NBER WORKING PAPER SERIES

ON THE DIRECT AND INDIRECT REAL EFFECTS OF CREDIT SUPPLY SHOCKS

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Working Paper 25458
http://www.nber.org/papers/w25458

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2019

We thank David Weinstein and Mary Amiti for kindly providing their codes and for comments and suggestions, Stéphane Bonhomme, Gabriel Chodorow-Reich, Sergio Correia, Julian Di Giovanni, Marco Di Maggio, Joseph G. Haubrich, Terry O'Malley, Victoria Ivashina, David Martinez-Miera, Friederike Niepmann, Jose Luis Peydro, Andrew Powell, Sergio Vicente, and participants in the First CEMFI - Banco de Espana Workshop, the MIT-Sloan seminar, the Federal Reserve Board seminar, the University of Barcelona seminar, the IADB seminar, the Kennedy School-LEP brown bag seminar, the UC3M seminar, the University of Groningen seminar, the Workshop on Financial Intermediation and Risk at the Barcelona GSE Summer Forum, the 1st Annual Workshop of the ESCB Research Cluster in Athens, the XX Workshop in International Economics and Finance in Buenos Aires, the III Winter Macroeconomics Workshop in Bellaterra, the Chicago Financial Institutions Conference, the Society for Economic Dynamics in Mexico, CEBRA-Frankfurt, and the 26th Finance Forum in Santander. An earlier version of this paper circulated under the title "Credit Supply Shocks, Network Effects and the Real Economy". The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 25458
January 2019
JEL No. E44,G21,L25

ABSTRACT

We consider the real effects of bank lending shocks and how they permeate the economy through buyer-supplier linkages. We combine administrative data on all firms in Spain with a matched bank-firm-loan dataset on the universe of corporate loans for 2003-2013 to identify bank-specific shocks for each year using methods from the matched employer-employee literature. We construct firm-specific exogenous credit supply shocks and estimate their direct and indirect effects on real activity using firm-specific measures of upstream and downstream exposure. Credit supply shocks have sizable direct and downstream propagation effects on investment and output throughout the period, especially during the 2008-2009 global financial crisis. In terms of mechanisms, trade credit extended by suppliers and price adjustments play a role in accounting for downstream propagation of financial shocks.

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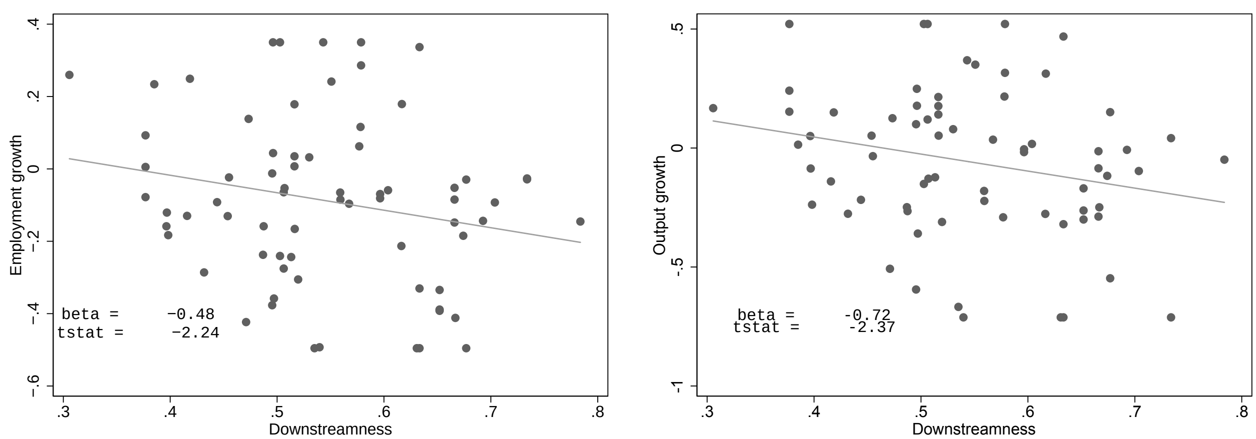
1 Introduction

In this paper we examine the real effects of the bank lending channel and how bank-lending shocks permeate the economy through buyer-seller interactions. Propagation through the production chain may substantially amplify the aggregate impact of bank lending shocks on real activity. We show that bank credit supply shocks do affect, and indeed permeate the real economy through input and output relations.

