the analysis in section C).

Fifth, I repeat the estimate adding the log change of collateral as a control variable to the baseline model in column 6 of 9; the estimated elasticity is (in absolute value) 2.1, lower than that of the baseline (2.3): indeed, by pledging collateral firms signal their type and are thus perceived as less risky by banks (Besanko and Thakor (1987)) and thus they may prevent an increase in the interest rate by the bank, thus reducing their willingness to switch to other banks.

Sixth, I repeat the estimate specifying the dependent variable, rather than with the log difference of credit, with the growth rate of Davis and Haltiwanger (1992) and used more recently by Chodorow-Reich (2014) and by Degryse et al. (2019): $\Delta(L_{b,f,t}) = \frac{L_{b,f,t}-L_{b,f,t-1}}{0.5(L_{b,f,t}+L_{b,f,t-1})}$; this specification encompasses both the new and terminating loans.[48] The estimate of the elasticity, in column 7 of 9, is slightly smaller (in absolute value) than the one estimated with the log form of the dependent variable.

Seventh, the elasticity is estimated on a dataset of only very competitive lending markets: I exclude commuting zones with an HHI less or equal to 0.18 and also a more stringent measure where this threshold is reduced to 0.15;[49] these estimates, reported in columns 8 and 9 of 9, show that the estimated elasticities are very similar to the ones obtained with the full sample.

Finally, it may be relevant to estimate the the elasticity of substitution for firms that have only one banking relationship. Such companies constitute the majority of firms in many economies, they are typically smaller, opaquer and when they want to substitute banks they need to find a new lender. Then, one would expect the elasticity to be lower due to higher switching costs. Luckily the available data allow to expand the dataset to include also "single bank" firms.[50] Empirically, this implies a slight modification of the identification equation (7). Indeed, for firms having a credit relationship with only one bank, the firm-time fixed effect is perfectly collinear with the bank-time fixed effect. To overcome this point I follow Degryse et al. (2019), by substituting the firm-time fixed effect with the commuting zone-industry-size-time fixed effect.

The elasticity of substitution is expected to be lower for single bank firms, as it is more difficult for these companies to switch among lenders. This prediction is confirmed by the results, shown in column 10 of table 9, where the estimated fixed effects are obtained with OLS. The elasticity is smaller (of about 20% in absolute value) than the one obtained in the dataset with multiple lending firms and using OLS for each specification (see column 5 of the same table). Overall, this result confirms the expectation that switching costs for single bank firms are higher than for multiple bank companies.

[48] Indeed, the growth rate values are in the interval [-2, 2]. $\Delta(L_{b,f,t})$=2 in the case of new loans ($\Delta L_{b,f,t-1}$)=0 and it is equal to -2 in the case of ending loans ($L_{b,f,t} = 0$).

[49] In the first case 102 out of 611 commuting zones are excluded, while with the more stringent assumption 146 local credit markets are dropped from the data.

[50] The descriptive statistics for this wider dataset (not showed here, but they are available under request) reveal that for most of the variables the mean and standard deviation are similar to multi-bank firms.

7 Conclusions

This paper provides insight on two important contributions to the literature. Firstly, it develops a simple methodology to estimate the elasticity of substitution across banks using matched bank-firm data on loans and on interest rates. It shows that this elasticity is a reliable proxy of the ease of borrowers to switch lenders, as it increases with firm size and firm age. The estimated elasticities are also robust with respect to various extensions of the baseline model (including moral hazard, type of loans, etc…).

Secondly, it shows that this substitutability is relevant as it shapes the effect of credit shocks on firms' investments. Credit supply shocks increase firms' investment rate as in much of the literature so far, but the effects are significant only for firms in industries with the lowest elasticity of substitution. Therefore, the distribution of the elasticity of substitution across firms is important to understand the functioning of the bank lending channel and its effects on the real economy. In this sense, it reveals an interesting heterogeneity in the effects of credit supply shocks on firms' investments, which, to the best of my knowledge, has never been found before.

The findings are also important for other reasons. They suggest that the elasticity of substitution is a reliable indicator of the ease of switching across lenders not just 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. Moreover, it provides a measure of firms sensitivity to the changes in the cost of external funds, which can be particularly relevant in the current period of increased interest rates. Finally, the paper provides a framework to assess the sensitivity of credit availability to changes in supply conditions for firms belonging to different industries. This could be relevant to evaluate the impact of supply shocks to the financial vulnerability of both firms and their lenders, with possible implications for systemic risk analyses and macroprudential policy decisions.

In conclusion, the results of this study provide implications for future research. The estimates in the paper are based on data from Italy, a country where firms are strongly reliant on bank credit. It would be interesting to investigate how further research could expand the analysis to other advanced countries to explore how the results may differ based on differences in banking sector, economic structure and other factors. The heterogeneous response across industries could be considered for a deeper scrutiny of the effects of monetary policy shocks which translate into credit supply shifts.

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Table 1: Descriptive statistics

	Variable	Obs	Mean	Std.Dev.	Min	Max
		Panel A: multiple lending firms				
Bank-firm-year-quarter variables	$L_{b,f,t}$	4,946,204	822,801.2	1,191,716	77,809	10,019,060.6
	$r_{b,f,t}$	4,964,730	5.16	4.19	0.47	45.60
	$\Delta\ln(L_{b,f,t})$	5,036,614	-0.02	0.25	-1.14	0.89
	$\Delta\ln(r_{b,f,t})$	5,036,614	0.09	0.37	-1.38	1.73
	$\Delta\ln(r_{b,f,t}/R_{c,t})$	5,036,614	0.02	0.35	-1.83	2.02
	$\Delta\ln(r_{b,f,t}/R_{f,t})$	5,000,393	-0.01	0.40	-4.28	2.91
	$\Delta\ln(r_{b,f,t}/R_{j,t})$	4,953,555	0.02	0.35	-1.80	1.92
	$\Delta\ln(r_{b,f,t}/R_{r,t})$	4,976,265	0.02	0.35	-1.81	1.98
	$\Delta\ln(r_{b,f,t}/R_{p,t})$	4,979,132	0.03	0.024	-1.77	1.95
	$\Delta\ln(r_{b,f,t}/R_{r,j,t})$	4,944,825	0.02	0.35	-1.83	2.02
	$\Delta\ln(r_{b,f,t}/R_{size,t})$	4,949,572	0.03	0.35	-1.79	2.03
	$\Delta\ln(r_{b,f,t}/R_{score,t})$	4,944,366	0.03	0.35	-1.79	1.97
Firm-year-quarter variable	$\alpha^{AW}_{f,t}$	1,788,016	0.01	0.16	-0.43	0.67
Firm-year variables	$Credit\ score_{f,t}$	471,460	4.91	1.70	1	9
	$Employees_{f,t}$	615,317	34.91	251.44	1	54,158.33
	$Age_{f,t}$	464,295	23.80	13.30	0	162
	$Inv.\ rate_{f,t}$	350,253	0.13	0.26	0	3.09
Bank-year-quarter variable	$\beta^{AW}_{b,t}$	5,687	0.00	0.06	-0.13	0.19
Bank-year variables	$IBK\ ratio_{b,t}$	1,624	0.26	0.27	0.00	1.00
	$FOR\ ratio_{b,t}$	1,624	0.10	0.23	0.00	1.00
	$Tier\ 1\ ratio_{b,t}$	1,376	13.05	7.09	3.98	128.35
	$Total\ Cap.\ Ratio_{b,t}$	1,376	14.93	7.73	5.53	145.11

1

Table 2: Validation of the instrumental variable I

	(1)	(2)	(3)	(4)
IBK ratio	-0.041***			
	[0.005]			
Foreign ratio		-0.038***		
		[0.007]		
Tier 1 ratio			0.000***	
			[0.000]	
Total cap. ratio				0.000***
				[0.000]
Constant	0.012***	0.005***	0.002	0.002
	[0.002]	[0.001]	[0.001]	[0.001]
Observations	1,624	1,624	1,376	1,376
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
#Banks	195	195	195	195

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"). All data are trimmed at 1% at both tails. Heteroskedastic robust standard errors, clustered at the bank and province level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Baseline estimates

	(1)	(2)	(3)	(4)
	2nd stage			
$\Delta \ln \frac{r_{b,f,t}}{R_{c,t}}$	-4.212***	-4.524***	-2.835***	-2.290***
	[0.700]	[0.689]	[0.248]	[0.156]
$\Delta\alpha^{AW}_{f,t}$		0.148***	0.231***	0.252***
		[0.030]	[0.010]	[0.007]
	1st stage			
$\beta^{AW}_{b,t}$	-0.104***	-0.114***	-0.194***	-0.240***
	[0.017]	[0.017]	[0.017]	[0.015]
F-test	36.67	43.80	135.3	242.2
Observations	5,036,618	5,036,618	5,036,618	5,036,618
# Firms	114,987	114,987	114,987	114,987
# Banks	210	210	210	210
Time FE	No	No	Yes	No
Cmz&Time FE	No	No	No	Yes
Industry&Time FE	No	No	No	Yes

The table reports the 2SLS estimates of credit demand. The dependent variable is the natural log change of loans. $\Delta \ln \frac{r_{b,f,t}}{R_{c,t}}$ is the relative interest rate. $\Delta\alpha^{AW}_{f,t}$ is the firm-time FE's estimated with the AW estimator. $\Delta\beta^{AW}_{b,t}$ 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 middle rows. The variable definitions are in table A1. Fixed effects at time, commuting zone-quarter (Cmz&time) and at industry-quarter (Industry&time) are included ("Yes"), not included ("No"). 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.

Table 4: Estimated σ by industry (year averages)

sector	sigma	sector	sigma
Other services	1.09	Agriculture & mining	2.25
Professional	1.26	Chemical & Pharmac.	2.29
Other manufacturing	1.55	Paper & print	2.36
Info and Communication	1.58	Construction	2.37
Support services	1.72	Metal products	2.47
Leather	1.73	Retail trade	2.49
Wholesale trade	1.75	Hotels and restaurants	2.50
Apparel	1.90	Machinery	2.51
Textiles	1.99	Real estate	2.92
Public services	2.01	Utilities	2.96
Furniture	2.05	Rubber	3.19
Transport & courier	2.08	Beverages & tobacco	3.20
Wood	2.12	Non metallic minerals	3.57
Motor and veihicles	2.17	Basic metals	4.05
Computer & electrical	2.22	Food	4.50

The table reports the estimated sigma by industry, averaged across years, where the industries are defined as follows: Agriculture & mining (NACE Rev. 2 codes 1 ,2 ,3 ,5 ,6 ,8 and 9), Food (code 10), Beverages & tobacco (11 and 12), Textiles (13), Apparel (14), Leather (15), Wood (16), Paper & print (17 and 18), Chemical & Pharma (19, 20 and 21), Rubber (22), Non metallic minerals (23), Basic metals (24), Metal products (25), Computer & electrical (26 and 27), Machinery (28), Motor and vehicles (29 and 30), Furniture (31), Other manufacturing (32 and 33), Utilities (35, 36, 37, 38 and 39), Construction (41, 42 and 43), Wholesale trade (45 and 46), Retail trade (47), Transport & courier (49, 50, 51, 52, 53), Hotels and restaurants (55, 56), Info and Communication (58, 59, 60, 61, 62 and 63), Real estate (68), Professional (69, 70, 71, 72, 73, 74 and 75), Support services (77, 78, 79, 80, 81 and 82), Public services (84, 85, 86, 87 and 88), Other services (90, 91, 92, 93, 94, 95 and 96).

