The Bank Lending Channel and Industrial Competition Dynamics: Evidence from Matched Firm-Bank Data

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Dissertation written under the supervision of Joana Silva and Diana Bonfim

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Abstract

This thesis explores how bank lending shocks affect competition dynamics between firms. We argue that a bank lending shock dampens a firm's competitive position, instead advantaging her rivals, which reap benefits from the firm's distress. Using matched firm-bank data from the Portuguese credit register (2006-2017), we show that a bank lending shock hitting a firm's competitors is associated with higher capital, sales and employment growth rates for that firm. However, this impact is not significant at a 5% level, suggesting that the industrial competition channel is not a substantial mechanism in our main sample. Instead, we find significant effects on a subset of firms: i) larger firms and ii) firms operating in more concentrated industries, which exhibit higher sales and employment growth rates when their competitors go into financial distress. This has an important implication: credit shocks could have distributional impacts across firms. We present evidence that both credit and market shares distribution became increasingly concentrated during the Great Financial Crisis. Finally, while we cannot make inference at the macroeconomic level, the industrial competition channel hypothesis suggested by our results is consistent with the reallocation process observed.

Keywords: Bank Lending Channel, Industrial Competition, Great Recession.

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Resumo

Esta tese explora como os choques bancários afetam a dinâmica da concorrência entre empresas. Argumentamos que um choque bancário reduz a posição competitiva de uma empresa, favorecendo, em vez disso, seus rivais, que colhem benefícios do sofrimento da empresa. Usando dados combinados de empresa-banco do registro de crédito português (2006-2017), mostramos que um choque bancário que atinge os concorrentes de uma empresa está associado a taxas de crescimento de capital, vendas e emprego mais elevadas para essa empresa. No entanto, esse impacto não é significativo em um nível de 5%, sugerindo que o canal de competição industrial não é um mecanismo substancial em nossa amostra completa. Em vez disso, encontramos efeitos significativos em um subconjunto de empresas: i) empresas maiores e ii) empresas que operam em indústrias mais concentradas, que apresentam taxas de crescimento de vendas e emprego mais elevadas quando seus concorrentes entram em dificuldades financeiras. Isso tem uma implicação importante: choques de crédito podem ter impactos distributivos entre empresas. Apresentamos evidências de que tanto a distribuição de crédito quanto de participação de mercado se tornaram cada vez mais concentradas durante a Grande Crise Financeira. Finalmente, embora não possamos fazer inferências em nível macroeconômico, a hipótese do canal de competição industrial sugerida por nossos resultados é consistente com o processo de realocação observado.

Palavras-chave: Canal de Empréstimos Bancários, Concorrência Industrial, Grande Recessão.

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Contents

1 Introduction

Does credit matter for competition dynamics between firms? We argue that a bank lending sock dampens a firm's competitive position, instead advantaging her rivals, which are able to reap benefits from the firm's distress. Through this *industrial competition channel*, a bank lending shock hitting a firm propagates to all firms operating in the same industry, and has a distributional impact across them.

Using matched firm-bank data from the Portuguese credit register (2006-2017), we show that a 1pp bank lending shock hitting a firm's competitors is associated with a 0.44% higher capital accumulation rate for that firm, with smaller effects for employment and sales growth. While this impact is not significant at a 5% level, we find that it is stronger and significant for i) larger firms and ii) firms operating in more concentrated industries, suggesting that an industrial competition channel could be active for this subset of firms.

Our work relates to the large literature on the bank lending channel. In a seminal contribution, Kashyap & Stein (1994) show how, in a fragmented credit market, a shock to bank liabilities can impact credit creation and, through this channel, firms' investment decisions. Importantly, the impact is due to the presence of bank-dependent borrowers. In their conceptual framework, a crucial assumption is that firms whose bank is in distress can't completely adjust switching to new credit sources.

Early empirical evidence was gathered by Slovin, Sushka, & Polonchek (1993). Exploiting the crisis of Continental Illinois Bank, they show that the bank's borrowers stock prices were correlated with news on the bank's fortunes. In last three decades, better data availability and improved econometric methodologies have allowed gathering abundant evidence on the bank lending channel.

There is now a robust consensus that shocks hitting banks transmit to firms which borrow from them. For instance, Ivashina & Scharfstein (2010) show that banks more exposed to Lehman Brothers cut their lending volumes after its collapse in September 2008. Similarly, Santos (2011) shows that pre-crisis exposure to mortgage-backed securities is associated with higher interest rates charged on corporate loans in the post-crisis period.

Lower credit volumes at higher interest rates put a severe burden on firms. Chodorow-Reich (2014) shows that firms borrowing from more distressed banks experienced a sharper contraction in employment during the Great Financial Crisis. In different data settings, Cingano, Manaresi, & Sette (2016) find the same result for firms' investment and value added, while Jasova, Mendicino, Panetti, Peydró, & Supera (2021) document effects on wages and hours worked.

In a recent paper, Amiti & Weinstein (2018) (henceforth AW) give an important methodological contribution. While previous research has relied on quasi-experimental settings to identify bank lending shocks, the authors propose a framework to estimate them from matched firm-bank data. Their method, comparable to a fixed effects model with firm-time and bank-time effects, relies on multi-bank firms to control for variations in credit demand. This offers an agnostic and always available empirical setting to test for the bank lending channel hypothesis.

We implement their methodology in a different data setting. Their sample is restricted to traded firms, with as little as 3% of them having a single bank relation. Instead, we deal with a broader and more representative sample, in which as much as 54% of firms borrow from a single bank[1]. We show that applying their method to larger samples produces noisier bank shock estimates. However, after winsorizing the estimates at the 2.5% level, the bank shocks show credible percentages values.

Recent literature called attention to credit shock propagation beyond the directly affected firms. For instance, Alfaro et al. (2021) find that bank lending shocks hitting a firm also affect her customers (upstream propagation) and suppliers (downstream propagation), which get "infected" by their trade partner's disease.

We contribute to this literature strand exploring a new propagation channel. We argue that, when a credit shock hits a firm, its impact does not limit to the firm itself; instead, it propagates to all firms operating in the same market through an industrial competition channel. We propose a Cournot model to illustrate this mechanism, and construct an empirical setting to test for its presence. Consistent with our guess, we find that a 1pp bank lending shock hitting a firm's competitors is associated with a 0.44% higher firm's capital accumulation rate. The same result, but with smaller magnitudes, holds for employment and sales growth.

A well-established fact is that credit shocks have a heterogeneous impact conditional on firm size. Chodorow-Reich (2014) and Khwaja & Mian (2008), among others, find that small firms tend to be hit harder. We provide evidence that the inverse result holds for the industrial competition channel. When assessing heterogeneous effects conditional on firms' characteristics, we find that only i) large firms and ii) firms operating in concentrated markets gain a significant benefit when their competitors go into financial distress.

This finding has important implications. As small firms are more likely to suffer from their own financial distress, and large firms are better able to reap benefits from their competitors' one, then a credit shock has a distributional impact across firms.

Interestingly, we find that all industrial concentration measures spiked during the Great Financial Crisis. This phenomenon is driven by small and micro enterprises contracting harder than their larger competitors. At the same time, we observe bank lending redirecting towards the latter. Do

[1] This is the typical situation in most economies. Among similar applications of the AW approach to credit registers, see Alfaro, Garcia-Santana, & Moral-Benito (2021) and Amador & Nagengast (2015), who use data from Spain and Portugal respectively.

financial factors play a role in the reallocation process?

This question is even more interesting now, as a growing literature strand points to rising market concentration (Autor, Dorn, Katz, Patterson, & Van Reenen, 2020) and market power (De Loecker, Eeckhout, & Unger, 2020) in USA[2]. While market concentration is commonly interpreted as a long-run phenomenon, due to structural changes ongoing in advanced economies, some authors called attention to its interaction with financial cycle dynamics. For instance, Kroen, Liu, Mian, & Sufi (2021) study the relation between market concentration and monetary policy.

We argue that macro-financial downturn could prompt a rise in market concentration, and present evidence suggesting that credit shocks can play a role in industrial competition dynamics. However, our micro-data setting does not allow to draw conclusion on the macroeconomic relevance of this effect.

The rest of this work is organized as follows. In Section 2 we propose a Cournot model in which credit shocks affect competition dynamics between firms. In Section 3 we present our data setting, and discuss some descriptive statistics on credit aggregates and industrial concentration measures in our sample. In Section 4 we build an empirical framework to test for our hypothesis and discuss the underlying identification assumption. In Section 5 we present and interpret the results, and we make a robustness check in Section 6. Finally, Section 7 concludes.

2 Conceptual Framework

In this section, we develop a Cournot model in which credit plays a role in competition dynamics between firms. The economic intuition is that idiosyncratic credit shocks (i.e. credit shocks that hit firms heterogeneously) are a disadvantage factor in industrial competition. When a firm goes into financial distress, her costs increase with respect to her competitors' average, resulting in market share reallocation towards them. Conversely, when her competitors go into financial distress, the firm benefits from a comparative cost advantage, and market shares are reallocated towards her.

Let's consider an economy populated by N firms. These firms produce an homogeneous output (Q) using labour (L) and capital (K). Labour is remunerated at a rate $\bar{w}$ constant across firms. Instead, capital is remunerated at rate $r_i = \bar{i} + x_i$, where $\bar{i}$ is the risk-free interest rate and x_i is a firm-specific component representing firm i's capital cost in excess of the risk-free interest rate.

In other words, firms are identical in all but in the idiosyncratic capital cost factor x_i. We can think of x_i as capturing the effects of firm-specific financial distress.