The Spanish economy witnessed an unprecedented boom-bust cycle over the 2003-2013 period, both in terms of real activity and credit. The correlation between the growth rate of credit to non-financial corporations and GDP throughout those different periods is 0.88, which points to strong feedback effects between both variables.[1] Interestingly, a simple look at the cross section of industries in Spain shows that employment and real output fell the most during the crisis in industries located downstream in the Spanish production network (see Figure 1). This implies that industries more dependent on suppliers were hit relatively more by the global financial crisis. Downstream propagation of the global financial shock rationalizes this negative association.

Figure 1: Downstreamness vs employment and output growth by industry



Notes. Output/Employment growth refers to the change in real value added/employment by industry over the 2006-2010 period. Downstreamness refers to the downstream position of each industry in the production chain. In particular, it is computed as the ratio of aggregate final direct use of industry's output to aggregate use of industry's output as an input. Some examples of high downstream industries are *Human Health Services* (0.75) and *Travel Agency, Tour Operator* (0.68). Some examples of low downstream industries are *Electricity Services* (0.38), *Warehousing and Support Services for Transportation* (0.39), and *Basic Metals* (0.44). See discussion in Alfaro, Antrás, Chor, and Conconi (Forthcoming).

We analyze the direct and indirect effects of credit supply shocks on Spanish firms' employment,

[1]See Section 2 for details on this correlation and Figure 3.

output, and investment over the 2003-2013 period. The exercise of quantifying the consequences of financial shocks on real variables and buyer-supplier (input-output) relations is very demanding. Firm firm-level data linking credit information to outcome variables (employment, investment, output, etc.) is required as well as a plausibly exogenous source of variation in credit growth.[2] To address this challenge, we identify bank-year-specific credit supply shocks through differences in credit growth between banks lending to the same firm as in Amiti and Weinstein (2018).[3] Importantly, we illustrate that the estimated shocks remain very similar when also accounting for bank-firm specific factors as shown by Amiti and Weinstein (2018).

We validate our bank-supply-shocks in several ways. First, we divide the sample into healthy and weak banks ones, as in Bentolila, Jansen, and Jimenez (2018).[4] We find that weak banks experienced stronger supply shocks until 2006 and weaker afterwards. We interpret this evolution as clear evidence favoring the plausibility of our estimated bank supply shocks. Second, if our identified bank-specific credit shocks capture meaningful supply factors, a bank that experiences a greater shock should grant more loans to a given firm, conditional on the firm applying for a loan. Using loan application information, available in the credit registry dataset, we show this to be the case.

To estimate the real effects of banks' credit supply shocks and their propagation through input-output linkages, we combine the Spanish Input-Output structure and firm-specific measures of downstream and upstream exposure. Based on di Giovanni, Levchenko, and Mejean (2018), we measure whether firms are indirectly affected by the fact that industries in which their suppliers operate are hit by the shocks (downstream effects). Similarly, we also measure whether firms that sell goods to industries whose firms are hit by the shocks are indirectly affected (upstream effects). Crucially, our dataset, which combines administrative data for all firms in Spain with matched bank-firm-loan information on the universe of corporate loans (Spanish Credit Registry, CIR), replicates to a nearly complete picture the Spanish economy.

We find both the direct effects and propagation effects on real variables to be sizable. Our es-

[2]An important concern in the literature has been identifying plausible exogenous shocks to disentangle the bank lending-channel (or bank-specific shock) from the firm borrowing-channel (i.e., a firm's ability, or lack thereof, to borrow from alternative sources). Firms may be able to undo a particular negative bank supply shock by resorting to another bank or other sources of funds. Kashyap, Stein, and Wilcox (1993) and Adrian, Colla, and Shin (2012) find that firms are able to substitute to other forms of credit in the presence of loan supply shocks. Klein, Peek, and Rosengren (2002) stress the difficulties of substituting loans from one bank with loans from another. Midrigan and Xu (2014) emphasize the role of self-financing; see Khwaja and Mian (2008), and Jimenez, Mian, Peydro, and Saurina (2014) for further discussion.

[3]To be more concrete, we use matched employer-employee techniques that enable us to recover multiple time-varying firm and bank fixed effects (see Abowd, Kramarz, and Margolis (1999)). This approach overcomes limitations faced by previous work that restricted analysis to smaller samples of firms or particular bank-specific supply shocks, such as the 2007 liquidity drought in interbank markets.