Table 5: Investment rate regressions using σ estimated on industries and years

	2009-2015				2010-2015			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Linear	Linear	Linear ihst	PPML	Linear	Linear	Linear ihst	PPML
$Bank\ Shock_{f,t}$	0.105***				0.113**			
	[0.040]				[0.047]			
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=1)$		0.196***	0.195***	1.307***		0.162***	0.164***	0.858**
		[0.051]	[0.041]	[0.378]		[0.056]	[0.045]	[0.432]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2)$		0.065	0.071*	0.275		0.086	0.091**	0.365
		[0.048]	[0.039]	[0.362]		[0.057]	[0.045]	[0.441]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=3)$		0.010	0.008	-0.005		0.027	0.024	0.122
		[0.057]	[0.045]	[0.420]		[0.065]	[0.052]	[0.522]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=4)$		0.070	0.063	0.302		0.018	0.027	-0.062
		[0.060]	[0.048]	[0.443]		[0.087]	[0.069]	[0.697]
$\log(Employees_{f,t-1})$	-0.066***	-0.066***	-0.056***	-0.269***	-0.063***	-0.063***	-0.054***	-0.239***
	[0.004]	[0.004]	[0.003]	[0.028]	[0.005]	[0.005]	[0.004]	[0.033]
$Age_{f,t}$	-0.009***	-0.009***	-0.008***	-0.063***	-0.010***	-0.010***	-0.009***	-0.073***
	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.003]
$Credit\ Score_{f,t-1}$	0.013***	0.013***	0.012***	0.103***	0.013***	0.013***	0.012***	0.105***
	[0.001]	[0.001]	[0.001]	[0.005]	[0.001]	[0.001]	[0.001]	[0.006]
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	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]
$(Bank\ Shock_{f,t})\times(LAR_f)$	0.146	0.152	0.116	1.631	0.262*	0.267*	0.210*	2.692**
	[0.123]	[0.123]	[0.097]	[0.997]	[0.144]	[0.144]	[0.114]	[1.232]
$(Bank\ Shock_{f,t})\times(BAR_f)$	-0.182	-0.181	-0.210	-0.608	-0.122	-0.115	-0.160	0.693
	[0.312]	[0.312]	[0.243]	[2.573]	[0.360]	[0.360]	[0.280]	[3.142]
$Industry\&year$	0.863***	0.871***	0.797***	7.171***	1.001***	1.004***	0.927***	8.718***
	[0.071]	[0.071]	[0.057]	[0.530]	[0.076]	[0.077]	[0.062]	[0.588]
Observations	293.426	293.426	293.426	293.405	255,596	255,596	255,596	255,050
# Firms	61,350	61,350	61,350	61,341	58,646	58,646	58,646	58,427
Adj. R-squared	0.281	0.281	0.299		0.301	0.301	0.320	
Pseudo R-squared				0.156				0.163

The table reports the estimates of the investment rate, as the ratio between investment in tangible assets at time t and tangible capital in $t-1$. Columns 1 to 4 report the estimates for the period 2009-2015. The estimates starting from 2010 are reported in columns 4 to 8. The estimator is linear with large fixed effects (reghdfe) in columns 1, 2, 3, 5, 6 and 7; it is PPML with large firm fixed effects (ppmlhdfe) in columns 4 and 8. The dependent variable is the investment rate expressed in the inverse hyperbolic sine transformation (ihst) in columns 3 and 7. The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In columns 2, 3, 4, 6, 7 and 8 this is interacted with dummy indicators $\mathbf{1}(\iota)$ of the four bins defined by the quartile values of the estimated σ by industry and year 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 firm fixed effects and year fixed effects. 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 6: Investment rate regressions - bank specialization by industry

	2009-2015				2010-2015			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Linear	Linear	Linear ihst	Linear ihst	Linear	Linear	Linear ihst	Linear ihst
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=1)$		0.159**		0.167***		0.185**		0.177***
		[0.064]		[0.050]		[0.072]		[0.057]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2)$		0.027		0.042		0.110		0.105*
		[0.064]		[0.050]		[0.074]		[0.058]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=3)$		0.040		0.033		0.132*		0.111*
		[0.068]		[0.052]		[0.078]		[0.061]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=4)$		0.040		0.036		0.061		0.055
		[0.072]		[0.057]		[0.101]		[0.080]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\psi=1)$	0.074		0.079*		0.144**		0.134***	
	[0.055]		[0.043]		[0.065]		[0.051]	
$(Bank\ Shock_{f,t})\times\mathbf{1}(\psi=2)$	0.078	0.020	0.079*	0.020	0.078	-0.048	0.086*	-0.030
	[0.054]	[0.061]	[0.043]	[0.048]	[0.063]	[0.071]	[0.050]	[0.056]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\psi=3)$	0.134**	0.061	0.132***	0.056	0.078	-0.059	0.088*	-0.040
	[0.054]	[0.060]	[0.043]	[0.047]	[0.062]	[0.070]	[0.050]	[0.055]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\psi=4)$	0.134**	0.055	0.126***	0.036	0.147**	-0.002	0.145***	0.003
	[0.053]	[0.063]	[0.042]	[0.050]	[0.063]	[0.073]	[0.050]	[0.057]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	293,426	293,426	293,426	293,426	255,596	255,596	255,596	255,596
# Firms	61,350	61,350	61,350	61,350	58,646	58,646	58,646	58,646
Adj. R-squared	0.281	0.281	0.299	0.299	0.301	0.301	0.320	0.320

The table reports the estimates of the investment rate, defined as the ratio between investment in tangible assets at time t and tangible capital in $t-1$. The dependent variable is the investment rate expressed in the inverse hyperbolic sine transformation (ihst) in columns 3, 4, 7 and 8 (ihst). Columns 1 to 4 report the estimates for the period 2009-2015. The estimates starting from 2010 are reported in columns 4 to 8. The estimator is linear with large fixed effects (reghdfe). The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. This is interacted (in columns 2, 4, 6 and 8) with dummy indicators $\mathbf{1}(\iota)$ of the four bins defined by the quartile values of the σ by industry and year estimated in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009). $Bank\ Shock_{f,t}$ is also interacted (in all columns) with dummy indicators $\mathbf{1}(\psi)$ of the four bins defined by the quartile values of the specialization measure by industry estimated in the three years preceding the reference year (e.g: 2007, 2008 and 2009 for the year 2009). Controls include: the log of employees in *t-1* ($\log(Employees_{f,t-1})$); firm age ($Age_{f,t}$); the credit score in *t-1* ($Credit\ Score_{f,t-1}$); cash flow t over capital *t-1* ($Cash\ Flow_{f,t}/Capital_{f,t-1}$); the mean loans-to-assets ratio of firm f defined as the average ratio of loans to assets over the sample period (LAR_f); the mean bonds-to-assets ratio (BAR_f), similarly defined; the median of credit demand shocks ($\alpha^{AW}_{f,t}$) across firms by industry and year ($Industry\&year$). The variable definitions are in table A1. All estimates include firm fixed effects and year fixed effects. 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 7: Estimates on firm total debts and interest rates

	(1)	(2)	(3)	(4)	(5)	(6)
dep. vars.:	ln(financial debt$_{f,t}$)		ln(bank debt$_{f,t}$)		ln($r_{f,t}$)	
$Bank\ Shock_{f,t}$	0.335		0.494*		-0.525***	
	[0.253]		[0.259]		[0.064]	
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=1)$		0.819***		1.007***		-1.409***
		[0.301]		[0.308]		[0.076]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2)$		0.264		0.361		-0.411***
		[0.305]		[0.312]		[0.074]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=3)$		-0.138		0.098		0.053
		[0.338]		[0.348]		[0.080]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=4)$		0.242		0.371		0.095
		[0.374]		[0.387]		[0.090]
$\log(Employees_{f,t-1})$	0.508***	0.508***	0.547***	0.547***	-0.053***	-0.053***
	[0.026]	[0.026]	[0.026]	[0.026]	[0.005]	[0.005]
$Age_{f,t}$	-0.082***	-0.081***	-0.077***	-0.077***	0.070***	0.070***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.000]	[0.000]
$Credit\ Score_{f,t-1}$	-0.064***	-0.064***	-0.063***	-0.063***	-0.007***	-0.007***
	[0.004]	[0.004]	[0.004]	[0.004]	[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]
$(Bank\ Shock_{f,t})\times(LAR_f)$	-0.877	-0.862	-1.335**	-1.320**	-1.244***	-1.274***
	[0.614]	[0.614]	[0.631]	[0.631]	[0.177]	[0.177]
$(Bank\ Shock_{f,t})\times(BAR_f)$	-1.253	-1.259	-1.622	-1.624	0.148	0.159
	[1.457]	[1.458]	[1.867]	[1.867]	[0.497]	[0.498]
$Industry\&year$	-1.428***	-1.386***	-1.630***	-1.585***	-1.914***	-1.980***
	[0.485]	[0.485]	[0.496]	[0.496]	[0.102]	[0.103]
Observations	293,426	293,426	293,426	293,426	293,426	293,426
R-squared	0.752	0.752	0.747	0.747	0.713	0.714
# Firms	61,350	61,350	61,350	61,350	61,350	61,350

The table reports the estimates of the natural log of total financial debt (columns 1 and 2), log of total bank debt (columns 3 and 4) and of the log of the interest rate (columns 5 and 6). The estimates start from 2009 to 2015. The estimator is linear with large fixed effects (reghdfe). The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In columns 2, 4 and 6 this is interacted with dummy indicators $\mathbf{1}(\iota)$ of the four bins defined by the quartile values of the σ by industry and year estimated 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 firm fixed effects and year fixed effects. 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: robustness checks of elasticity of substitution (I)

	(1) $R_{f,t}$	(2) $R_{j,t}$	(3) $R_{p,t}$	(4) $R_{r,t}$	(5) $R_{r,j,t}$	(6) $R_{size,t}$	(7) $R_{score,t}$	(8) $r_{b,f,t}$
	2nd stage							
$\Delta \ln \frac{r_{b,f,t}}{R_t}$	-3.231***	-2.287***	-2.277***	-2.301***	-2.298***	-2.344***	-2.335***	
	[0.256]	[0.155]	[0.156]	[0.159]	[0.158]	[0.165]	[0.159]	
$\Delta \ln r_{b,f,t}$								-2.214***
								[0.038]
$\Delta\alpha_{f,t}^{AW}$	0.529***	0.253***	0.253***	0.252***	0.254***	0.251***	0.255***	
	[0.016]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	
	1st stage							
$\beta_{b,t}^{AW}$	-0.170***	-0.241***	-0.241***	-0.238***	-0.239***	-0.235***	-0.236***	-0.244***
	[0.013]	[0.015]	[0.016]	[0.016]	[0.015]	[0.016]	[0.015]	[0.004]
F-test	174.4	242.9	238.4	234.5	238.3	224.7	240.2	3577
Observations	5,000,397	4,953,555	4,979,132	4,976,267	4,944,826	4,949,571	4,944,370	4,858,735
# Firms	114,724	114,539	114,849	114,846	114,568	114,531	114,491	112,537
# Banks	210	210	210	210	210	210	210	210
Cmz&time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Industry&time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Firm&time FE	No	No	No	No	No	No	No	Yes