Firm i produces its output through a Leontieff function $q_i = min(\alpha L_i, \beta K_i)$. For simplicity, let's

[2] Bajgar, Berlingieri, Calligaris, Criscuolo, & Timmis (2019) evidence a similar pattern in Europe.

set $\alpha = \beta = 1$. Firm i's cost minimization problem has the trivial solution $L_i = K_i = q_i$, from which we can derive the cost function $c(q_i) = q_i(\bar{w} + \bar{i} + x_i)$. Let's define $c = \bar{w} + \bar{i}$ so that we can rewrite the cost function as $c(q_i) = q_i(c + x_i)$.

Firm i competes à la Cournot with her $N - 1$ rivals. The demand function is linear, so that firm i faces an inverse residual demand function: $P(q_i) = A - b(q_i + \sum_{j \neq i}^{N} q_j)$.

Firm i chooses to produce the quantity q_i that maximizes her profits π_i. This is equivalent to solving the optimization problem:

$$\max_{q_i} \quad \pi_i = q_i(A - bq_i - b\sum_{j \neq i}^{N} q_j - c - x_i)$$

From which we derive the first order condition (FOC):

$$\frac{\delta \pi_i}{\delta q_i} = A - 2bq_i - b\sum_{j \neq i}^{N} q_j - c - x_i = 0 \tag{1}$$

As the second order condition is always satisfied[3], the FOC gives the optimal solution. Rearranging equation (1), we get firm i's best response function:

$$q_i = \frac{A - c - x_i}{2b} - \frac{\sum_{j \neq i}^{N} q_j}{2} \tag{2}$$

This equation expresses firm i's optimal response as a function of her $j \neq i$ rivals' choices. In equilibrium, all $i = 1, 2, ..., N$ firms choose their optimal response given their rivals' ones. As such, equilibrium is given by the intersection point of the N firms' best response functions. As we have a linear system in N unknowns and N variables, a solution exists and is unique. Firm i's equilibrium output will be[4]:

$$q_i^* = \frac{1}{N+1}\left(\frac{A - c - x_i - N(\bar{x} - x_i)}{b}\right) \tag{3}$$

where $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ is the average firm-specific cost factor x_i in the industry.

According to Equation (3), equilibrium output is a function of:
(i) common demand and supply factors A, b and c

[3] The second order condition is $\frac{\delta^{(2)}\pi_i}{\delta^{(2)}q_i} = -2b < 0$, which is satisfied $\forall b > 0$. This is quite a weak assumption, as it just requires the demand function to be decreasing in prices.

[4] An explicit solution can be easily derived exploiting the method proposed by Bergstrom & Varian (1985).

(ii) firm-specific idiosyncratic capital cost (x_i)
(iii) industry-specific idiosyncratic capital cost ($\bar{x}$)

We are interested in how firm i reacts to a credit shock. In our framework, we can model a credit shock as an increase in the excess cost of capital x. In particular, we are interested in two cases: a shock that hits firm i (an increase in x_i) and a shock that hits her competitors (an increase in $\bar{x}$). A simple comparative statics exercise allows us to derive the following propositions:

Proposition I - Direct Transmission Channel
A credit shock that hits firm i decreases firm i's equilibrium output.

$$\frac{\delta q_i^*}{\delta x_i} = -\frac{1}{x_i} < 0 \qquad\qquad \forall b > 0$$

Proposition II - Industrial Competition Channel
A credit shock that hits firm i's competitors increases firm i's equilibrium output.

$$\frac{\delta q_i^*}{\delta \bar{x}} = \frac{N}{N+1}\frac{1}{b} > 0 \qquad\qquad \forall b, N > 0$$

Proposition I captures the well-documented direct transmission channel: a credit shock hitting a firm has a negative impact on the firm itself. Proposition II, instead, captures the industrial competition channel: a credit shock hitting the firm's competitors has a positive impact on the firm.

This model is grounded on the simplistic assumption that firms operate in a Cournot oligopoly. This is not a realistic assumption for all firms in our sample; however, it could be for a subset of them. In particular, we argue that such a mechanism could be at work for large firms operating in an oligopolistic environment.

Following this conceptual framework, in Section 5 we test whether the effect captured in Proposition II is heterogeneous conditional on i) firm size and ii) degree of industrial concentration. We now turn to describing our data sources.

3 Data

3.1 Data Sources

We employ three data sources managed by Banco de Portugal:

Firm-level data. We use Central Balance Harmonized Panel (CBHP), which provides annual balance sheet information on firms. This dataset covers all private non-financial corporations operating in Portugal, except those whose legal form is self-employed workers[5].

Bank-level data. We use Historical Series of the Portuguese Banking Sector (SLB), which provides quarterly balance sheet and regulatory information on credit institutions. This dataset covers all Monetary Financial Institutions (MFIs) operating in Portugal. The information is aggregated at the banking group level.

Loan-level data. We use Central Credit Responsibility (CCR), which provides monthly data on outstanding credit relations between firms and credit institutions. This dataset covers all credit relations originated by credit-granting institutions (both MFIs and non-MIFs)[6] operating in Portugal.

We select the largest sample period (2006-2017) for which data is available in the three datasets. We collapse the bank- and loan-level data at a yearly frequency to make it consistent with the firm-level data[7].

Then, we merge the three datasets through their firm and bank identifiers. The datasets are constructed using administrative information subject to mandatory reporting and, as such, cover entirely their respective reference populations. However, merging the three datasets leads to some information loss. This happens because the reference population in CCR is slightly different from the ones in CBHP and SLB, both when firms and banks are concerned:

1) **Mismatch between CCR and CBHP**. Around half of firms appearing in CBHP do not have active borrowing relations, so they do not appear in CCR.

2) **Mismatch between CCR and SLB**. CCR provides information on all credit-granting institutions with active lending relations, including - for instance - factoring and leasing companies. Instead, SLB only provides information on institutions subject to Banco de Portugal's supervision. As such, some credit institutions that appear in CCR don't appear in SLB.

Table 1 shows some aggregate statistics on the merged dataset. The merged dataset covers as much as 429,460 firms and 213 banks, for a total of 5,769,350 firm-bank credit relations. These credit relations sum up to a total of 129 billion euros per year on average.

The reference populations in the merged dataset are non-financial firms (excluding self-employed workers) and MFIs operating in Portugal. For simplicity, we'll refer to such entities as firms and banks from now on.

[5]Those companies are referred to as *empresas individuais*, being defined as companies in which the owner is also the only employee.

[6]The MFIs include the traditional agents in the credit market, such as banks and other deposit-taking financial intermediaries. Instead, non-MFIs include institutions - such as leasing and factoring companies - that provide credit but do not take deposits.

[7]In doing so, we adopt a period-end criterion. For instance, we keep all SLB's and CCR's observations registered in $Quarter = 2010Q4$ and $Month = 12/2010$, respectively, recoding their time variables as $Year = 2010$.

3.2 Sample Selection

First, we drop inactive firms and all firm-bank-time observations related with them. We consider a firm to be inactive in year t when it has either no assets, no sales or no employees in that year. We also drop all firm-bank observations with an outstanding credit amount lower than 50€[8].

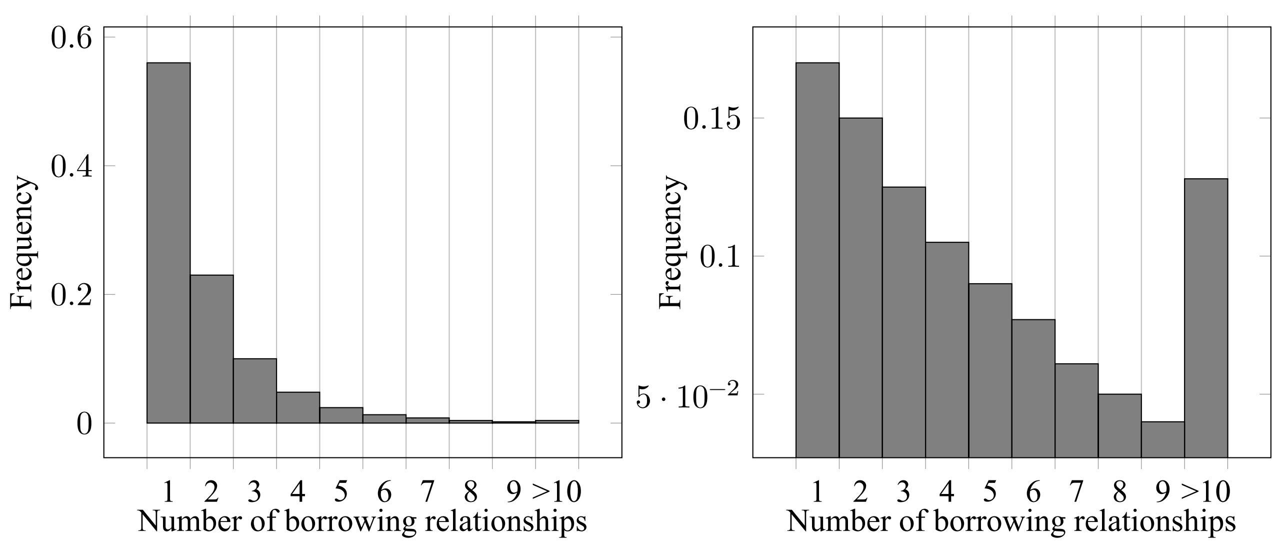
We estimate bank lending shocks according to AW's methodological framework. This is equivalent to regressing the firm-bank level credit growth rate on firm-time and bank-time FEs. As such, all information contained in singleton observations is lost. In this context, singletons are those firm-bank-time observations whose firm or bank only appears in that observation for that year. In practice, there is no single-firm bank in our sample. Instead, single-bank firms are a common thing.