[4]Bentolila, Jansen, and Jimenez (2018) define weak banks as those that were bailed out by the Spanish government as part of the restructuring process during the financial crisis.

timates imply that a one standard deviation increase in firms' credit supply generates increases of 0.30 pp., 0.10 pp., and 0.80 pp. in the change of employment, output and investment, respectively. In terms of the indirect effects, our estimates corroborate the importance of downstream propagation from suppliers to customers in quantifying the real effects of credit shocks. A one standard deviation increase in our downstream effects measure (how much firms buy inputs from industries in which credit supply expands) generates increases of 0.30 pp., 0.35 pp., and 0.69 pp. in the change of employment, output and investment. In contrast, evidence of the importance of the upstream propagation shock from customers to suppliers is mixed, in terms of both the significance and size of the effect. Finally, it is worth highlighting that our estimates point to significantly larger effects around the Global Financial Crisis.

In order to rationalize the downstream propagation of credit supply shocks we explore the role of two possible mechanisms, namely, trade credit and price adjustments in general equilibrium. Trade credit chains provide a channel through which credit shocks can propagate downstream. Affected suppliers, for example, may reduce the trade credit offered to their customer firms which might then cut production if they are financially constrained (Kiyotaki and Moore (1997)). Indeed, Costello (2017) documents that U.S. firms more exposed to a large decline in bank lending during the Global Financial Crisis reduced substantially the trade credit extended to their customers. In order to explore this mechanism, we include in our regressions accounts payable (trade credit received from suppliers) and find that our downstream coefficient decreases in magnitude but remains significant and quantitatively relevant. We thus conclude that trade credit adjustment plays a significant role but it is not able to explain our estimated downstream propagation of credit shocks.

Another possible channel of propagation is through changes in relative prices. A negative credit shock to a particular supplier/industry may induce an increase in the price of its product affecting customer decisions (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)). If a firm gets hit by a negative credit supply shock, its relative supply will fall, implying a higher price of the good produced by this firm in equilibrium. This will imply a higher production cost for this firm's customers, which will end up reducing their demand for the good produced by the affected firm and decreasing their total output. In order to check whether this channel is empirically plausible, we first construct changes in price indexes between 2007 and 2010 for several Spanish industries and correlate them with our estimated direct and downstream shocks. As predicted by the standard GE models with IO linkages, we find that industries that were hit harder by negative direct and indirect shocks suffered higher increases in their price indexes.

To further evaluate the extent to which the Spanish production structure may have amplified the effects of our estimated financial shocks, we quantify the aggregate impact of the price adjustments channel by using a general equilibrium model with buyer-supplier relations under the presence of financial frictions, as in Bigio and La'o (2017). The model predicts, for instance, that during the financial crisis, -0.60 pp. of annual employment growth between 2009 and 2010 was due to a negative credit supply shock (actual growth was -3.28%), with -0.29 pp. due to direct effects, and -0.31 pp. to propagation effects. Finally, we use the model to investigate the relative importance of each sector in accounting for the aggregate effects during the financial crisis period. In particular, we compute counterfactual economies in which we only shock one industry at a time. Perhaps not surprisingly, we find that the sector that generates the highest output drop is the real estate sector. Our model predicts that shocking just the real estate sector would generate an aggregate output loss of 0.24%. While being particularly hit by the credit supply shock at the time of the crisis, the real estate is intensively used by other sectors. Indeed, we find that shocking other central sectors, such as electricity services and wholesale, also generated large output losses.

Related Literature: Our paper contributes to the research that identifies the economic effects of credit supply shocks by isolating the bank lending channel. Papers in this strand include Khwaja and Mian (2008), Chodorow-Reich (2014), Jimenez, Mian, Peydro, and Saurina (2014), Greenstone, Mas, and Nguyen (2015), Cingano, Manaresi, and Sette (2016), and Bentolila, Jansen, and Jimenez (2018). In relation to this literature, instead of observed supply shocks (e.g., liquidity in Khwaja and Mian (2008) or Huber (Forthcoming), securitization in Jimenez, Mian, Peydro, and Saurina (2014), or higher capital requirements in Blattner, Farihan, and Rebelo (2017)), we estimate time-variant bank credit shocks and study their real effects on employment, output, and investment. Employment effects, for example, substantially differ during the expansion period and the financial crises.[5] We also contribute to this strand of the literature by considering the propagation of bank lending shocks through input-output linkages.

Methodologically, our paper is closest to Amiti and Weinstein (2018). The authors estimate the direct effect of credit supply on firms' investment by exploiting a sample of around 150 banks and 1,600 listed firms in Japan over a 20-year period (1990-2010). By using methods from the matched employer-employee literature, we are able to estimate year-by-year supply shocks for a broader sample (more than 200 banks and demand shocks for more than 700,000 firms). As our data covers the quasi-population of Spanish firms, aggregation bias is less of a concern.[6]

[5] Greenstone, Mas, and Nguyen (2015) and Gilchrist, Siemer, and Zakrajsek (2018) find small or no effect of credit supply shocks during the boom period in the United States. Our analysis, similarly to their work, expands the sample beyond the Global Financial Crisis while including all firms in the economy, including small and medium-size firms. Their identifications strategy exploits geographical differences in the origin of business lending- loans (Greenstone, Mas, and Nguyen (2015)) or mortgages (Gilchrist, Siemer, and Zakrajsek (2018)).