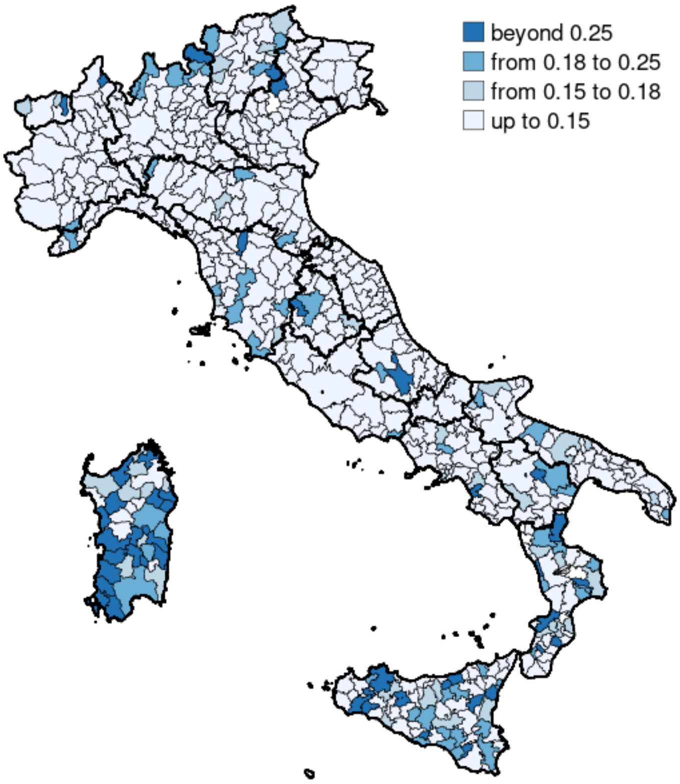
The table reports the 2SLS (2nd and 1st stage) estimates of credit demand with different definitions of the interest rates. The dependent variable is the log change of loans. Column 1 reports the estimate where the aggregate interest rate is defined at firm-time level. Columns 2 reports the estimate where the aggregate interest rate is defined at industry-time level. In columns 3 to 7 it is defined at province-time, region-time, region-industry-time level, size bin-time, credit score bin-time, respectively. Column 8 reports the estimates using the single rate specification defined in equation 10. $\alpha_{f,t}^{AW}$ is the firm&year FE's estimated with the AW estimator. $\beta_{b,t}^{AW}$ is the instrumental variable, the bank&time FE's estimated with the AW estimator. The variable definitions are in table A1. Estimates from column 1 to 8 include commuting zone&time and industry&time fixed effects. Estimates in column 9 uses firm&time fixed effects. 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.

Table 9: robustness checks of elasticity of substitution (II)

	(1) Moral Hazard	(2) Transactions lending	(3) Relationship Lending	(4) OLS	(5) Bank groups	(6) Collateral	(7) Alternative growth rate of lending	(8) Least concen-trated markets I	(9) Least concen-trated markets II	(10) Add single bank firms
	2nd stage									
$\Delta \ln \frac{r_{b,f,t}}{R_{c,t}}$	-2.283***	-2.630***	-3.579***	-7.494***	-1.275***	-2.049***	-2.148***	-2.289***	-2.282***	-5.899***
	[0.156]	[0.414]	[0.166]	[1.305]	[0.083]	[0.141]	[0.143]	[0.156]	[0.157]	[0.585]
$\Delta\alpha^{AW}_{f,t}$	0.253***	0.327***	0.135***	0.003	0.292***	0.257***	0.246***	0.252***	0.253***	
	[0.007]	[0.015]	[0.006]	[0.059]	[0.004]	[0.006]	[0.006]	[0.007]	[0.007]	
$\Delta\delta_{c,j,s,t}$										0.051
										[0.035]
$\Delta \ln C_{b,f,t}$						0.005***				
						[0.001]				
	1st stage									
$\beta^{AW}_{b,t}$	-0.241***	-0.241***	-0.112***	-0.125***	-0.408***	-0.259***	-0.246***	-0.240***	-0.241***	
	[0.016]	[0.037]	[0.005]	[0.022]	[0.027]	[0.016]	[0.015]	[0.015]	[0.016]	
$\beta^{OLS}_{b,t}$										-0.151***
										[0.015]
F-test	239	41.4	416.8	33.6	234.6	247.7	254.4	240.2	238.0	106.1
Observations	4,998,895	2,085,923	2,259,990	4,825,445	3,168,470	4,794,936	4,927,888	5,003,935	4,971,387	9,839,848
# Firms	114,882	73,306	73,952	112,308	99,332	113,811	114,702	113,923	112,884	188,885
# Banks	210	179	177	210	159	210	210	210	210	212
Cmz&time FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province&time FE	Yes	No	No	No	No	No	No	No	No	No
Sector&time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

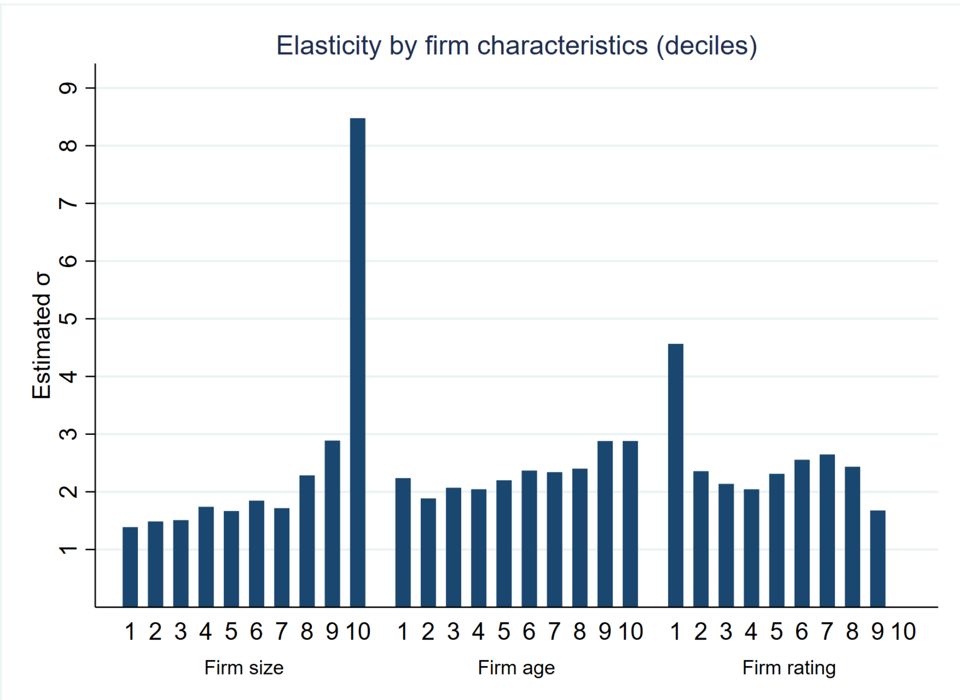
The table reports the 2SLS estimates (2nd and 1st stage) of credit demand. The dependent variable is the log change of loans, and the aggregate interest rate is calculated at commuting zone level; in column 1 this rate is a modified version of the one at commuting zone level, as defined by equation E.1 in section (E) of the online Appendix. The estimates are of the credit demand with moral hazard (column 1), of transactions lending (col. 2), of relationship lending (col. 3), using the OLS for the bank-time and firm-time fixed effects (col. 4), considering bank groups (col. 5), adding collateral (col. 6), with an alternative definition of the dependent variable (col. 7), keeping only commuting zones with an $HHI \leq 0.18$ (col. 8), keeping only commuting zones with an $HHI \leq 0.15$ (col. 9), adding single banks to the dataset (col. 10). $\alpha^{AW}_{f,t}$ is the firm&time FE's estimated with the AW estimator. $\beta^{AW}_{b,t}$ is the instrumental variable, the bank&time FE's estimated with the AW estimator in columns 1 to 9; in column 10, the instrumental variable is the OLS estimated fixed effect ($\beta^{OLS}_{b,t}$). $\delta_{c,j,s,t}$ is the commuting zone-industry-size-time fixed effect estimated with OLS. The variable definitions are in table A1. All estimates include commuting zone&time and industry&time fixed effects. 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.

Figure 1: Concentration in local credit markets



The figure shows the average HHI calculated on corporate loans in each commuting zone between 2007 and 2015. The thicker lines denote the borders of regions (NUTS level 2).

Figure 2: Elasticity of substitution by firm characteristic



The elasticities are computed using equation 5, where the denominator of the relative price is the aggregate interest rated defined at commuting zone level.

Online Appendix

A The Amiti and Weinstein estimator

In this section I sum up the main features of the AW estimators of credit demand and supply shocks used in the paper. Amiti and Weinstein (2018) develop a new methodology to disentangle credit demand and credit supply shocks using matched bank-firm data. Starting from the equation originally formulated by Khwaja and Mian (2008):

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

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 A.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 Amiti and Weinstein (2018) implies that estimation of supply and demand components is made by imposing an additional constraint which states that changes in credit growth 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 bank b total credit growth 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, Amiti and Weinstein (2018)) retrieve $\alpha^{AW}_{f,t}$ and $\beta^{AW}_{b,t}$ by solving the following system of equations:

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

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

Equation (A.2) states that bank b's 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 (A.3) shows that firm f's total credit growth is given by its credit demand ($\alpha^{AW}_{f,t}$) and by 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:

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

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

B Validation of IV

In this section I describe show that the instrumental variable (the estimated bank-time fixed effect) does not depend on demand components. The procedure, which follows Altavilla et al. (2022), is in two stages. In the first stage I recover the bank-time fixed effect from the estimation of equation 7 with the AW shock ($\beta^{AW}_{b,t}$). In the second step, after collapsing data at bank-time level I regress the estimated bank-time fixed effect ($\hat{\beta}^{AW}_{b,t}$) on the bank's log change in the average interest rate ($\Delta \ln r_{b,t}$):

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

Because of reverse causality, $\Delta \ln r_{b,t}$ is instrumented with the average of the demand shifter measured with the AW procedure weighted at bank-time level ($\hat{\alpha}^{AW}_{f,t}$) or the weighted growth rate of lending by industry as suggested by Altavilla et al. (2022): $x_{b,s,t}$. In detail, $x_{b,s,t}$ is given by the product of bank b growth rate of lending to industry s at time t and the exposure of the same bank to the same industry in $t-1$:[51] $x_{b,s,t} = \sum_{s=1}(\frac{L_{-b,s,t}}{L_{-b,s,t-1}} - 1)\lambda_{b,s,t-1}$ where $L_{-b,s,t}$ is total lending to industry s at time t (in leave out form for bank b). The weight $\lambda_{b,s,t-1}$ is given by bank b lending to industry s relative to its total lending four quarters before time t: $\lambda_{b,s,t-1} = \frac{L_{b,s,t-1}}{L_{b,t-1}}$.

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

C Bank size and length of the relationship

In this section I analyze the elasticity of substitution by bank size and with respect to the length of the bank-firm relationships.

Starting with the bank size distribution, Berger et al. (2005) argue that bank size matters in the ability of collecting soft information from borrowers; they show that small banks are better able to collect and act on soft information than large banks. If higher levels of soft information make firms less willing to move to other lenders, accepting Berger et al. (2005)'s argument in favor of small banks, one should expect that the elasticity of substitution increases with bank size. Differently, the relationship might be

[51] I exploit variation across industries. Indeed, the average growth rate of lending varies between -4.3% in the real estate industry and 0.3% in the chemical & pharmaceutical industry.

inverse if one considers that larger banks, by having more resources and a wider range of customers, have an informational comparative advantage on smaller banks, especially on SME's which are typically more opaque. Indeed, larger banks may be better able at providing financial services for the firm (such as digital payments, etc...). In this second view they are better able at creating an informational lock-in, as in Rajan (1992).

Given these opposite predictions, the relationship between bank size and the elasticity of substitution is to be determined empirically. To this aim, I focus on the main lenders. In detail, I rank lenders using the amount of loans in $t-1$ and I consider as "main" the banks for which the relationship with the firm is most relevant, that is to say that the overall sum of loans is at least 50% in each period. Using this preliminary selection I compute the weighted average of bank size using the share of loans in $t-1$ as weight. Finally, I compute bank size deciles using this weighted bank size measure by the firm. Figure A.4 shows that the estimated elasticities are, even if not monotonically, smaller as bank size increases. Thus the data provide weak evidence in support of the lock-in view.