Figure 1 shows the number of bank relations per firm, both in absolute and credit-weighted frequencies. Relying on multi-bank firms for identification amounts to dropping the majority of firms, as single-bank firms account for as much as 56% of firms in our sample. However, as those firms tend to be smaller, they only account for 17% of aggregate credit.

Instead, as practically all banks are multi-firm banks, it would be technically possible to estimate fixed effects for all banks in our sample. However, we decide to drop credit institution with less than ten firm relations in a given year, as their FEs estimates would rely on a small number of observations and thus be highly unstable.

Figure 1: Number of borrowing relationships per firm

(a) Non-Weighted (b) Credit-Weighted



(a) Non-Weighted (b) Credit-Weighted

[8]The mandatory loan reporting threshold is 50€ for CCR. As such, information on credit relations below 50€ is provided on a voluntary basis by the firms and is not exhaustive.

Figure 2: Number of lending relationships per bank

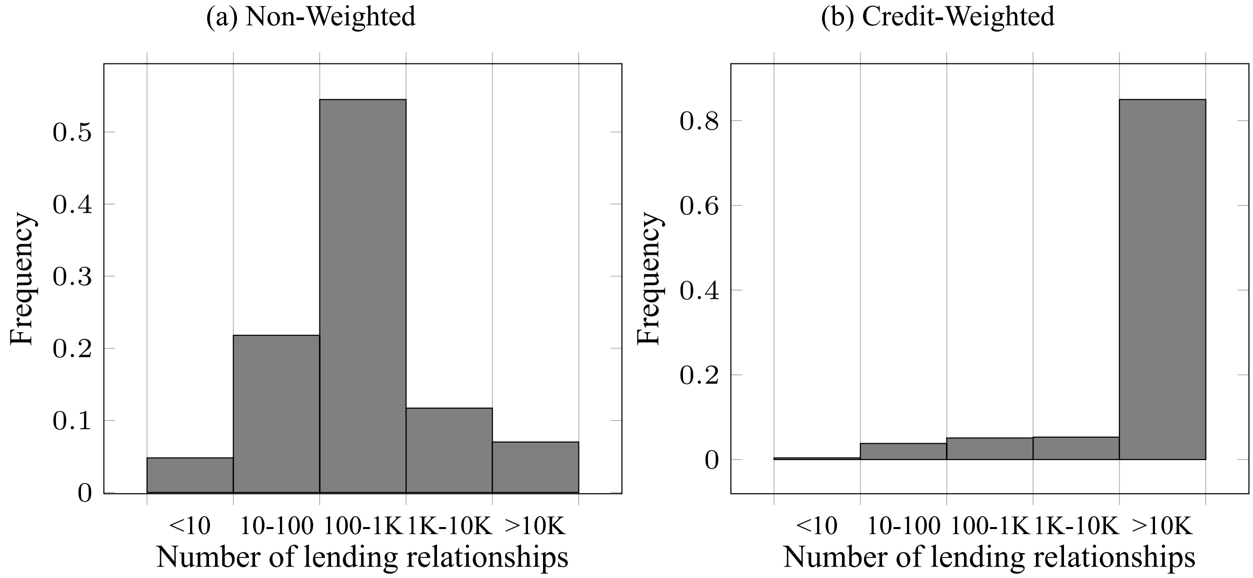


Figure 3: Number of years per firm

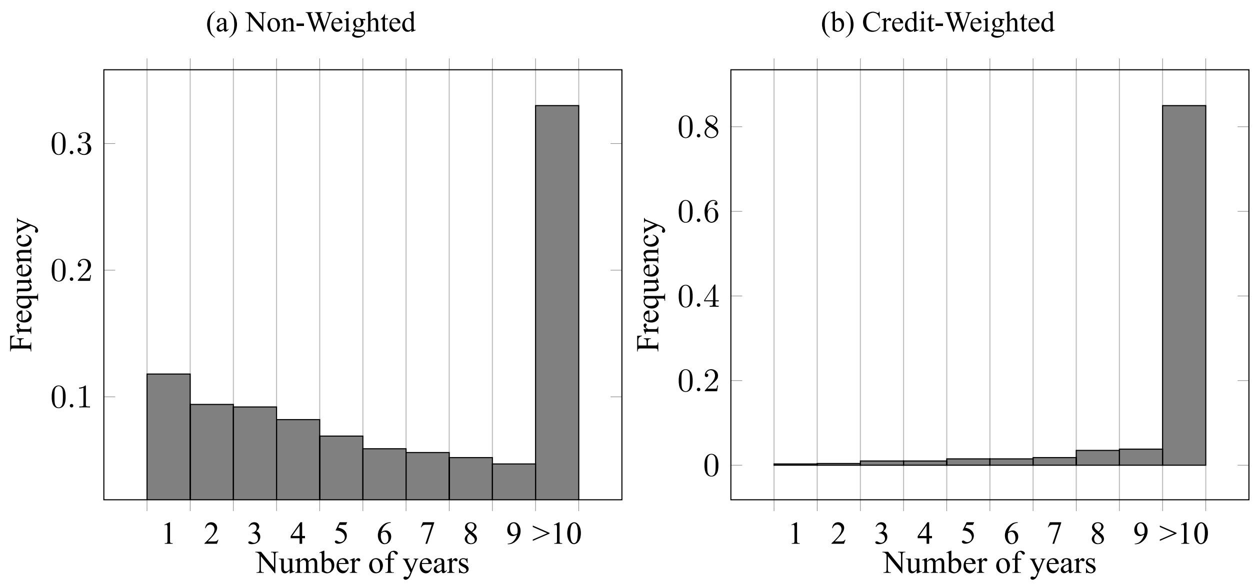


Figure 2 shows the number of firm relations per bank, both in absolute and credit-weighted frequencies. Banks with less than 10 firm relations account for 4.8% of banks in our sample. However, being much smaller than the average, they only account for 0.4% of aggregate credit.

Finally, we drop firms which we only observe for one year. This is necessary as in the main analysis we use firm FEs. Figure 3 shows the number of yearly observation per firm, both in absolute and credit-weighted frequencies. Again, while 11.8% of firms appear for only one year, those firms account for as little as 0.3% of aggregate credit in our sample.

Table 1 compares the information contained in the merged sample with the information contained in the sample we use for estimation. Our estimation sample only contains 38% of firms and 89.7% of banks. However, these firms and banks account for 60.6%, 76.9% and 70.8% of aggregate credit, sales and employment respectively. Table 9 shows firm-level descriptive statistics on the estimation sample.

Table 1: Merged vs Estimation Samples

	Obs	Firms	Banks	Credit	Sales	Employment
Merged Sample	5,769,350	429,460	213	1.294e+11	2.980e+11	2.320e+06
Estimation Sample	2,571,279	163,124	191	7.844e+10	2.291e+11	1.643e+06
Estimation Sample (%)	44.6%	38.0%	89.7%	60.6%	76.9%	70.8%

This table compares the information contained in the merged sample with the information contained in the estimation sample. The columns "Sales", "Credit" and "Employment" indicate the average yearly aggregate values for these variables; the first two are denominated in euros, while the latter indicates the number of workers.

We now turn to presenting some aggregate statistics on Portuguese economy during our sample period. We collect time series on credit aggregates from Banco de Portugal's open database[9]. Instead, firms' balance sheet aggregates are computed using CBHP's data. As in this section we don't need to match firms and banks, we make use of the full sample.

3.3 Descriptive Statistics

Our sample captures an interesting period for Portuguese economy, in which the country was hit by multiple macroeconomic shocks. First, the Great Recession: the original demand shock in US spread to the world through the international trade channel. Portugal's quarter-on-quarter GDP growth rate entered negative territory in 2008-Q2, and didn't turn back positive until 2009-Q4. When the economy had just started recovering, another shock hit country. The European sovereign debt crisis, originated in the government bonds markets, impaired the banking system. The resulting credit crunch forced Portuguese economy in another prolonged recession period between 2010-Q3 and 2011-Q4.

Figure 4 shows quarterly GDP at constant prices; the shaded area indicates the period between the first and the last recession quarters. The pattern is evident: the initial shock in 2008-2009, a partial recovery in 2010 and then the second shock in 2011-2012. This combination of trade and credit shocks was lethal for Portuguese economy, which couldn't catch pre-crisis GDP levels until 2017.

[9] Time series on credit aggregates are available at https://bpstat.bportugal.pt

This makes it the ideal empirical setting to study the bank lending channel, as the bank lending shock came at a moment in which firms were most in need for additional funding.