[6] Amiti and Weinstein (2018) methodology also accounts for general equilibrium constraints such that micro and macro features of the data are mutually consistent. In particular, aggregation of their estimated bank- and firm-specific shocks exactly replicates the aggregate evolution of credit (even accounting for new lending relationships).

In terms of literature on the importance of input-output linkages, Acemoglu, Akcigit, and Kerr (2016) quantify the propagation effects of different types of supply and demand shocks, relying on instrumental variables for identification, showing their transmission effects to the aggregate economy to be of first order importance. Our paper contributes to this literature by investigating the effects of a well defined shock, that is, firm-level credit supply shocks, and quantify the direct and indirect effects on other firms through connections in the production network.[7] Recent work also investigates the role of propagation in accounting for the effects of financial shocks. Dewachter, Tielens, and Hove (2017), using mostly single bank-firm relations in Belgium and exploiting value added information, analyze the propagation effects of shocks. Demir, Javorcik, Michalski, and Ors (2018) show that a negative shock to the cost of import financing of liquidity constrained firms gets propagated to their customers. Giannetti and Saidi (2017) analyze the extent to which the propagation of credit market shocks depends on the structure of the banking system and the lenders' share of the loans outstanding in an industry.

Turning to the mechanisms explaining propagation of financial shocks through buyer-seller relations, Costello (2017) documents that firms with greater exposure to a large decline in bank lending reduced the trade credit extended to their customers resulting in negative effects on their real outcomes. Trade credit may also explain upstream propagation of financial shocks if debtor (customer) failure triggers supplier's losses through both credit losses and demand shrinkage (see for instance Jacobson and Schedvin (2015)). While we provide evidence in favor of the downstream propagation mechanism in Costello (2017), it does not explain the whole effect of our estimates.

Price and quantity adjustments in general equilibrium may also play a role as shown in a series of recent papers that have investigated the aggregate effects of shocks that propagate through the economy's IO network, such as Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). Our paper relates to recent work by Bigio and La'o (2017), who quantify the effects of financial shocks in a general equilibrium model in which industries are connected through the IO network. Instead of credit spreads, we use credit registry data to identify financial shocks at the firm level. We then aggregate these shocks at the industry-level to show that industries experiencing negative financial shocks suffered higher price increases, and use the model to quantify the implied aggregate effects over time.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 disentangles the banking-lending channel from the firm-borrowing channel and discusses the empirical specification. Section 4 presents the direct real effects of the bank lending shocks as well as our

[7] A series of papers in the literature have exploited natural disasters as exogenous shocks, finding input-output propagation to account for sizable effects, see Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016), Barrot and Sauvagnat (2016) and Boehm, Flaaen, and Pandalai-Nayar (2016).

estimates for downstream and upstream propagation effects of the credit shocks. Section 5 explores the mechanisms rationalizing our main findings and quantifies the aggregate effects of the credit shocks. Section 6 concludes.

2 Data

We use three data sets: loan-level data on credit in the domestic banking sector from the Central Credit Register (CIR) of Banco de España, administrative data on firm-level characteristics from the Spanish Commercial Registry, and IO tables provided by the INE ("Instituto Nacional de Estadística").

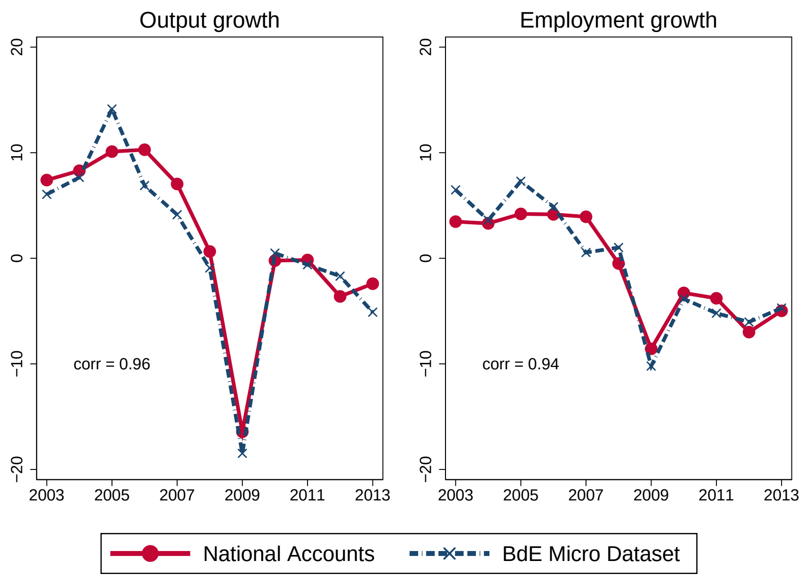
Credit Registry The Central Credit Register (CIR), maintained by the Bank of Spain in its role as primary banking supervisory agency, contains detailed monthly information on all outstanding loans exceeding 6,000 euros granted to non-financial firms by all banks operating in Spain since 1984. Given the low reporting threshold, virtually all firms with outstanding bank debt appear in the CIR.