Moving to the length of the relationship, one would expect that the longer the relationship is, the more difficult it is for the firm to switch to new lenders, because switching is costly (Darmouni (2020)) or because relationship banks provide insurance against aggregate shocks (Bolton et al. (2016)). Also for the bank it is more difficult to quit longer relationships: indeed, since acquiring borrower-specific proprietary information ("soft information") is costly, they would charge the borrower an interest rate above the competitive one as the relationship matures (Haubrich (1989)). Then, according to this line of reasoning, one should expect that the elasticity of substitution decreases with the length of the relationship with the bank. However, it is also possible that firms prefer quitting longer relationships, for example if new borrowing opportunities look attractive by other lenders.[52] In this second case, one should expect that the elasticity of substitution is positively correlated with the length of the relationship.

Given the opposite predictions of the two arguments above, the matter is, as for the previous case, an empirical issue. The right hand graph of figure A.4 shows that the estimated elasticity of substitution does not vary monotonically with the length of the credit relationship, thus the evidence is not conclusive on any of the two views exposed above.

D Bank specialization

In this section I first show the construction of the comparative advantage measure of bank specialization, by adapting that of Paravisini et al. (2023), and then I show how to insert this measure into the estimating equation of the investment rate.

For the first point, I consider a measure of bank b's comparative advantage specific to industry j.

[52] For example, Ongena and Smith (2000) show that the likelihood of relationship termination increases with the duration, suggesting that firms do not become more locked in long relationships.

Define the portfolio share of lending of bank b towards industry j by the lending of the bank towards to all its borrowing firms $f = 1, ..., F_j$ in industry j (i.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 towards all industries ($L_{b,t} = \sum_{j=1}^{J} L^j_{b,t}$).[53] Formally this is given by the following:

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

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

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

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. Note that what matters is not the cardinal value of $S^j_{f,t}$, but the position of relative to its distribution over all firms. To this aim, in the empirical specification, I use a set of dummies $D(S^j_{f,t} \in Q_q)$ which are equal to 1 if the firm is in quartile ψ=1,...,4 of the distribution of $S^j_{f,t}$. Using quartile dummies allows studying non-linearity in the relationship between the measure of specialization and firm outcome.

In the second step I plug the previous dummies (interacted with the $Bk\ Shock_{f,t}$) into the investment rate equation, as in the following:

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

Equation D.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).

E Moral Hazard

This section extends the model to the case of moral hazard, where the firm repays only a fraction of the lending costs. In this case, the cost minimization plan of the firm requires the minimization of expected repayment costs where only a fraction $\mu_t (0 \leq \mu_t \leq 1)$ of these costs will be actually repaid by the borrower (for example, due to the relative efficiency of local courts): $\mu_t \sum_b r_{b,f,t} L_{b,f,t}$.

In this case, the FOC wrt $L_{b,f,t}$ is: $\mu_t r_{b,f,t} = \lambda \frac{\sigma}{\sigma-1} [\sum_b \varphi_{b,f,t} L_{b,f,t}^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}$. Manipulating the previous expression as in a standard Dixit-Stiglitz model gives the following demand:

$$\ln L_{b,f,t} = -\sigma \ln r_{b,f,t} + \sigma \ln \varphi_{b,f,t} + \sigma \ln \mu_t - \sigma \ln \tilde{R}_t + \frac{\sigma}{\sigma-1} \ln [\sum_b \varphi_{b,f,t} L_{b,f,t}^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} + \epsilon_{b,f,t}$$

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

where

$$\tilde{R}_t = \left[\sum_{b=1} \varphi_{b,f,t} \left(\frac{r_{b,f,t}}{\mu_t \varphi_{b,f,t}} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{1-\sigma}} \tag{E.1}$$

Replacing notation:

$$\ln(L_{b,f,t}) = -\sigma \ln r_{b,f,t} + \ln \tilde{R}_t + \sigma\mu_t + \alpha_{f,t} + \epsilon_{b,f,t}$$

where $\alpha_{f,t}$ is the firm fixed effect; $\ln \varphi_{b,f,t}$ and $\frac{\sigma}{\sigma-1} \ln [\sum_b \varphi_{b,f,t} L_{b,f,t}^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}$ enter in the error term. I Assume that the μ_t varies across provinces, because of, for example, the different efficiency of local courts: $\mu_t = \mu_{p,t}$. Then, taking first differences the previous equation becomes:

$$\Delta \ln(L_{b,f,t}) = -\sigma[\Delta \ln(r_{b,f,t}/\tilde{R}_{p,t}) + \Delta \ln \mu_{p,t}] + \Delta\hat{\alpha}_{f,t} + \epsilon_{b,f,t} \tag{E.2}$$

where $\Delta\hat{\alpha}_{f,t} = \hat{\alpha}_{f,t} - \hat{\alpha}_{f,t-1}$. Empirically, equation E.1 is very similar to equation 5 in the text, except for two terms: a) the aggregate interest rate is replaced by $\tilde{R}_t = [\sum_{b'} \frac{w_{b,f,t-1} r_{b,f,t}}{\mu_{p,t}}]$; b) $\Delta \ln \mu_{p,t}$ is replaced by province-time fixed effects. Data on the length of proceedings are from the Ministry of Justice and cover the years 2005 to 2014. They include ordinary litigious civil cases, such as disputes on contracts and other subjects like property, tort, bankruptcy and labor disputes. For each local court, I collapse data (on new cases, on pending cases and on cases ended) at province-year level. Then, I compute a measure of the length of civil proceedings $\Lambda_{p,t}$ using the formula originally suggested by Clark and Merryman (1976), that has also been used in more recent works using Italian data (Giacomelli and Menon (2017)):

$$\Lambda_{p,t} = \frac{P_{p,t} + F_{p,t}}{E_{p,t}} \tag{E.3}$$

where $P_{p,t}$ is the number of pending cases at the beginning of the year t, $F_{p,t}$ refers to the new cases filed during the year and $E_{p,t}$ to the cases that ended with a judicial decision or were withdrawn by the parties during the year. I take the normalized measure between 0 and 1,$\bar{\Lambda}_{p,t}$, and compute the inverse measure of moral hazard as: $\mu_{p,t} = 1 - \bar{\Lambda}_{p,t}$.

Table A1: Variables description

Variable	Description	Frequency	Source[1]
Loans	Outstanding loan amount	quarterly	CR
Interest rate	Interest rate	quarterly	Taxia
Employees	Number of employees	yearly	INPS
Credit score	Credit score variable	yearly [2]	CADS
Investment	Firm investments	yearly	CADS
capital	firm capital	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 capita1 ratio	Ratio of a bank's core tier 1 capital plus core tier 2 capital to total r.w. assets[3]	yearly	SR
Capital	Capital stock built with tangible fixed assets, using PIM	yearly	CADS
Investment	Investment built with tangible fixed assets	yearly	CADS
Judicial cases	Judicial cases: pending, ending and new cases at year start	yearly	Italian Dep.t of Justice

(1): CR is the Credit Register; CADS is the Company Accounts dataset; (2): integer variable with values from 1 to 9, where higher values mean a higher probability of default. (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.

Table A2: Validation of the instrumental variable II

	(1)	(2)	(3)	(4)
Instrumental variable:	$\hat{\alpha}^{AW}_{f,t}$	$\hat{\alpha}^{AW}_{f,t}$	$x_{s,t}$	$x_{s,t}$
$\Delta r_{b,t}$	-12.340	1.477	-0.036	-0.007
	[66.585]	[1.106]	[0.035]	[0.023]
Constant	1.822		0.008	
	[9.896]		[0.005]	
Observations	5,656	5,655	5,656	5,655
F-test	0.0344	1.786	16.27	11.43
Bank FE	No	Yes	No	Yes
#banks	210	209	210	209

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 average growth rate of lending by bank at time t ($\Delta r_{b,t}$) and a constant. The instrumental variable is the firm-time fixed effect estimated with the AW procedure ($\hat{\alpha}^{AW}_{f,t}$) in columns 1 and 2 or the industry growth rate ($x_{s,t}$) as defined in the Appendix (B) in columns 3 and 4. All variable definitions are in Table A1. Heteroskedastic robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.1: Estimated σ by industry - year (1/4)

sector	year	sigma	p value	# Firms	# Banks	# Obs	bin
Agriculture & mining	2009	-18.68	0.82	435	145	6,698	1
	2010	2.42	0.06	436	151	6,183	3
	2011	1.85	0.02	426	149	5,844	2
	2012	2.48	0.08	430	152	6,126	3
	2013	3.22	0.13	414	140	5,931	3
	2014	4.88	0.40	405	138	5,509	4
	2015	17.68	0.82	405	131	5,011	4
Food	2009	5.91	0.01	2,568	179	51,798	4
	2010	3.38	0.00	2,571	185	47,872	3
	2011	4.76	0.00	2,465	182	44,609	4
	2012	4.35	0.00	2,415	179	46,038	4
	2013	3.10	0.00	2,401	167	45,419	3
	2014	5.34	0.03	2,382	167	44,156	4
	2015	4.67	0.02	2,388	158	40,518	4
Beverages & tobacco	2009	5.17	0.16	400	140	7,754	4
	2010	3.87	0.08	400	146	7,348	4
	2011	3.77	0.10	392	142	7,114	3
	2012	50.62	0.89	392	143	7,354	4
	2013	-54.46	0.91	376	133	7,081	1
	2014	5.71	0.30	364	131	6,752	4
	2015	2.53	0.04	359	129	6,163	3
Textiles	2009	3.19	0.18	1,892	161	34,044	3
	2010	1.26	0.00	1,807	162	30,272	1
	2011	1.41	0.00	1,662	153	26,822	1
	2012	2.18	0.01	1,589	157	24,571	2
	2013	2.78	0.04	1,432	142	22,309	3
	2014	2.49	0.07	1,511	142	21,393	3
	2015	1.83	0.01	1,475	137	19,189	2
Apparel	2009	2.93	0.01	1,589	159	25,452	3
	2010	1.66	0.00	1,569	164	23,253	2
	2011	1.56	0.00	1,430	161	20,767	1
	2012	1.84	0.00	1,378	161	20,761	2
	2013	1.93	0.00	1,323	148	19,341	2
	2014	1.89	0.00	1,258	146	17,357	2
	2015	1.51	0.00	1,242	137	15,554	1
Leather	2009	9.91	0.49	1,469	134	25,972	4
	2010	2.06	0.00	1,408	137	23,252	2
	2011	1.81	0.00	1,285	132	20,183	2
	2012	3.14	0.30	1,235	135	20,341	3
	2013	1.91	0.07	1,233	125	18,943	2
	2014	1.42	0.02	1,179	127	16,026	1
	2015	1.45	0.00	1,183	122	14,632	1
Wood	2009	2.80	0.01	1,621	172	27,462	3
	2010	1.32	0.00	1,642	175	26,784	1
	2011	1.43	0.00	1,583	173	24,672	1
	2012	1.97	0.00	1,564	171	24,089	2
	2013	5.92	0.22	1,481	159	22,483	4
	2014	3.39	0.02	1,452	159	20,748	3
	2015	1.79	0.00	1,433	154	18,287	2
Paper & print	2009	49.58	0.85	2,427	177	41,480	4
	2010	1.12	0.00	2,426	179	38,908	1
	2011	1.33	0.00	2,353	175	35,540	1
	2012	2.98	0.00	2,242	174	34,515	3
	2013	2.82	0.01	2,148	162	32,246	3
	2014	3.13	0.05	2,126	162	30,271	3
	2015	2.77	0.01	2,114	154	27,234	3

The table reports the estimated values of σ using equation (5), with the aggregate interest rate defined by commuting zone ($R_{c,t}$). Estimates run by splitting the sample int?? industries and using the 2 years before the reference year. Bin 1 includes industries with values of $\hat{\sigma}$ in the first quartile; bin 2 includes values in the second quartile, etc... The percentiles of the estimated σ are: 1.65 (25th perc.), median=2.38 (median), 3.66 (75th perc.).