Figure 4: Quartely GDP in Portugal (2007-2019)

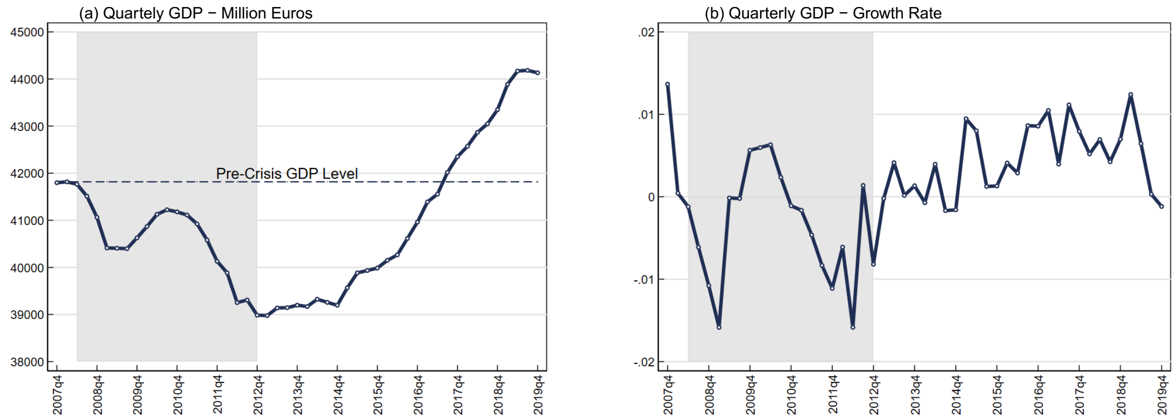
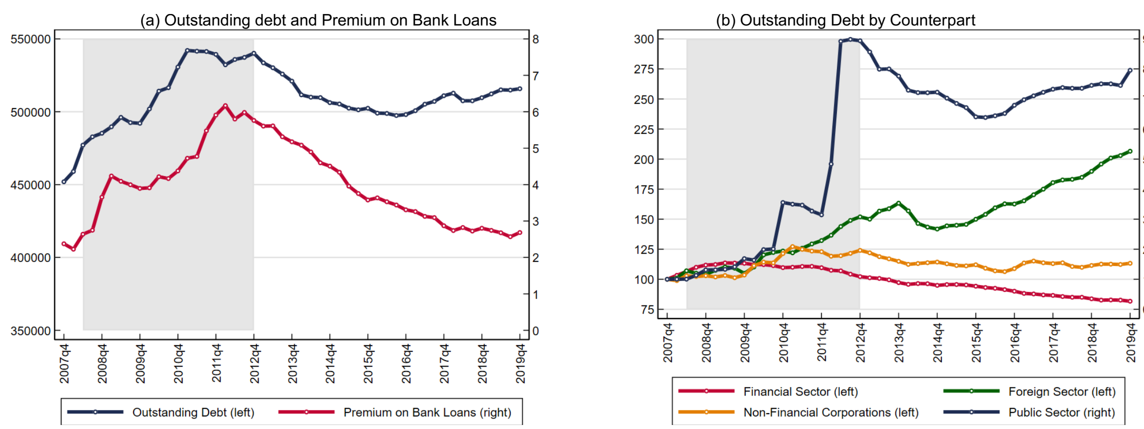


Figure 5 (left) shows non-financial corporations (NFCs) outstanding debt levels. NFCs increased remarkably their debt exposure following the first macroeconomic shock. The prolonged recession had inflicted them severe losses; in this environment, availability of bank credit was crucial for their survival.

Figure 5: NFCs' Outstanding Debt and Premium on Bank Loans



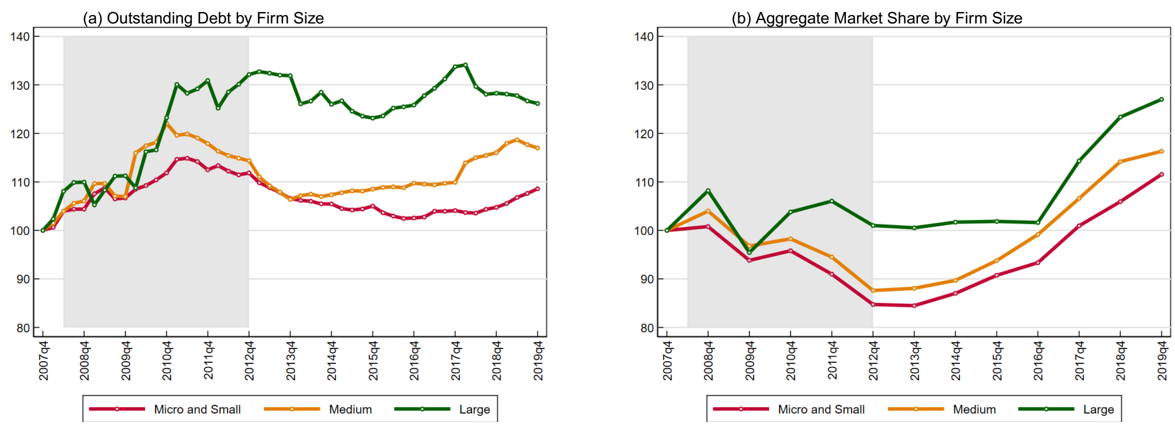
However, the banking sector was in distress as well, and thus unable to cope with firms' increased demand. Figure 5 (left) shows the premium on bank loans[10], which reaches a striking 6% in 2011. Figure 5 (right) plots NFCs' outstanding debt levels by institutional counterpart. Strikingly, the financial sector started *decreasing* its lending activity at the recession's onset. Lacking funds from the financial sector were substituted with increased exposure to the foreign and public sectors. In

[10] We define it as the difference between the weight-average interest rate charged on new loans to NFCs and the EONIA rate.

particular, the latter increased its outstanding credit to NFCs by a factor of 9 in the period 2007-2012 - an increase so big that it's impossible to plot its values on the same scale as the others.

That's what happened at the aggregate level. However, something happened in the distribution as well. Figure 6 (left) plots NFCs' outstanding debt levels by firm size. While no appreciable difference is observed in the pre-crisis period, the series start diverging starkly after 2009-Q4. Large enterprises increased their debt exposure much more than medium, small and micro enterprises. This gap widened during the sovereign debt crisis (2011-2012), to narrow back only after several years (2017-2018).

Figure 6: Outstanding Debt and Market Share by Firm Size



This trend is observed not only in credit, but on real variables as well. Figure 6 (right) plots aggregate market share by firm size. We observe the same trend as in credit: after 2009-Q4, a gap opened between large and small firms. The gap widened during the sovereign debt crisis (2011-2012), when firms were in the most severe financial distress, to partially narrow back later on (2016-2017).

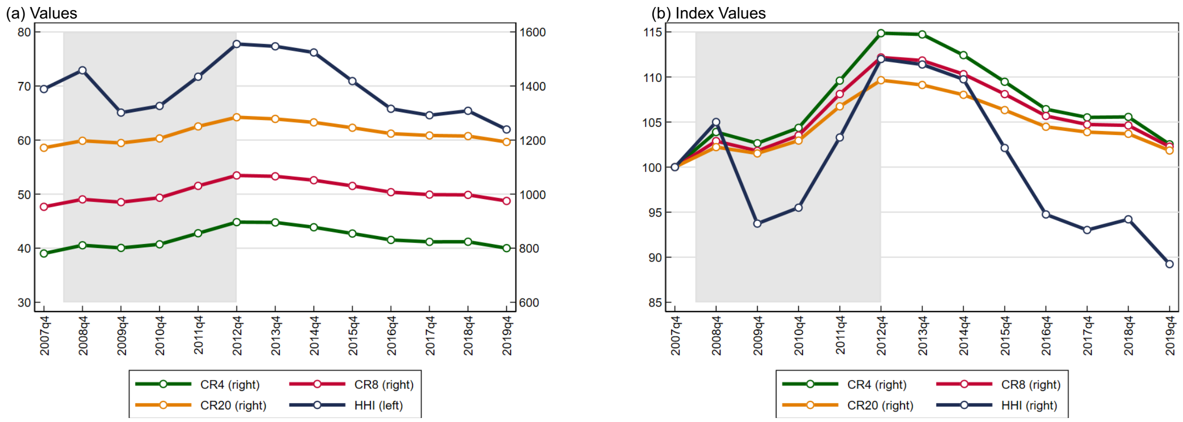
Figure 7 plots the main industrial concentration indexes[11], both in absolute (right) and index (left) values. Those indexes exhibit the same behavior as the other time series: started growing after 2009-Q4, peaked during the sovereign debt crisis (2011-2012) and then slowly reverted to their pre-crisis levels.

The evidence we presented allows us to establish a stylized fact: during the whole recessionary period (2008-Q2/2012-Q4), the distribution of both credit and market shares became increasingly concentrated. What is behind the observed comovement?

There are two possible interpretation for this phenomenon. The first explanation sees credit as a *consequence*: small firms could have suffered from a competitive disadvantage in the product market - for instance, being more exposed to the demand shock. This would have lowered their market

[11]We compute the indexes at the 5-digit industry level, and then weight-average them at the aggregate level using sales as weights.

Figure 7: Industrial Concentration Measures



share and - consequently - their credit demand, resulting in the observed comovement between market shares and credit distribution.

The second explanation sees credit as a *cause*: small firms could have suffered from a competitive disadvantage in the credit market. This would have dampened their ability to finance capital accumulation and employment growth, instead advantaging their larger competitors with better access to credit. As a result, market shares would have been reallocated towards the latter.

The credit shocks' transmission channel proposed in Proposition II - the industrial competition channel - is consistent with the second interpretation. Testing for this hypothesis requires disentangling variations in credit demand from variations in credit supply. We address this empirical challenge in the next section.

4 Empirical Framework

4.1 The AW Estimator

We want to study the firm-level effects of a credit shock. In order to answer our research question, we need a firm-level credit shock measure that is exogenous to firm-level outcomes.