Table A3.2: Estimated σ by industry - year (2/4)

sector	year	sigma	p value	# Firms	# Banks	# Obs	bin
	2009	8.82	0.22	1,342	164	26,693	4
	2010	2.53	0.00	1,323	169	25,063	3
	2011	2.55	0.00	1,271	168	23,937	3
Chemical & Pharma	2012	2.39	0.00	1,235	165	24,200	3
	2013	1.64	0.00	1,199	155	23,345	1
	2014	2.35	0.02	1,216	155	22,265	2
	2015	3.90	0.14	1,190	147	19,871	4
	2009	3.80	0.01	2,706	175	47,500	4
	2010	1.69	0.00	2,682	177	44,625	2
	2011	2.12	0.00	2,600	172	41,911	2
Rubber	2012	3.38	0.01	2,472	171	41,333	3
	2013	3.96	0.03	2,373	157	38,891	4
	2014	4.98	0.07	2,349	157	36,923	4
	2015	2.43	0.00	2,326	152	33,151	3
	2009	4.79	0.01	2,204	177	37,900	4
	2010	1.76	0.00	2,169	181	36,206	2
	2011	2.02	0.00	2,101	179	33,810	2
Non metallic minerals	2012	5.78	0.09	2,038	177	33,525	4
	2013	4.26	0.03	1,968	166	31,295	4
	2014	3.72	0.02	1,927	164	28,178	3
	2015	2.64	0.00	1,889	157	24,653	3
	2009	24.45	0.63	1,128	156	25,429	4
	2010	4.77	0.02	1,123	163	23,750	4
	2011	12.41	0.39	1,083	159	22,341	4
Basic metals	2012	58.40	0.86	1,030	158	21,792	4
	2013	10.28	0.38	971	146	19,818	4
	2014	6.75	0.28	971	145	18,405	4
	2015	3.33	0.03	965	141	16,727	3
	2009	3.90	0.00	9,528	178	145,764	4
	2010	1.18	0.00	9,524	183	141,337	1
	2011	1.57	0.00	9,319	179	133,716	1
Metal products	2012	3.58	0.00	8,916	181	130,609	3
	2013	3.66	0.01	8,529	167	122,163	3
	2014	1.97	0.00	8,470	167	114,958	2
	2015	1.42	0.00	8,436	159	102,564	1
	2009	3.60	0.01	2,272	170	37,542	3
	2010	1.20	0.00	2,236	175	35,383	1
	2011	1.50	0.00	2,155	170	32,399	1
Computer & electrical	2012	3.50	0.03	2,032	169	30,989	3
	2013	2.70	0.02	1,926	157	29,277	3
	2014	1.61	0.00	1,913	159	27,516	1
	2015	1.44	0.00	1,878	152	23,942	1
	2009	3.30	0.00	4,782	177	80,260	3
	2010	1.43	0.00	4,718	181	75,939	1
	2011	1.74	0.00	4,592	176	70,967	2
Machinery	2012	4.28	0.02	4,355	179	68,715	4
	2013	2.87	0.00	4,168	165	64,300	3
	2014	2.09	0.00	4,090	165	59,731	2
	2015	1.90	0.00	3,944	159	52,041	2
	2009	4.10	0.08	845	155	13,947	4
	2010	1.46	0.00	840	163	13,291	1
	2011	1.37	0.00	820	160	12,596	1
Motor and veihicles	2012	3.99	0.12	783	159	12,358	4
	2013	7.20	0.43	731	147	11,424	4
	2014	2.19	0.04	708	147	10,347	2
	2015	1.76	0.02	674	139	9,031	2

The table reports the estimated values of σ using equation (5), with the aggregate interest rate defined by commuting zone ($R_{c,t}$). Estimates run by splitting the sample into industries and using the 2 years before the reference year. Bin 1 includes industries with values of $\hat{\sigma}$ in the first quartile; bin 2 includes values in the second quartile, etc... The percentiles of the estimated σ aare: 1.65 (25th perc.), median=2.38 (median), 3.66 (75th perc.).

Table A3.3: Estimated σ by industry - year (3/4)

sector	year	sigma	p value	# Firms	# Banks	# Obs	bin
Furniture	2009	9.45	0.37	1,985	163	33,792	4
	2010	1.70	0.00	1,957	166	31,926	2
	2011	1.61	0.00	1,894	159	29,348	1
	2012	2.69	0.05	1,817	158	28,237	3
	2013	1.96	0.01	1,708	149	25,505	2
	2014	1.87	0.00	1,654	149	23,150	2
	2015	2.49	0.00	1,588	143	20,229	3
Other manufacturing	2009	2.17	0.00	2,191	169	30,552	2
	2010	1.31	0.00	2,097	173	28,695	1
	2011	1.66	0.00	2,003	168	26,317	2
	2012	1.49	0.00	1,948	168	25,936	1
	2013	1.73	0.00	1,888	157	24,559	2
	2014	1.46	0.00	1,864	155	22,484	1
	2015	1.03	0.00	1,825	150	19,519	1
Utilities	2009	3.48	0.05	883	183	13,120	3
	2010	2.55	0.01	910	184	13,204	3
	2011	3.27	0.04	884	181	12,868	3
	2012	3.93	0.13	889	180	13,390	4
	2013	4.72	0.16	875	168	13,288	4
	2014	4.07	0.13	887	164	12,993	4
	2015	2.53	0.04	896	156	11,891	3
Construction	2009	3.57	0.00	8,917	184	126,762	3
	2010	1.65	0.00	9,072	188	126,170	2
	2011	1.48	0.00	8,801	183	119,608	1
	2012	1.69	0.00	8,660	183	121,735	2
	2013	4.11	0.01	8,573	170	117,976	4
	2014	2.51	0.00	8,439	171	109,296	3
	2015	1.55	0.00	8,249	163	93,099	1
Wholesale trade	2009	2.35	0.00	15,339	185	277,218	2
	2010	1.34	0.00	15,113	190	258,157	1
	2011	1.29	0.00	14,520	187	239,116	1
	2012	1.48	0.00	14,146	187	241,148	1
	2013	2.09	0.00	13,929	176	233,168	2
	2014	2.02	0.00	13,900	172	220,217	2
	2015	1.70	0.00	13,735	164	195,642	2
Retail trade	2009	6.20	0.11	3,683	182	49,559	4
	2010	2.11	0.00	3,681	187	46,818	2
	2011	2.15	0.00	3,534	182	43,240	2
	2012	4.86	0.05	3,560	182	46,009	4
	2013	6.64	0.21	3,689	171	47,036	4
	2014	2.12	0.00	3,763	171	46,295	2
	2015	1.22	0.00	3,769	165	41,576	1
Transport & courier	2009	3.95	0.01	2,789	183	38,996	4
	2010	1.23	0.00	2,877	188	38,443	1
	2011	1.39	0.00	2,745	184	36,023	1
	2012	3.99	0.14	2,618	186	35,681	4
	2013	2.77	0.02	2,563	175	33,943	3
	2014	1.65	0.00	2,552	177	32,244	2
	2015	1.50	0.00	2,524	167	29,297	1
Hotels and restaurants	2009	3.48	0.22	2,108	177	21,551	3
	2010	1.95	0.02	2,147	179	21,151	2
	2011	3.57	0.20	2,075	175	19,675	3
	2012	-3.03	0.17	2,098	174	21,213	1
	2013	15.95	0.75	2,059	165	21,059	4
	2014	-121.33	0.96	1,972	164	19,402	1
	2015	3.06	0.05	1,970	159	17,626	3

The table reports the estimated values of σ using equation (5), with the aggregate interest rate defined by commuting zone ($R_{c,t}$). Estimates run by splitting the sample into industries and using the 2 years before the reference year. Bin 1 includes industries with values of $\hat{\sigma}$ in the first quartile; bin 2 includes values in the second quartile, etc... The percentiles of the estimated σ are: 1.65 (25th perc.), median=2.38 (median), 3.66 (75th perc.).

Table A3.4: Estimated σ by industry - year (4/4)

sector	year	sigma	p value	# Firms	# Banks	# Obs.	bin
Info and Communication	2009	1.72	0.00	1,643	175	20,486	2
	2010	0.90	0.00	1,630	178	20,122	1
	2011	1.03	0.00	1,542	175	18,428	1
	2012	2.37	0.03	1,498	173	18,375	2
	2013	5.46	0.38	1,471	164	18,206	4
	2014	2.21	0.01	1,503	164	17,478	2
	2015	1.25	0.00	1,439	153	15,253	1
Real estate	2009	4.56	0.03	3,057	188	46,442	4
	2010	1.86	0.00	2,811	189	40,176	2
	2011	2.09	0.00	2,414	182	33,394	2
	2012	3.25	0.05	2,100	185	30,167	3
	2013	4.40	0.14	1,829	174	25,580	4
	2014	4.31	0.14	1,558	169	20,318	4
	2015	2.85	0.03	1,380	158	15,488	3
Professional	2009	8.43	0.48	1,463	177	18,861	4
	2010	1.02	0.00	1,500	183	18,908	1
	2011	1.22	0.00	1,454	181	17,800	1
	2012	3.41	0.19	1,427	177	17,941	3
	2013	1.74	0.02	1,434	165	17,356	2
	2014	1.31	0.00	1,443	164	16,284	1
	2015	1.02	0.00	1,422	158	14,290	1
Support services	2009	5.09	0.21	1,634	181	21,251	4
	2010	1.47	0.00	1,635	184	20,470	1
	2011	1.61	0.00	1,540	179	19,343	1
	2012	2.75	0.02	1,496	176	19,607	3
	2013	1.93	0.00	1,448	162	19,036	2
	2014	1.30	0.00	1,439	161	18,142	1
	2015	1.25	0.00	1,426	158	16,322	1
Public services	2009	17.96	0.81	1,084	166	13,121	4
	2010	2.51	0.04	1,114	168	12,699	3
	2011	2.80	0.11	1,036	164	11,685	3
	2012	11.68	0.77	1,028	161	12,143	4
	2013	2.57	0.03	1,058	148	12,202	3
	2014	1.32	0.00	1,051	149	11,984	1
	2015	1.64	0.01	1,014	143	10,569	2
Other services	2009	-2.25	0.07	560	154	6,555	1
	2010	2.05	0.09	562	158	6,383	2
	2011	0.95	0.01	541	158	5,869	1
	2012	1.73	0.09	523	160	5,900	2
	2013	2.67	0.12	514	147	5,802	3
	2014	2.30	0.06	504	147	5,588	2
	2015	1.76	0.02	510	136	5,205	2

The table reports the estimated values of σ in each year using equation (5), with the aggregate interest rate defined by commuting zone ($R_{c,t}$). Estimates run by splitting the sample into industries and using the 2 years before the reference year. Bin 1 includes industries with values of $\hat{\sigma}$ in the first quartile; bin 2 includes values in the second quartile, etc... The percentiles of the estimated σ are: 1.65 (25th perc.), median=2.38 (median), 3.66 (75th perc.).

Table A4.1: Investment rate regressions in less concentrated markets

	Panel a: HHI≤0.18							
	2009-2015				2010-2015			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Linear	Linear	Linear ihst	PPML	Linear	Linear	Linear ihst	PPML
$(Bank\ Shock_{f,t})$	0.106***				0.111**			
	[0.040]				[0.047]			
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=1)$		0.192***	0.192***	1.279***		0.158***	0.160***	0.829*
		[0.051]	[0.041]	[0.380]		[0.057]	[0.045]	[0.434]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2)$		0.066	0.071*	0.281		0.085	0.090**	0.361
		[0.049]	[0.039]	[0.363]		[0.057]	[0.045]	[0.443]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=3)$		0.067	0.058	0.210		0.100	0.091*	0.476
		[0.057]	[0.045]	[0.422]		[0.066]	[0.052]	[0.524]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=4)$		0.081	0.073	0.376		0.028	0.037	0.011
		[0.060]	[0.048]	[0.445]		[0.087]	[0.069]	[0.702]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	291,387	291,387	291,387	291,366	253,807	253,807	253,807	253,269
# Firms	60,890	60,890	60,890	60,881	58,202	58,202	58,202	58,202
Adj R-squared	0.281	0.281	0.299		0.301	0.301	0.319	
Pseudo R-squared				0.156				0.163

	Panel b: HHI≤0.15							
	2009-2015				2010-2015			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Linear	Linear	Linear ihst	PPML	Linear	Linear	Linear ihst	PPML
$Bank\ Shock_{f,t}$	0.108***				0.116**			
	[0.040]				[0.047]			
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2)$		0.194***	0.195***	1.288***		0.161***	0.164***	0.837*
		[0.051]	[0.041]	[0.381]		[0.056]	[0.045]	[0.435]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2)$		0.070	0.075*	0.310		0.092	0.096**	0.393
		[0.049]	[0.039]	[0.365]		[0.057]	[0.045]	[0.444]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=3)$		0.066	0.058	0.199		0.098	0.090*	0.442
		[0.058]	[0.045]	[0.425]		[0.065]	[0.052]	[0.525]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=4))$		0.079	0.071	0.355		0.033	0.041	0.028
		[0.060]	[0.048]	[0.447]		[0.088]	[0.070]	[0.705]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	290,187	290,187	290,187	290,172	252,774	252,774	252,774	252,180
# Firms	60,453	60,453	60,453	60,444	57,784	57,784	57,784	57,784
Adj R-squared	0.280	0.280	0.299		0.300	0.300	0.319	
Pseudo R-squared				0.156				0.163

The table reports the estimates of the investment rate, as the ratio between investment in tangible assets at time t and tangible capital in $t-1$. 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. Columns 1 to 4 report the estimates of the sample from 2009 to 2015. In columns 5 to 8 the estimates run from 2010 to 2015. The estimator is linear with large fixed effects (reghdfe) in columns 1, 2, 3, 5, 6 and 7; it is PPML with large firm fixed effects (ppmlhdfe) in columns 4 and 8. The dependent variable is the investment rate expressed in the inverse hyperbolic sine transformation (ihst) in columns 3 and 7. The main explanatory variable is the credit supply shock at firm-year level $(Bank\ Shock_{f,t})$ as defined by equation (8) interacted with dummy indicators $\mathbf{1}(\iota)$ of the four bins defined by the quartile values of the σ by industry and year estimated in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009). Controls include the following variables: age, log of employees in $t-1$, credit score in $t-1$, cash flow over capital, the mean loans-to-assets ratio of firm f defined as the average ratio of loans to assets over the sample period (LAR_f), the mean bonds-to-assets ratio (BAR_f) similarly defined, and the median of credit demand shocks $(\alpha^{AW}_{f,t})$ across firms by industry and year $(Industry\&year)$. The variable definitions are in table A1. All estimates include firm fixed effects and year fixed effects. 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, $^{+}$ p<0.11.

Table A4.2: Investment rate regressions - adding intangible assets

	2009-2015				2010-2015			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Linear	Linear	Linear ihst	PPML	Linear	Linear	Linear ihst	PPML
$(Bank\ Shock_{f,t})$	0.114**				0.128**			
	[0.048]				[0.057]			
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=1)$		0.225***	0.226***	1.186***		0.194***	0.192***	0.873**
		[0.062]	[0.047]	[0.346]		[0.068]	[0.052]	[0.392]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2)$		0.082	0.091**	0.346		0.107	0.109**	0.506
		[0.059]	[0.045]	[0.335]		[0.068]	[0.052]	[0.400]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=3)$		0.086	0.082*	0.247		0.109	0.105*	0.439
		[0.065]	[0.050]	[0.375]		[0.076]	[0.058]	[0.466]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=4)$		0.004	0.020	-0.102		-0.060	-0.033	-0.394
		[0.072]	[0.055]	[0.426]		[0.104]	[0.079]	[0.653]
$\log(Employees_{f,t-1})$	-0.073***	-0.073***	-0.058***	-0.217***	-0.070***	-0.070***	-0.057***	-0.193***
	[0.005]	[0.005]	[0.004]	[0.024]	[0.006]	[0.006]	[0.004]	[0.028]
$Age_{f,t}$	-0.011***	-0.011***	-0.009***	-0.058***	-0.012***	-0.012***	-0.010***	-0.065***
	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.002]
$Credit\ Score_{f,t-1}$	0.023***	0.023***	0.020***	0.129***	0.023***	0.023***	0.020***	0.134***
	[0.001]	[0.001]	[0.001]	[0.005]	[0.001]	[0.001]	[0.001]	[0.005]
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	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]
$(Bank\ Shock_{f,t})\times(LAR_f)$	0.218	0.226	0.157	1.515*	0.320*	0.328*	0.251*	2.139**
	[0.149]	[0.149]	[0.113]	[0.886]	[0.173]	[0.173]	[0.132]	[1.077]
$(Bank\ Shock_{f,t})\times(BAR_f)$	-0.413	-0.414	-0.399	-1.891	-0.137	-0.127	-0.180	0.612
	[0.373]	[0.373]	[0.277]	[2.372]	[0.428]	[0.428]	[0.319]	[2.866]
$Industry\&year$	0.894***	0.902***	0.798***	5.876***	1.006***	1.009***	0.908***	6.900***
	[0.086]	[0.086]	[0.066]	[0.482]	[0.092]	[0.092]	[0.071]	[0.530]
Observations	293,736	293,736	293,736	293,717	255,835	255,835	255,337	255,835
# Firms	61,501	61,501	61,501	61,493	58,760	58,760	58,564	58,760
Adj. R-squared	0.315	0.315	0.343		0.335	0.335		0.364
Pseudo R-squared				0.168			0.175	

The table reports the estimates of the investment rate, as the ratio between investment in tangible and intangible assets at time t and tangible and intangible capital in $t-1$. Columns 1 to 4 report the estimates for the period 2009-2015. The estimates starting from 2010 are reported in columns 5 to 8. The estimator is linear with large fixed effects (reghdfe) in columns 1, 2, 3, 5, 6 and 7; it is PPML with large firm fixed effects (ppmlhdfe) in columns 4 and 8. The dependent variable is the investment rate expressed in the inverse hyperbolic sine transformation (ihst) in columns 3 and 7. The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In columns 2, 3, 4, 6, 7 and 8 this is interacted with dummy indicators $\mathbf{1}(\iota)$ of the four bins defined by the quartile values of the σ by industry and year estimated 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 firm fixed effects and year fixed effects. 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 A4.3: Investment rate regressions - by sectors

	Linear model				Linear model with depvar in ihs form			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manufacturing		Services		Manufacturing		Services	
$(Bank\ Shock_{f,t})$	0.110*		0.096		0.106**		0.103**	
	[0.061]		[0.061]		[0.049]		[0.048]	
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=1)$		0.250***		0.141*		0.238***		0.159***
		[0.078]		[0.077]		[0.063]		[0.060]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2)$		0.088		0.078		0.095		0.079
		[0.080]		[0.067]		[0.063]		[0.054]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2)$		0.029		0.106		0.030		0.073
		[0.078]		[0.152]		[0.061]		[0.120]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=4)$		0.081		-0.049		0.068		-0.028
		[0.078]		[0.131]		[0.063]		[0.107]
$\log(Employees_{f,t-1})$	-0.075***	-0.075***	-0.071***	-0.070***	-0.062***	-0.062***	-0.059***	-0.059***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.005]	[0.005]	[0.005]	[0.005]
$Age_{f,t}$	-0.007***	-0.007***	-0.011***	-0.011***	-0.006***	-0.006***	-0.010***	-0.010***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
$Credit\ Score_{f,t-1}$	0.015***	0.015***	0.011***	0.011***	0.013***	0.014***	0.011***	0.011***
	[0.001]	[0.001]	[0.001]	[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]
$(Bank\ Shock_{f,t})\times(LAR_f)$	0.173	0.171	0.088	0.093	0.148	0.148	0.043	0.050
	[0.195]	[0.195]	[0.180]	[0.180]	[0.154]	[0.154]	[0.143]	[0.143]
$(Bank\ Shock_{f,t})\times(BAR_f)$	-0.497	-0.492	-0.173	-0.163	-0.458	-0.454	-0.248	-0.237
	[0.477]	[0.477]	[0.492]	[0.493]	[0.369]	[0.369]	[0.379]	[0.380]
$Industry\&year$	0.815***	0.822***	0.148	0.152	0.719***	0.724***	0.180*	0.186*
	[0.105]	[0.105]	[0.134]	[0.134]	[0.083]	[0.084]	[0.108]	[0.109]
Observations	147,833	147,833	107,953	107,953	147,833	147,833	107,953	107,953
# Firms	30,032	30,032	23,231	23,231	30,032	30,032	23,231	23,231
Adj. R-squared	0.278	0.278	0.289	0.289	0.296	0.296	0.309	0.309

The table reports the estimates of the investment rate, as the ratio between investment in tangible assets at time t and tangible capital in $t-1$, expressed in the inverse hyperbolic sine transformation (ihst). The estimates are for the period 2009-2015. The estimator is linear with large fixed effects (reghdfe). The estimates in columns 1, 2, 5 and 6 are on manufacturing firms (NACE Rev. 2 codes from 10 to 33), the others are on services (codes from 45 to 96). The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8. In columns 2, 4, 6 and 8 this is interacted with dummy indicators $\mathbf{1}(\iota)$ of the four bins defined by the quartile values of the σ by industry and year estimated 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 firm fixed effects and year fixed effects. 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 A4.4: Investment rate regressions - other robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	σ estimated with rating, size and age FE's				Multiple and single bank firms			
$(Bank\ Shock_{f,t})$	0.105***				0.084***			
	[0.032]				[0.028]			
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=1)$		0.159***		0.160***		0.089**		0.094*
		[0.043]		[0.053]		[0.039]		[0.048]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=2))$		0.165***		0.166***		0.091***		0.095**
		[0.040]		[0.052]		[0.034]		[0.043]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=3)$		0.023		0.028		0.087**		0.090**
		[0.043]		[0.051]		[0.035]		[0.045]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\iota=4)$		0.034		0.041		0.032		0.036
		[0.047]		[0.057]		[0.051]		[0.059]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\psi=1)$			0.062	-0.027			0.066*	-0.022
			[0.044]	[0.049]			[0.039]	[0.045]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\psi=2)$			0.125***	0.014			0.097**	0.008
			[0.044]	[0.049]			[0.041]	[0.048]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\psi=3)$			0.130***	0.001			0.083**	-0.002
			[0.043]	[0.049]			[0.041]	[0.048]
$(Bank\ Shock_{f,t})\times\mathbf{1}(\psi=4)$			0.102**				0.088**	
			[0.044]				[0.039]	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	286,993	286,993	286,993	286,993	393,300	393,300	393,299	393,299
#firms	60,516	60,516	60,516	60,516	95,460	95,460	95,460	95,460
R-squared	0.301	0.301	0.301	0.301	0.330	0.330	0.330	0.330