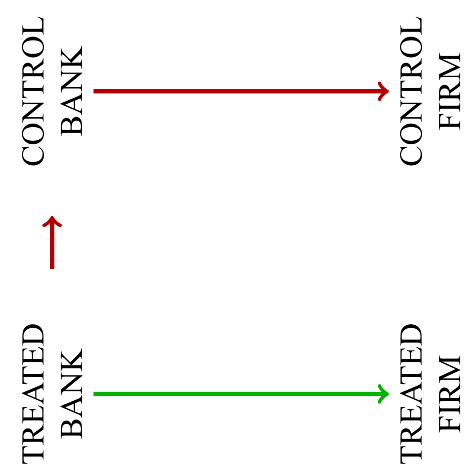
A common approach in applied literature is to construct a bank-level measure of exposure to a particular source of financial shock. For instance, previous research has used banks' heterogeneous exposure to Lehman Brothers before its collapse[12] or increases in capital requirements which impact banks heterogeneously[13]. Then, a firm-level exposure to the bank-level shock is computed, and this exposure is used to assess firm-level effects of bank lending shocks.

[12] For instance, see Chodorow-Reich (2014).

[13] See Aiyar, Calomiris, Hooley, Korniyenko, & Wieladek (2014) and De Marco, Kneer, & Wieladek (2021).

This methodological approach presents some shortcomings. First, it requires an assumption on the most relevant source of bank distress. During the sovereign debt crisis, Portuguese banks were exposed to several shock sources: exposure to the housing market, sovereign bond holdings, and excessive reliance on the interbank market were all factors determining financial distress and - potentially - affecting their ability to originate new loans. Isolating a single distress factor in the middle of a broader financial downturn would indeed be limiting.

Figure 8: Interbank Contagion and Spillover Effects



Second, this approach is not robust to spillover effects between banks. Contagion between banks through the interbank market plays an important role in the transmission of financial shocks[14]. In this case, the control group would end up including indirectly-treated banks, resulting in biased firm-level ATE estimates. Figure 8 gives an intuitive representation, indicating in green the correctly identified causal links, and in red the spillover effects.

To avoid these shortcomings, we adopt AW's methodological framework. Their approach consists in assuming that banks' and firms' credit growth rates are the sum of a firm-specific $\alpha_{f,t}$ and a bank-specific $\beta_{b,t}$ component, being represented by the following system of equations:

$$D_{b,t} = \beta_{b,t} + \sum_{f=1}^{F} \phi_{f,b,t-1} * \alpha_{f,t} \qquad \forall b = 1, 2, ..., B \tag{4}$$

$$D_{f,t} = \alpha_{f,t} + \sum_{b=1}^{B} \theta_{f,b,t-1} * \beta_{b,t} \qquad \forall f = 1, 2, ..., F \tag{5}$$

[14] For instance, Schnabl (2012) shows that Peruvian banks suffered the effects of Russian financial crisis in 1998.

where $D_{f,t}$ and $D_{b,t}$ are the (observed) firm- and bank-level credit growth rates, $\phi_{f,b,t-1}$ and $\theta_{f,b,t-1}$ are the (observed) firm-bank credit weights, and $\alpha_{f,t}$ and $\beta_{b,t}$ are the (unknown) firm and bank components in the credit growth rates. AW prove that, in absence of new lending relations, their estimates are equivalent[15] to those obtained estimating the following equation through WLS with weights equal to lagged credit:

$$D_{f,b,t} = \alpha_{f,t} + \beta_{b,t} + \epsilon_{f,b,t} \tag{6}$$

We estimate time-varying bank shocks accordingly. This framework presents several advantages. First, it's an *agnostic* measure, as it does not require making assumptions about the most relevant financial shock source in our sample. Second, it's a *complete* measure, and as such it's robust to spillover effects due to contagion events across banks. Third, under a simple assumption, the bank shock estimates $\hat{\beta}_{b,t}$ are exogenous to variations in credit demand and, as such, not spuriously correlated with our firm-level outcomes of interest.

4.2 Identification Assumption

The estimates $\hat{\beta}_{b,t}$ are exogenous to variations in credit demand as long as the firm-time components $\hat{\alpha}_{f,t}$ are able to control for them. This is tantamount to assuming that the equilibrium credit growth rate at the firm-bank level is an *additively separable function* of firm-specific credit demand and bank-specific credit supply characteristics alone:

$$D^*_{f,b,t} \equiv f(L^S_{b,t}, L^D_{f,t}) = g(L^S_{b,t}) + h(L^D_{f,t}) \tag{7}$$

where $D^*_{f,b,t}$ is equilibrium credit growth, and $L^S_{b,t}$ and $L^D_{f,t}$ are vectors of credit supply and demand characteristics, respectively. This assumption is met when the true model is described by Equation 6. However, when could it be violated? An intuitive way to think about the identification assumption is that, in order for the estimated $\hat{\beta}_{b,t}$ to be exogenous to variations in credit demand, we need such variations to spread equally across banks.

Paravisini, Rappoport, & Schnabl (2015) points to an interesting case in which this assumption is violated. Let's suppose that banks are specialized in financing exports to some specific countries. In this case, a country-specific shock would result in a credit demand shock for firms exporting to that country. However, the credit demand shock would not spread equally across banks, instead hitting more those which are specialized in financing exports to that country. As a result, the estimated $\hat{\beta}_{b,t}$ for those banks would be affected by a variation in credit demand. This is just a special case of the

[15] Up to the choice of a numeraire.

more general model:

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

in which the firm-bank-time fixed effects $\gamma_{f,b,t} \neq 0$ for at least one firm-bank pair. Under this model, the identification assumption expressed in Equation 7 is violated and, as such, estimating Equation 6 would produce biased estimates. Unfortunately, Equation 8 can't be estimated as the number of coefficients for the firm-bank-time effect alone is by construction equal to the number of observations.

Paravisini et al. (2015) propose a way to circumvent the problem, specifying the model with a firm-bank interaction variable rather than firm-bank fixed effects. This allows them to test whether the true model can be approximated by Equation 6, or the firm-bank interactions play a decisive role as in 8.

Our data does not allow us to replicate their setting, as we don't have firm-country level information on export destinations. The inability to account for potential biases in estimated bank shocks calls for the implementation of rigorous controls in the regression analysis. When assessing firm-level effects of bank lending shocks, we include firm- and region-time FEs to control for unobserved firm heterogeneity, and exploit the estimated firm components $\hat{\alpha}_{f,t}$ to control for variations in firm-level credit demand.

4.3 Bank Shocks Estimation

Following AW, we normalize the linear system in 4 and 5 so that the median firm and bank shocks are equal to zero in each time period. Thus, we solve the linear system:

$$D_{b,t} = c_t + \ddot{\beta}_{b,t} + \sum_{f=1}^{F} \phi_{f,b,t-1} * \ddot{\alpha}_{f,t} \qquad \forall b = 1, 2, ..., B \tag{9}$$

$$D_{f,t} = c_t + \ddot{\alpha}_{f,t} + \sum_{b=1}^{B} \theta_{f,b,t-1} * \ddot{\beta}_{b,t} \qquad \forall f = 1, 2, ..., F \tag{10}$$

where the term c_t captures the shock hitting the median firm-bank credit relation at time t, while $\ddot{\alpha}_{f,t}$ and $\ddot{\beta}_{b,t}$ are the deviations of firm f's and bank b's shocks from the median. This is a linear system in $F + B$ variables and $F + B$ unknowns and, as such, a unique solution exists, which can be computed through simple matrix algebra.

Table 2 shows the distribution of our shock estimates at the firm-bank-time level. While the estimates are interpretable as credible percentage changes between the 1st and the 99th percentiles, there are evident outliers in the tails. The minimum bank shock computed in the sample, -859.60%, isn't a credible percentage change.

Table 2: Shock Estimates Distribution

	min	p1	p10	p25	p50	p75	p90	p99	max
Original									
$\hat{\ddot{\alpha}}_{f,t}$	-21.288	-0.896	-0.380	-0.166	0.028	0.304	1.112	15.968	136986
$\hat{\ddot{\beta}}_{b,t}$	-8.596	-0.645	-0.254	-0.170	-0.051	0.026	0.197	1.146	55.036
$\hat{c}_t$	-0.057	-0.057	-0.044	-0.005	-0.001	0.029	0.115	0.115	0.115
Winsorized at 2.5%									
$\hat{\ddot{\alpha}}_{f,t}$	-0.711	-0.711	-0.380	-0.166	0.028	0.304	1.112	5.526	5.526
$\hat{\ddot{\beta}}_{b,t}$	-0.523	-0.523	-0.254	-0.170	-0.051	0.026	0.197	0.590	0.590
$\hat{c}_t$	-0.057	-0.057	-0.044	-0.005	-0.001	0.029	0.115	0.115	0.115

This table shows the firm-bank-time level distribution of firm ($\hat{\ddot{\alpha}}_{f,t}$), bank ($\hat{\ddot{\beta}}_{b,t}$) and common shock ($\hat{c}_t$) estimates, both in their original values and after winsorizing at the 2.5% level.

This is in stark contrast with the situation in AW, where the minimum bank shock is -54.8%. We argue that this is due to our specific data setting. While their sample is restricted to large traded firms, we deal with a broader sample including any firm operating in the economy, as long as it has multiple bank relationships. Intuitively, as the firm and bank shock estimates sum up to match the observed firm- and bank-level credit growth rates, a higher variance in the credit growth rates distribution results in noisier shock estimates.

Following Amador & Nagengast (2015), we winsorize the firm and bank shocks at the 2.5% level. This allows us to keep those observations in the sample, while ensuring that abnormal bank shock values don't make our estimates unstable. After winsorization, our bank shock estimates range between -52.3% and +59%, which are indeed credible percentage changes.

4.4 Empirical Model

According to our conceptual framework, a firm can be affected by two types of credit shocks:

i) A shock that hits the firm itself (Proposition I)
ii) A shock that hits the firm's competitors (Proposition II)

Thus, once obtained estimates for the bank lending shocks $\hat{\ddot{\beta}}_{b,t}$, we define our firm-level direct shock measure as her weight-average bank shock, using as weights her lagged bank exposures $\theta_{f,b,t-1}$:

$$Firmshock_{f,t} = \sum_{b=1}^{B} \theta_{f,b,t-1} * \hat{\hat{\beta}}_{b,t}$$

Similarly, we define our firm-level indirect shock measure as the weight-average bank shock in the 5-digit industry i in which she operates:

$$Indshock_{f,t} = \sum_{b=1}^{B} \theta_{i,b,t-1} * \hat{\hat{\beta}}_{b,t}$$

where we exclude firm f from the industry, so that $Indshock_{f,t}$ only measures her competitors' exposure to bank shocks. To make our measures more easily interpretable, we multiply them by -100. In this way, a unit variation in the shock measures corresponds to a -1pp contraction in bank credit supply.

In an analogous manner, we construct the credit demand controls $Firmcontrol_{f,t}$ and $Indcontrol_{f,t}$, weight-averaging $\hat{\hat{\alpha}}_{f,t}$ (rather than $\hat{\hat{\beta}}_{b,t}$) at the firm and at the industry level, respectively. Note that, by construction, firm-level idiosyncratic credit growth rate $D_{f,t} - c_t$ is equal to $Firmshock_{f,t} + Firmcontrol_{f,t}$, and her rivals' one to $Indshock_{f,t} + Indcontrol_{f,t}$.

In other words, we decompose idiosyncratic variations in bank lending in a supply and a demand component; we use variations in supply as our shock measures and include the variations in demand as controls. Once obtained our shock measures, we estimate the equation:

$$\Delta log(Y)_{f,t} = \alpha_f + \alpha_{t,r} + \beta_1 Firmshock_{f,t} + \beta_2 Indshock_{f,t} + X_{f,t}\gamma + \epsilon_{f,t} \tag{11}$$

where α_f and $\alpha_{t,r}$ are firm and region-time fixed effects, respectively, and $X_{f,t}$ is a vector of credit demand controls. We estimate the equation using capital, employment and sales as an outcome. As we take their logarithmic differences, our coefficients of interest β_1 and β_2 are to be interpreted as the impact of a 1pp bank lending shock on the log growth rate of the respective outcomes.

As stated in Section 2, we expect the coefficient β_1 to be negative and the coefficient β_2 to be positive. Consistent with our prior that the industrial competition channel is more likely to be at work for large firms operating in oligopolistic industries, we also explore whether this channel has a heterogeneous impact on firms conditional on i) firm size and ii) the degree of concentration of the industry they operate in.

To do so, we construct two vectors of dummy variables. The vector $Size_{f,t}$ includes four dummy variables, each taking value one when firms are either micro, small, medium or large enterprises[16].

[16] We sort firms into size categories according to the European Commission classification, which uses a triple criterion based on employees, turnover and total assets.

Then, we sort industries into quartiles of Herfindahl-Hirschman Index, and construct the vector $HHI_{i,t}$, which also includes four dummy variables, each taking value one when the industry i in which firm f operates is in a given HHI's quartile. Then, we estimate the model:

$$\Delta log(Y)_{f,t} = \alpha_f + \alpha_{t,r} + Indshock_{f,t} \times Size_{f,t}\beta_{Size} + Indshock_{f,t} \times HHI_{i,t}\beta_{HHI} + X_{f,t}\gamma + \epsilon_{f,t} \quad (12)$$

where we choose as the omitted category micro-enterprises operating in the least concentrated industries. Thus, the vectors of coefficients β_{Size} and β_{HHI} include three coefficients each, capturing the differential impact in that group with respect to the reference group. For instance, the coefficient $\beta_{Size=Large}$ represents the increase in $Indshock_{f,t}$'s effect when a firm moves from the micro to the large enterprises category, for a given level of HHI. Instead, the coefficient $\beta_{HHI=q4}$ represents the increase in $Indshock_{f,t}$'s effect when a firm moves from a competitive industry to a very concentrated one, for a given level of firm size.

In model 12, the vector $X_{f,t}$ includes the credit demand controls interacted with the dummies for firm size and industrial concentration, also controlling for the main effects of the latter. It also includes $Firmshock_{f,t}$ and $Firmcontrol_{f,t}$ to control for the effects of the direct transmission channel. Consistent with our conceptual framework, we expect β_{Size} and β_{HHI} to be higher for larger firms and for more concentrated industries, respectively.

5 Results

Tables 3, 4 and 5 show the results from estimating Equation 11 using capital, employment, and sales as an outcome, respectively. In each model, column (1) and (2) show the results from regressing the outcomes on either $Firmshock_{f,t}$ or $Indshock_{f,t}$ and firm and time FEs. In the successive specifications, we progressively saturate the model with controls: column (3) includes both regressors of interest, column (4) adds controls for variations in credit demand and column (5) replaces time FEs with region-time FEs.

Some clear patterns are observed in the data. First, coefficients' estimates have the expected direction: $Firmshock_{f,t}$ is associated with negative outcomes' growth rates, while $Indshock_{f,t}$ with positive ones. This result is robust across almost all specifications, both with different outcomes and different controls.

Second, as we progressively saturate the model with controls, the coefficients have greater magnitudes and higher statistical significance. For instance, while $Indshock_{f,t}$ has a +0.27% impact on capital accumulation in the baseline specification (2), introducing region-time FEs and credit demand controls increase it to +0.44%, making it almost significant at the 5% level. This reassures us that the results are not driven by unobserved firm heterogeneity.

Table 3: Effects on Capital Accumulation Rate

	Dependent Variable: $\Delta log(Capital_{f,t})$				
	(1)	(2)	(3)	(4)	(5)
$Firmshock_{f,t}$	0.000412		0.000162	-0.00140	-0.00133
	(0.000683)		(0.000740)	(0.000901)	(0.000891)
$Indshock_{f,t}$		0.00275	0.00258	0.00485	0.00445
		(0.00194)	(0.00211)	(0.00253)	(0.00236)
Observations	776726	776726	776726	776726	776656
R-Squared	0.183	0.183	0.183	0.190	0.209
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	No
Region-Time FE	No	No	No	No	Yes
Credit Demand Controls	No	No	No	Yes	Yes

This table shows the effects on firm-level capital accumulation rate of 1 a pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

Table 4: Effects on Employment Growth

	Dependent Variable: $\Delta log(Employment_{f,t})$				
	(1)	(2)	(3)	(4)	(5)
$Firmshock_{f,t}$	-0.000296		-0.000518	-0.000620	-0.000544
	(0.000758)		(0.000770)	(0.000802)	(0.000785)
$Indshock_{f,t}$		0.00175	0.00229	0.000903	0.0000941
		(0.00281)	(0.00287)	(0.00291)	(0.00279)
Observations	776726	776726	776726	776726	776656
R-Squared	0.183	0.183	0.183	0.190	0.209
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	No
Region-Time FE	No	No	No	No	Yes
Credit Demand Controls	No	No	No	Yes	Yes

This table shows the effects on firm-level employment growth of a 1 pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

Table 5: Effects on Sales Growth

	Dependent Variable: $\Delta log(Sales_{f,t})$				
	(1)	(2)	(3)	(4)	(5)
$Firmshock_{f,t}$	0.000181		0.0000991	-0.000209	-0.000203
	(0.000171)		(0.000171)	(0.000181)	(0.000179)
$Indshock_{f,t}$		0.000947	0.000845	0.000491	0.000329
		(0.000636)	(0.000641)	(0.000690)	(0.000662)
Observations	776726	776726	776726	776726	776656
R-Squared	0.183	0.183	0.183	0.190	0.209
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	No
Region-Time FE	No	No	No	No	Yes
Credit Demand Controls	No	No	No	Yes	Yes

This table shows the effects on firm-level sales growth of a 1 pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