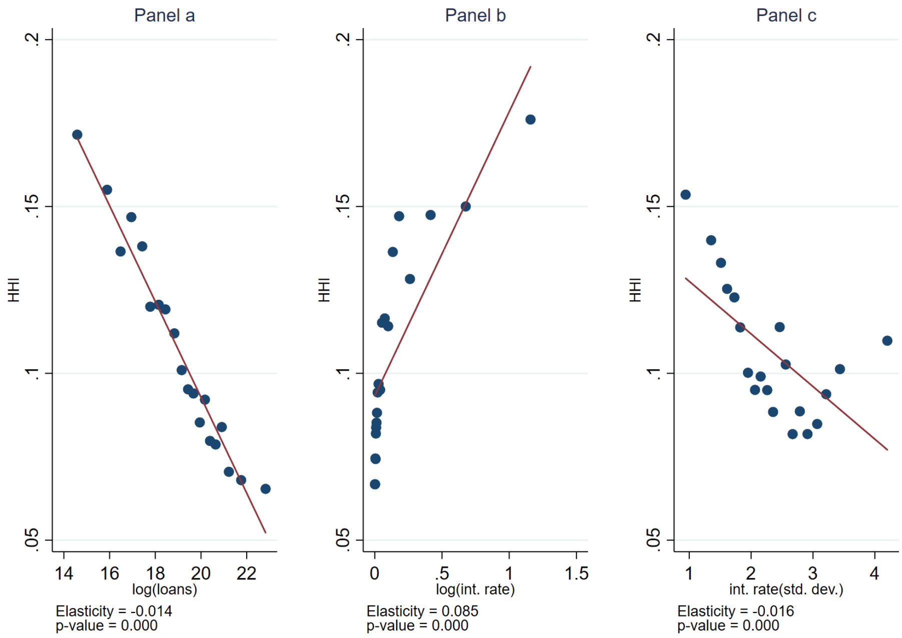
The table reports the estimates of the investment rate, as the ratio between investment in tangible assets at time t and tangible capital in $t-1$, expressed in the inverse hyperbolic sine transformation (ihst). The estimates are for the period 2009-2015. The estimator is linear with large fixed effects (reghdfe). The estimates of σ are by industry and using data of the two years before the reference year. In columns 2 to 4 σ is estimated adding firm rating FE's, size FE's and age FE's. The estimates in the other columns (5 to 8) include in the dataset also single bank firms. The main explanatory variable is the credit supply shock at firm-time level ($Bank\ Shock_{f,t}$) as defined by equation 8. In columns 2, 4, 6 and 8 this is interacted with dummy indicators $\mathbf{1}(\iota)$ of the four bins defined by the quartile values of the σ by industry and year estimated in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009). In columns 3, 4, 7 and 8 $Bank\ Shock_{f,t}$ is also interacted with dummy indicators $\mathbf{1}(\psi)$ of the four bins defined by the quartile values of the specialization measure by industry estimated in the three years preceding the reference year (e.g: 2007, 2008 and 2009 for the year 2009). Controls include: the log of employees in *t-1* ($\log(Employees_{f,t-1})$); firm age ($Age_{f,t}$); the credit score in *t-1* ($Credit\ Score_{f,t-1}$); cash flow t over capital *t-1* ($Cash\ Flow_{f,t}/Capital_{f,t-1}$); the mean loans-to-assets ratio of firm f defined as the average ratio of loans to assets over the sample period (LAR_f); the mean bonds-to-assets ratio (BAR_f), similarly defined; the median of credit demand shocks ($\alpha^{AW}_{f,t}$) across firms by industry and year ($Industry\&year$). The variable definitions are in table A1. All estimates include firm fixed effects and year fixed effects. 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 A4.5: Investment rate regressions - other robustness checks: bank specialization by province

	2009-2015				2010-2015			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Linear	Linear	Linear ihst	Linear ihst	Linear	Linear	Linear ihst	Linear ihst
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\iota = 1)$		0.193***		0.191***		0.186**		0.181***
		[0.064]		[0.051]		[0.073]		[0.057]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\iota = 2)$		0.063		0.067		0.110		0.109*
		[0.062]		[0.049]		[0.073]		[0.057]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\iota = 3)$		0.066		0.055		0.122		0.107*
		[0.068]		[0.053]		[0.081]		[0.063]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\iota = 4)$		0.066		0.059		0.042		0.045
		[0.070]		[0.056]		[0.097]		[0.077]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\zeta = 1)$	0.102*		0.099**		0.136**		0.131**	
	[0.055]		[0.044]		[0.066]		[0.052]	
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\zeta = 2)$	0.085	-0.017	0.088**	-0.011	0.077	-0.059	0.092*	-0.039
	[0.055]	[0.062]	[0.043]	[0.049]	[0.064]	[0.072]	[0.051]	[0.057]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\zeta = 3)$	0.195***	0.091	0.171***	0.070	0.177***	0.040	0.156***	0.024
	[0.053]	[0.061]	[0.042]	[0.048]	[0.063]	[0.072]	[0.050]	[0.056]
$(Bank\ Shock_{f,t}) \times \mathbf{1}(\zeta = 4)$	0.044	-0.060	0.061	-0.040	0.064	-0.073	0.079	-0.053
	[0.054]	[0.059]	[0.042]	[0.047]	[0.061]	[0.069]	[0.049]	[0.054]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	293,426	293,426	293,426	293,426	255,596	255,596	255,596	255,596
#firms	61,350	61,350	61,350	61,350	58,646	58,646	58,646	58,646
Adj. R-squared	0.0906	0.0906	0.114	0.114	0.0926	0.0926	0.117	0.117

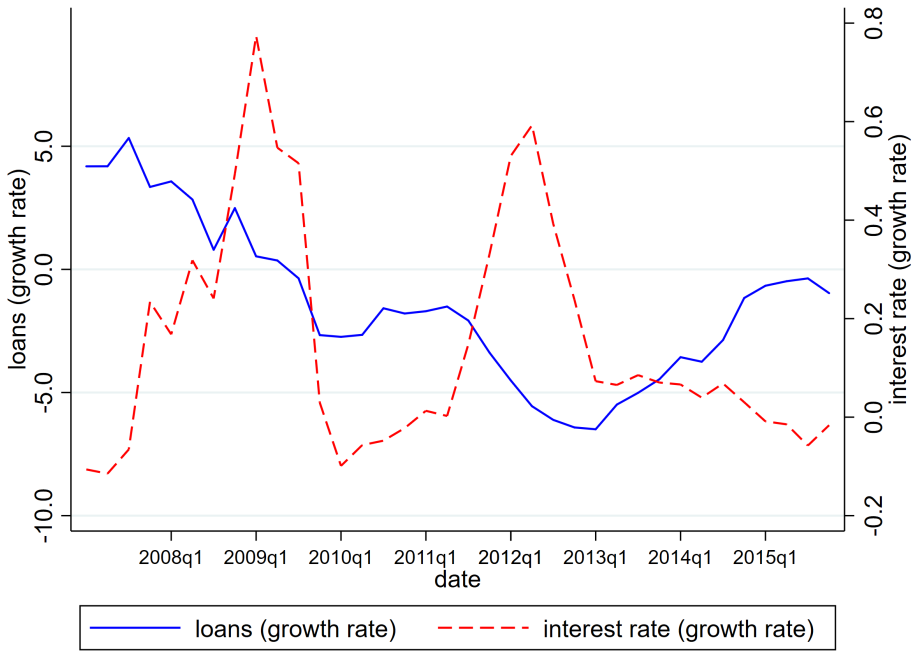
The table reports the estimates of the investment rate, as the ratio between investment in tangible assets at time t and tangible capital in $t-1$. This is expressed as the inverse hyperbolic sine transformation (ihst) in columns 3, 4, 7 and 8. The estimates are for the period 2009-2015 in columns 1 to 4 and 2010-2015 in the remaining columns. The estimator is linear with large fixed effects (reghdfe). The main explanatory variable is the credit supply shock at firm-year level ($Bank\ Shock_{f,t}$) as defined by equation 8 interacted with dummy indicators $\mathbf{1}(\iota)$ of the four bins defined by the quartile values of the σ by industry and year estimated in the two years preceding the reference year (e.g: 2007 and 2008 for the year 2009), and/or interacted with dummy indicators $\mathbf{1}(\zeta)$ of the four bins defined by the quartile values of the specialization measure by province estimated in the three years preceding the reference year (e.g: 2007, 2008 and 2009 for the year 2009). Controls include: the log of employees in *t-1* ($\log(Employees_{f,t-1})$); firm age ($Age_{f,t}$); the credit score in *t-1* ($Credit\ Score_{f,t-1}$); cash flow t over capital *t-1* ($Cash\ Flow_{f,t}/Capital_{f,t-1}$); the mean loans-to-assets ratio of firm f defined as the average ratio of loans to assets over the sample period (LAR_f); the mean bonds-to-assets ratio (BAR_f), similarly defined; the median of credit demand shocks ($\alpha^{AW}_{f,t}$) across firms by industry and year ($Industry\&year$). The variable definitions are in table A1. All estimates include firm fixed effects and year fixed effects. 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.

Figure A.1: Correlations of HHI with credit and interest rates



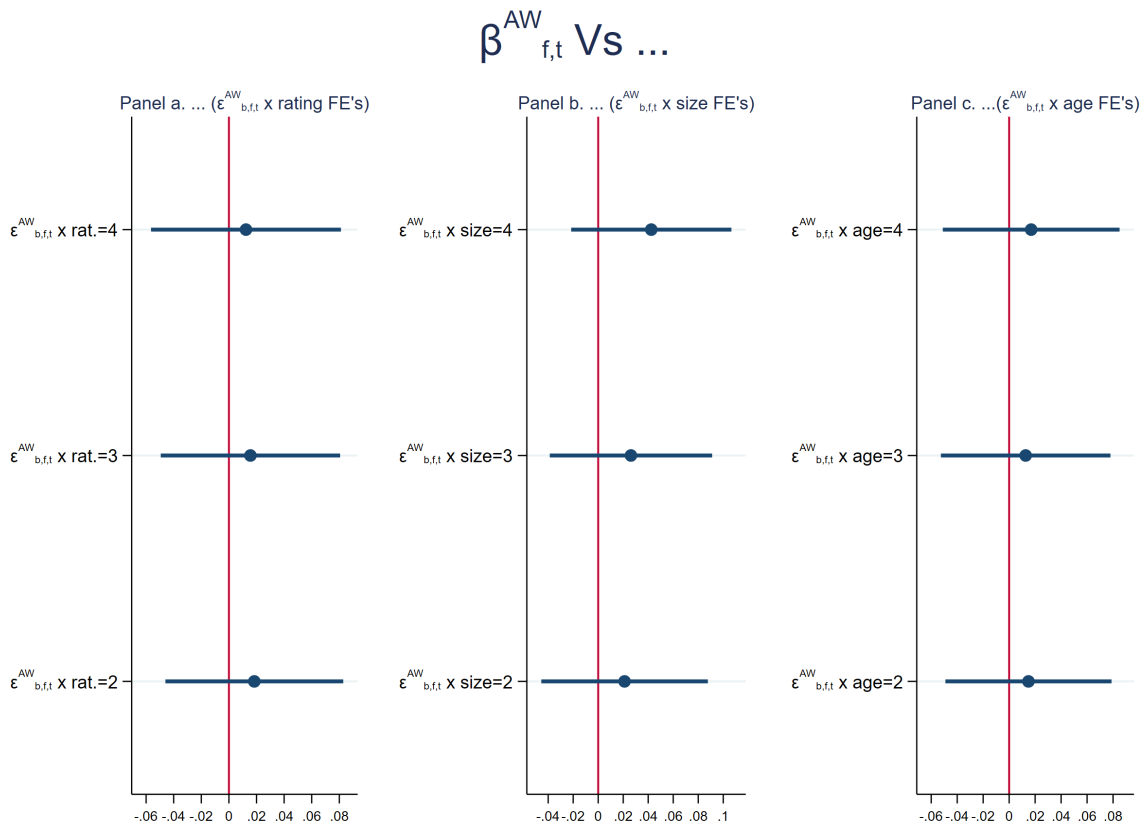
Binned scatter correlations of the HHI and the log of loans (panel a), the average interest rate in logs (panel b) and the standard deviation of the interest rates within each commuting zone (panel c).