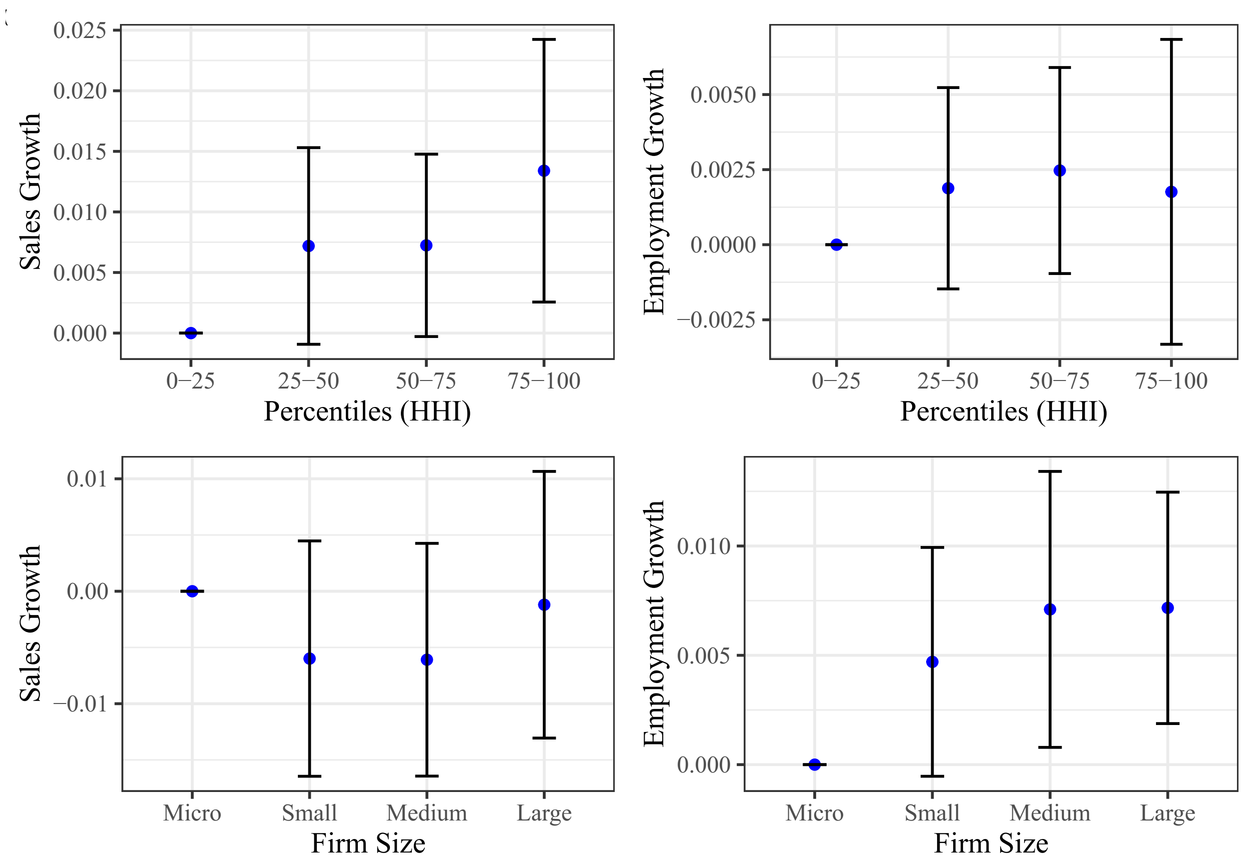
The estimates also seem credible in magnitude. Consistent with the idea that credit shocks are shocks to firms' capital cost, capital seems to be the most impacted variable. As in column (5), a 1pp bank lending shock hitting the firm is associated with a 0.13% lower capital accumulation rate. The effect on employment and sales is sensibly lower, amounting to a 0.05% and 0.02% contraction, respectively.

Instead, a 1pp bank lending shock hitting the firm's competitors is associated with a 0.44% higher capital accumulation rate. The effect on employment and sales is also in this case lower, amounting to a 0.009% and 0.07% increase, respectively.

However, the coefficients are not significant at the 5% significance level. Moreover, there is no sensible variation in the R^2 across the specifications in columns (1), (2) and (3), indicating that nor $Firmshock_{f,t}$ nor $Indshock_{f,t}$ contribute in a substantial way to explain the observed variability in the outcomes.

We conclude that the industrial competition channel is not a substantial mechanism in our main sample. Instead, it appears to be so for a subset of firms. Tables 6, 8 and 7 show the results from estimating Equation 12 using capital, employment and sales as an outcome, respectively. We observe an interesting pattern for sales and employment; Figure 9 plots coefficients and confidence intervals for these variables.

Figure 9: Firm Heterogeneity by Size and HHI



The industrial competition channel appears to be stronger in more concentrated industries. In the most concentrated industries, a 1pp bank lending shock hitting a firm's competitors is associated with a 1.34% higher sales growth than in the least concentrated industries. The coefficient for employment is lower (+0.17%), but still shows to be higher in more concentrated industries. Instead, larger employment effects are observed for larger firms, which react with a 0.75% higher employment growth than micro-enterprises.

Instead, heterogeneous effects on capital show no clear correlation nor with size nor with industrial concentration measures. For instance, coefficients are higher for the 3rd HHI quartile, but not for the 4th, while no interaction term with size is significant at the 5% level.

Table 6: Heterogeneous Effects on Capital Accumulation Rate

	(1)	(2)	(3)
Dependent Variable: $\Delta log(Capital_{f,t})$			
$Indshock_{f,t} \times (HHI = q2)$	0.00792	0.00855	0.00784
	(0.00590)	(0.00573)	(0.00548)
$Indshock_{f,t} \times (HHI = q3)$	0.0131*	0.0156*	0.0152*
	(0.00598)	(0.00661)	(0.00614)
$Indshock_{f,t} \times (HHI = q4)$	0.000495	0.00127	0.000691
	(0.00377)	(0.00382)	(0.00362)
$Indshock_{f,t} \times (Size = Small)$	0.00896	0.00946	0.00970
	(0.00603)	(0.00680)	(0.00639)
$Indshock_{f,t} \times (Size = Medium)$	-0.00173	-0.00122	-0.000968
	(0.00430)	(0.00468)	(0.00442)
$Indshock_{f,t} \times (Size = Large)$	0.000833	0.00184	0.00103
	(0.00416)	(0.00426)	(0.00410)
Observations	776726	776726	776656
R-Squared	0.191	0.198	0.217
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	No
Region-Time FE	No	No	Yes
Credit Demand Controls	No	Yes	Yes

This table shows the heterogeneous effects on firm-level capital accumulation rate of a 1 pp bank lending shock hitting the firm's competitors ($Indshock_{f,t}$), conditional on both the firm's size and the quartile of HHI of the industry in which the firm operates. The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

Overall, our evidence suggests that an industrial competition channel could be at work for larger firms operating in more concentrated industries. These firms appear to have stronger effects on sales and employment growth than their smaller counterparts operating in more competitive markets. This is consistent with our conceptual framework, that frames the industrial competition channel as a feature of oligopolistic markets.

Table 7: Heterogeneous Effects on Sales Growth

	(1)	(2)	(3)
Dependent Variable: $\Delta log(Sales_{f,t})$			
$Indshock_{f,t} \times (HHI = q2)$	0.00913*	0.00927*	0.00719
	(0.00449)	(0.00461)	(0.00414)
$Indshock_{f,t} \times (HHI = q3)$	0.00758	0.00738	0.00724
	(0.00491)	(0.00503)	(0.00384)
$Indshock_{f,t} \times (HHI = q4)$	0.0148*	0.0142*	0.0134*
	(0.00629)	(0.00636)	(0.00553)
$Indshock_{f,t} \times (Size = Small)$	-0.00686	-0.00679	-0.00599
	(0.00561)	(0.00551)	(0.00534)
$Indshock_{f,t} \times (Size = Medium)$	-0.00873	-0.00748	-0.00609
	(0.00575)	(0.00565)	(0.00528)
$Indshock_{f,t} \times (Size = Large)$	-0.00318	-0.00177	-0.00120
	(0.00628)	(0.00618)	(0.00605)
Observations	776726	776726	776656
R-Squared	0.227	0.229	0.244
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	No
Region-Time FE	No	No	Yes
Credit Demand Controls	No	Yes	Yes

This table shows the effects on firm-level sales growth of a 1 pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

Table 8: Heterogeneous Effects on Employment Growth

	(1)	(2)	(3)
Dependent Variable: $\Delta log(Employment_{f,t})$			
$Indshock_{f,t} \times (HHI = q2)$	0.00131	0.00204	0.00188
	(0.00183)	(0.00184)	(0.00171)
$Indshock_{f,t} \times (HHI = q3)$	0.000652	0.00141	0.00247
	(0.00307)	(0.00290)	(0.00175)
$Indshock_{f,t} \times (HHI = q4)$	0.000848	0.00161	0.00176
	(0.00285)	(0.00281)	(0.00259)
$Indshock_{f,t} \times (Size = Small)$	0.00401	0.00390	0.00470
	(0.00283)	(0.00290)	(0.00267)
$Indshock_{f,t} \times (Size = Medium)$	0.00728*	0.00695*	0.00710*
	(0.00321)	(0.00319)	(0.00322)
$Indshock_{f,t} \times (Size = Large)$	0.00674**	0.00736**	0.00717**
	(0.00261)	(0.00269)	(0.00270)
Observations	776726	776726	776726
R-Squared	0.227	0.234	0.257
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	No
Region-Time FE	No	No	Yes
Credit Demand Controls	No	Yes	Yes

This table shows the effects on firm-level employment growth of a 1 pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

6 Robustness

Our bank shock identification strategy relies on multi-bank firms to control for variations in credit demand. As shown earlier in Figure 1, in our data setting most firms have a single bank relation. This implies excluding from the sample over half of them.

In a recent contribution, Degryse, De Jonghe, Jakovljević, Mulier, & Schepens (2019) argue against excluding single-bank firms from the estimation sample. Their argument is that, as single-bank firms are on average smaller than multi-bank ones, and small firms are more incline to bear negative consequences from financial distress, accounting for them is crucial to capture the full effects of bank lending shocks.

In the AW framework, single-bank firms are singleton observations; however, such firms are not singletons in our main regression model. This implies that, while they do not bring additional information when estimating bank shocks, they do bring information when assessing their impact on firm-level outcomes.

In fact, in a similar data setting, Amador & Nagengast (2015) choose not to drop single-bank firms from their sample. In this robustness section, we follow them and estimate equations 11 and 12 on our whole sample, to check whether the results are robust to including single-bank firms.

Table 10, 11 and 12 show the results from estimating Equation 11 on the whole sample. These results are reassuring. We note that all data patterns observed in the multi-bank sample are observed in the whole sample as well. First, both $Firmshock_{f,t}$ and $Indshock_{f,t}$ have their expected sign. This result is robust across almost all specifications, both with different outcomes and different controls.

As we progressively saturate the model with controls, the coefficients have greater magnitude and higher statistical significance, which reassures us that the results are not driven by unobserved firm heterogeneity.

A 1pp bank lending shock appears to have stronger effects in the whole sample than in the multi-bank sample. After controlling for region-time FEs, the coefficient for $Firmshock_{f,t}$ is negative and statistically significant at the 5% level. This is consistent with the argument that including single-bank firm is crucial to capture the full effect of bank lending shocks.