Figure A.2: Interest rate and loans growth rates over time



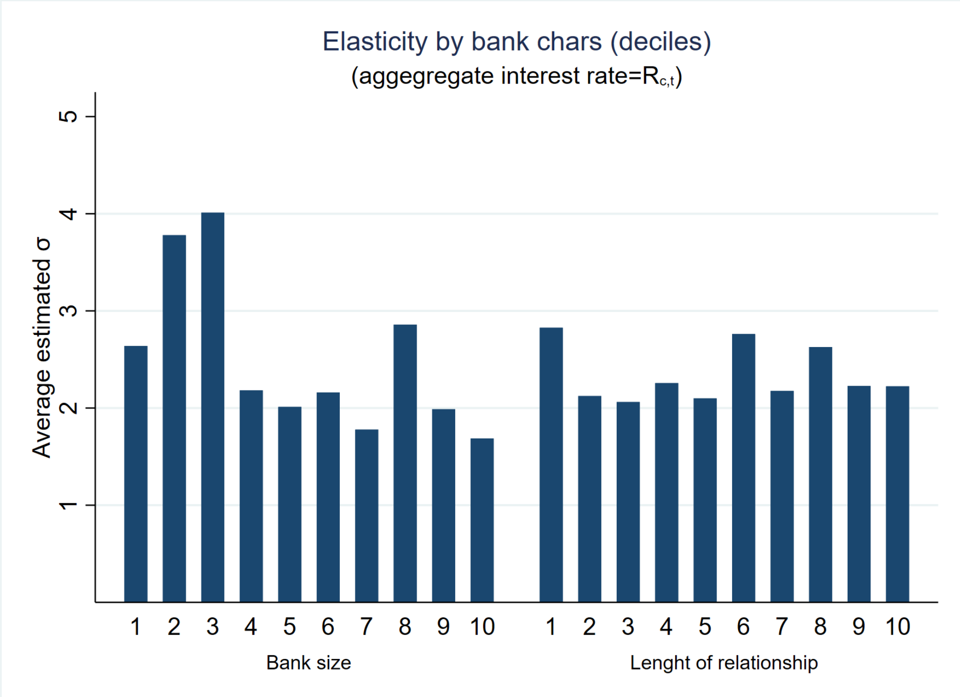
Growth rates are calculated on the corresponding quarter one year before. The reported variables are weighted averages by year and quarter, where the weight is the amount of loans to firm f by bank b in $t-1$.

Figure A.3: Validation of $\hat{\beta}^{AW}_{b,t}$ using firm chars. FE's and the residuals $\hat{\epsilon}^{AW}_{b,t}$



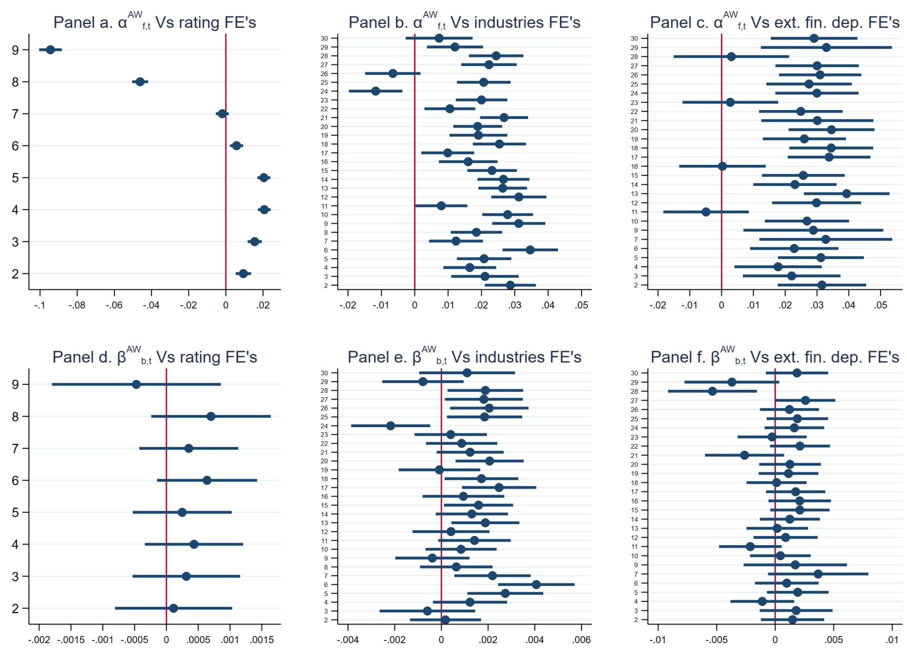
The figure shows the estimated coefficients (and their confidence intervals at 95%) of $\hat{\epsilon}^{AW}_{b,f,t}$ interacted with the fixed effects of firm rating (panel a), of firm size (panel) and of firm age (panel c). Fixed effects are expressed in bins using quartiles of each variable. The dependent variable is the bank-time fixed effect ($\hat{\beta}^{AW}_{b,t}$). Both $\hat{\beta}^{AW}_{b,t}$ and $\hat{\epsilon}^{AW}_{b,f,t}$ estimated using equation 7.

Figure A.4: Elasticity of substitution by bank size and length of relationship



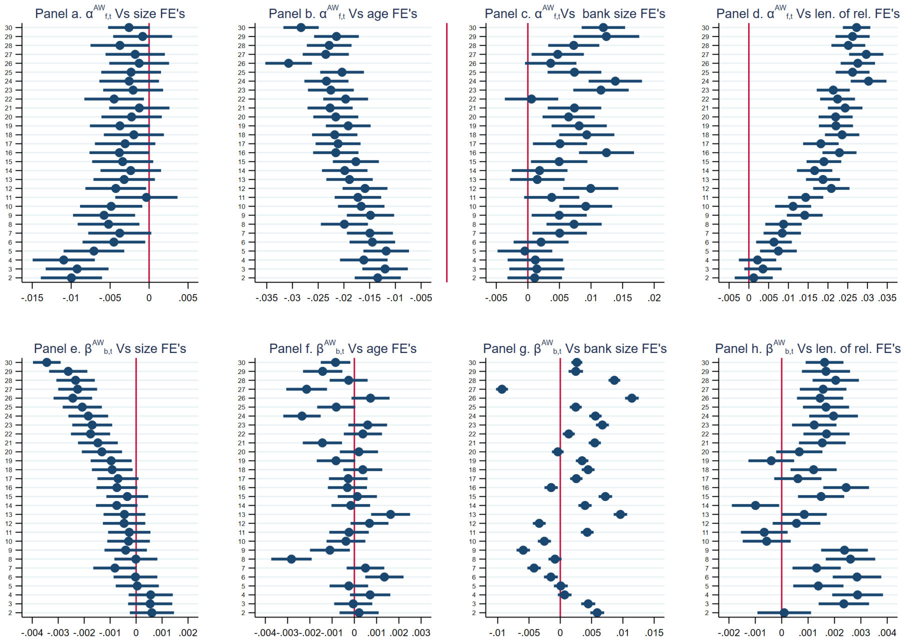
The elasticities are calculated using equation 5, where the denominator of the relative price is the aggregate interest rated defined at commuting zone.

Figure A.5: Correlations of $\hat{\alpha}^{AW}_{f,t}$ and of $\hat{\beta}^{AW}_{b,t}$ with firm characteristics (1/2)



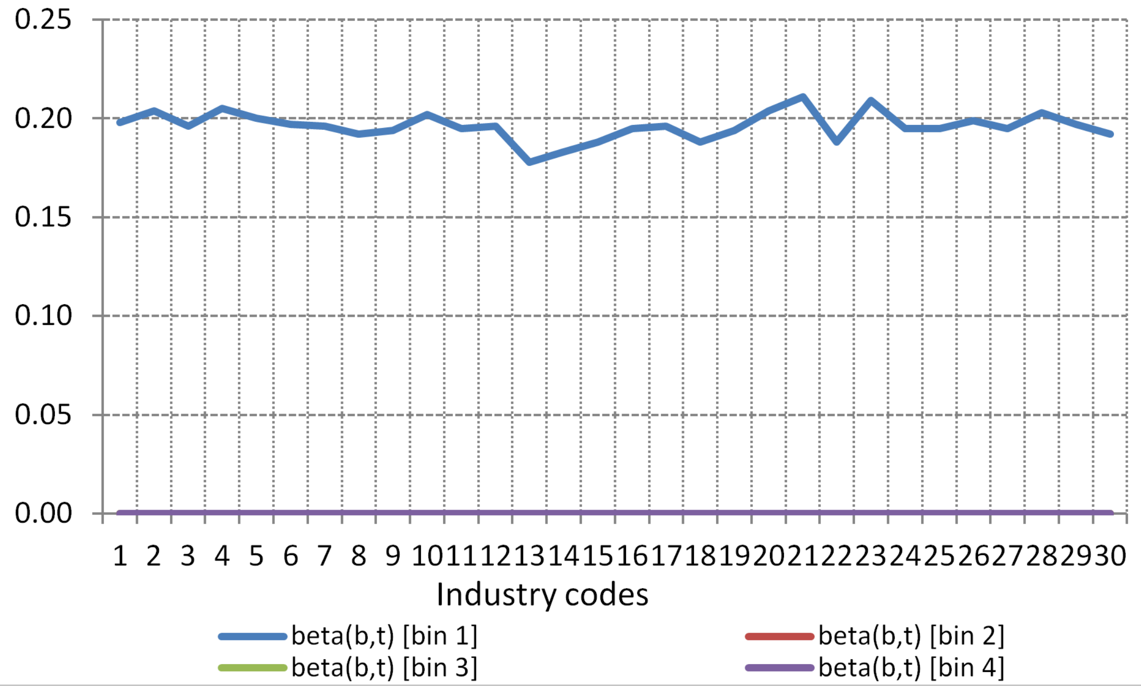
The figure shows the estimated coefficients (and their confidence intervals at 95%) of the fixed effects of firm rating (panels a and d), of the industries (panels b and e) and of external financial dependence expressed in 30 bins using percentiles (panels c and f). The definition of the industry codes (panels b and e) is in the caption of figure A.6. The dependent variable is the firm-time fixed effect ($\hat{\alpha}^{AW}_{f,t}$) in the first row and $\hat{\beta}^{AW}_{b,t}$ in the second row, both estimated using equation 7. The measure of external financial dependence is the one computed on Germany by Balta et al. (2013).

Figure A.5bis: Correlations of $\hat{\alpha}^{AW}_{b,t}$ and $\hat{\beta}^{AW}_{b,t}$ with firm and bank characteristics (2/2)



The figure shows the estimated coefficients (and their confidence intervals at 95%) of the fixed effects of each variable (firm size, firm age, bank size and length of relationship) expressed in 30 bins using percentiles. Higher values on the vertical axis correspond to higher percentile values. The dependent variable is the firm-time fixed effect ($\hat{\alpha}^{AW}_{f,t}$) in the first row and $\hat{\beta}^{AW}_{b,t}$ in the second row, both estimated using equation 7.

Figure A.6: Investment rate elasticity to the credit supply shock: sensitivity analysis



The figure shows the coefficients of the credit supply shocks on the investment rate by quartiles of the industry specific elasticity of substitution ($\beta_{b,t} bin = 1, ..., \beta_{b,t} bin = 4$) estimated using equation 9 and dropping one industry at a time. The values of $\beta_{b,t}$ in bins 2, 3 and 4 are all null and they overlap each other. The industry index is 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).