Table 13, 15 and 14 show the results from estimating Equation 12 on the whole sample. Again, we observe the same data patterns as in the multi-bank sample: stronger employment effects (+0.72%) are present for larger firms, while stronger sales effects (+1.26%) are present for firms operating in concentrated markets.

While the coefficients' magnitudes are similar across the two samples, accounting for single-bank firms improves their statistical significance. For instance, the coefficient for $Indshock_{f,t} \times (Size = Large)$ is significant at the 1% level in the whole sample.

We conclude that the results are not driven by excluding single-bank firms from our sample. On the contrary, consistent with the argument proposed by Degryse et al. (2019), accounting for these firms enhances their statistical significance.

7 Conclusions

This work explores a possible propagation channel for bank lending shocks - the industrial competition channel. Building on a simple conceptual framework, we propose a model in which a credit shock hitting a firm creates a competitive advantage for her competitors.

Consistent with this framework, we find that a 1pp shock in bank lending to a firm's competitors is associated with 0.44% higher capital accumulation rate for that firm; we also document smaller effects for employment and sales. This impact, however, is not significant at a 5% level, casting doubt that the industrial competition channel is a substantial mechanism in our main sample.

Instead, we find a stronger and significant effect on a subset of firms. We document that large firms operating in concentrated industries have stronger effects on sales (+1.34%) and employment growth (+0.71%), suggesting that an industrial competition channel could be at work for them. This finding has interesting implications: as large firms are better able to gain competitive advantage from their rivals' distress, credit shocks could have distributional implications.

We present evidence that both credit and market shares distribution became increasingly concentrated during the GFC, and show that the industrial competition channel hypothesis is consistent with the observed data. However, our data setting does not allow us to draw macroeconomic conclusions. Further work would be required to assess the aggregate relevance of this channel.

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Appendix

Table 9: Firm-Level Descriptive Statistics

	min	p25	p75	max	mean	sd
$Firmshock_{f,t}$	-59.04	-0.98	14.22	52.35	5.46	15.10
$FirmControl_{f,t}$	-552.61	-35.26	16.12	71.09	-37.22	117.99
$Indshock_{f,t}$	-46.61	1.69	7.46	41.14	4.47	4.57
$Indcontrol_{f,t}$	-549.09	-10.54	-0.86	70.39	-6.25	10.57
$\Delta log(Sales_{f,t})$	-9.85	-0.15	0.16	12.61	-0.01	0.52
$\Delta log(Capital_{f,t})$	-11.96	-0.21	0.08	17.04	0.01	0.65
$\Delta log(Employment_{f,t})$	-6.97	-0.06	0.09	6.16	0.01	0.33

Table 10: Effects on Capital Accumulation Rate (Whole Sample)

	Dependent Variable: $\Delta log(Capital_{f,t})$				
	(1)	(2)	(3)	(4)	(5)
$Firmshock_{f,t}$	0.0000675		-0.000118	-0.00156*	-0.00149*
	(0.000525)		(0.000555)	(0.000684)	(0.000680)
$Indshock_{f,t}$		0.00206	0.00218	0.00408	0.00383
		(0.00167)	(0.00177)	(0.00216)	(0.00203)
Observations	1397142	1397142	1397142	1397142	1397142
R-Squared	0.183	0.184	0.184	0.190	0.205
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	No
Region-Time FE	No	No	No	No	Yes
Credit Demand Controls	No	No	No	Yes	Yes

This table shows the effects on firm-level capital accumulation rate of 1 a pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

Table 11: Effects on Employment Growth (Whole Sample)

Dependent Variable: $\Delta log(Employment_{f,t})$					
	(1)	(2)	(3)	(4)	(5)
$Firmshock_{f,t}$	0.000274		0.000211	-0.000220	-0.000190
	(0.000235)		(0.000241)	(0.000259)	(0.000260)
$Indshock_{f,t}$		0.000961	0.000764	0.000190	0.0000354
		(0.00105)	(0.00109)	(0.00113)	(0.00111)
Observations	1397142	1397142	1397142	1397142	1397142
R-Squared	0.221	0.221	0.221	0.224	0.236
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	No
Region-Time FE	No	No	No	No	Yes
Credit Demand Controls	No	No	No	Yes	Yes

This table shows the effects on firm-level employment growth of a 1 pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

Table 12: Effects on Sales Growth (Whole Sample)

Dependent Variable: $\Delta log(Sales_{f,t})$					
	(1)	(2)	(3)	(4)	(5)
$Firmshock_{f,t}$	-0.000225		-0.000357	-0.000473	-0.000440
	(0.000593)		(0.000598)	(0.000624)	(0.000614)
$Indshock_{f,t}$		0.00119	0.00152	0.000569	0.000329
		(0.000636)	(0.000641)	(0.000690)	(0.000662)
Observations	1397142	1397142	1397142	1397142	1397142
R-Squared	0.182	0.182	0.182	0.183	0.194
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	No
Region-Time FE	No	No	No	No	Yes
Credit Demand Controls	No	No	No	Yes	Yes

This table shows the effects on firm-level sales growth of a 1 pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

Table 13: Heterogeneous Effects on Capital Accumulation Rate (Whole Sample)

	(1)	(2)	(3)
Dependent Variable: $\Delta log(Capital_{f,t})$			
$Indshock_{f,t} \times (HHI = q2)$	0.00707	0.00755	0.00681
	(0.00524)	(0.00514)	(0.00503)
$Indshock_{f,t} \times (HHI = q3)$	0.00965*	0.0106*	0.0103*
	(0.00477)	(0.00500)	(0.00468)
$Indshock_{f,t} \times (HHI = q4)$	0.00209	0.00273	0.00221
	(0.00317)	(0.00307)	(0.00307)
$Indshock_{f,t} \times (Size = Small)$	0.00730	0.00781	0.00790
	(0.00491)	(0.00566)	(0.00530)
$Indshock_{f,t} \times (Size = Medium)$	0.00001	0.000508	0.000484
	(0.00346)	(0.00384)	(0.00371)
$Indshock_{f,t} \times (Size = Large)$	0.00131	0.00236	0.00163
	(0.00321)	(0.00330)	(0.00325)
Observations	1397142	1397142	1397142
R-Squared	0.192	0.198	0.213
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	No
Region-Time FE	No	No	Yes
Credit Demand Controls	No	Yes	Yes

This table shows the heterogeneous effects on firm-level capital accumulation rate of a 1 pp bank lending shock hitting the firm's competitors ($Indshock_{f,t}$), conditional on both the firm's size and the quartile of HHI of the industry in which the firm operates. The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

Table 14: Heterogeneous Effects on Sales Growth (Whole Sample)

	(1)	(2)	(3)
	Dependent Variable: $\Delta log(Sales_{f,t})$		
$Indshock_{f,t} \times (HHI = q2)$	0.00679*	0.00736*	0.00554
	(0.00386)	(0.00399)	(0.00366)
$Indshock_{f,t} \times (HHI = q3)$	0.00635	0.00666	0.00700
	(0.00424)	(0.00446)	(0.00367)
$Indshock_{f,t} \times (HHI = q4)$	0.0131*	0.0132*	0.0126*
	(0.00539)	(0.00546)	(0.00488)
$Indshock_{f,t} \times (Size = Small)$	-0.00466	-0.00432	-0.00395
	(0.00428)	(0.00426)	(0.00412)
$Indshock_{f,t} \times (Size = Medium)$	-0.00574	-0.00420	-0.00338
	(0.00462)	(0.00462)	(0.00429)
$Indshock_{f,t} \times (Size = Large)$	-0.000648	0.000673	0.000943
	(0.00507)	(0.00504)	(0.00500)
Observations	1397142	1397142	1397142
R-Squared	0.226	0.228	0.239
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	No
Region-Time FE	No	No	Yes
Credit Demand Controls	No	Yes	Yes

This table shows the effects on firm-level sales growth of a 1 pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.

Table 15: Heterogeneous Effects on Employment Growth (Whole Sample)

	(1)	(2)	(3)
Dependent Variable: $\Delta log(Employment_{f,t})$			
$Indshock_{f,t} \times (HHI = q2)$	-0.000721	0.000239	0.00006
	(0.00215)	(0.00209)	(0.00199)
$Indshock_{f,t} \times (HHI = q3)$	-0.000383	0.000711	0.00144
	(0.00307)	(0.00290)	(0.00175)
$Indshock_{f,t} \times (HHI = q4)$	0.000308	0.00134	0.00138
	(0.00241)	(0.00244)	(0.00229)
$Indshock_{f,t} \times (Size = Small)$	0.00237	0.00215	0.00267
	(0.00212)	(0.00215)	(0.00196)
$Indshock_{f,t} \times (Size = Medium)$	0.00585*	0.00537*	0.00540*
	(0.00203)	(0.00208)	(0.00210)
$Indshock_{f,t} \times (Size = Large)$	0.00674**	0.00736**	0.00717**
	(0.00261)	(0.00269)	(0.00270)
Observations	1397142	1397142	1397142
R-Squared	0.248	0.252	0.265
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	No
Region-Time FE	No	No	Yes
Credit Demand Controls	No	Yes	Yes

This table shows the effects on firm-level employment growth of a 1 pp bank lending shock, both when hitting the firm itself ($Firmshock_{f,t}$) and her competitors ($Indshock_{f,t}$). The equations are estimated through WLS, with weights equal to $Credit_{f,t-1}$. Standard errors are clustered at the firm level.