The CIR identifies the parties involved in each loan, enabling us to match loan-level data from CIR with administrative data on firm-level characteristics. While the CIR data are available at the monthly frequency, firm-level characteristics are only available on a yearly basis. Therefore, we collapse the monthly loan-level data to the annual frequency in order to merge the two datasets. At the monthly level, each bank-firm relationship is understood as a loan by aggregating all outstanding loans from each bank-firm-month pair. Annual bank-firm credit exposure is computed as the average value of monthly loans between bank i and firm j. We end up with a bank-firm-year database covering 12 years from 2002 to 2013, 235 banks, 1,555,806 firms, and 18,346,144 bank-firm-year pairs (our so-called loans). Multibank firms represent nearly 75% of bank-firm-year relationships.

The CIR also contains loan application data. Banks receive borrower information (e.g. total indebtedness or defaults) from the CIR monthly. Because banks can obtain this information for any firm that makes a genuine attempt to secure credit, any requested information from a bank about a given firm can be interpreted as a loan application. Matching the monthly records on loan applications with the stock of credit enables us to infer whether a loan materialized. If not, either the bank denied it or the firm obtained funding elsewhere. We use this information in Section 3.1.2 to validate our estimated bank-specific credit shocks.

Quasi-Census Administrative Data For firm-level characteristics, we use administrative data from the Spanish Commercial Registry, which contains the balance sheets of the universe of Spanish companies which firms are legally obliged to report.[8] Included, among other variables, is information on: name, fiscal identifier; sector of activity (4-digit NACE Rev. 2 code); 5-digit zip code location; annual net operating revenue; material expenditures (cost of all raw materials and services purchased by the firm for the production process); number of employees, labor expenditures (total wage bill including social security contributions); and total fixed assets.

Figure 2: Micro-aggregated output and employment growth



Our final sample includes balance sheet information for 1,801,955 firms, with an average of 993,876 firms per year. The firm-level database covers 85%-95% of firms in the non-financial market economy for all size categories in terms of both turnover and number of employees. Moreover, the correlation between micro-aggregated employment (and output) growth and the National Accounts counterparts is approximately 0.95 over the 2003-2013 period (see Figure 2). Almunia, Lopez-Rodriguez, and Moral-Benito (2018) provide an in-depth analysis of this database.

Input-Output Tables We use the Input-Output tables provided by INE and constructed at the 64-industry-level of disaggregation (see Table J.1 for a list of industries). In order to use the most detailed IO that is available, and because prior year IO tables rely on an industry classification different from that used in our firm-level data, we use the IO table provided for the year 2010 throughout

[8]We combine two databases independently constructed from the Commercial Registry, Central de Balances Integrada (CBI) from the Banco de España and SABI (Spain and Portugal Business Registry). The resulting database, which includes approximately 1,000,000 firms in each year from 2000 to 2013, is available only to researchers undertaking projects for the Banco de España.

the paper.[9] Some examples of industries that are used intensively by many other industries (central sectors) are *Real Estate Services (44)*, *Wholesale (29)*, *Electricity Services (24)*, *Security and Investigation Services; Services to Buildings and Landscape; Office Administrative, Office Support and Other Business (53)* or *Basic Metals (15)*.

Time Coverage To explore whether the real effects of credit supply shocks might vary depending on the state of the economy, we divide the sample into three sub-periods: 2003-2007 (*expansion*), 2008-2009 (*financial crisis*), and 2010-2013 (*recession*). This division is based on the FRED recession indicators. We think of 2003-2007 as a boom-expansion era of easy access to credit, 2008-2009 as a crisis period driven by the collapse of the banking sector during the Global Financial Crisis, and 2010-2013 as the post crisis period of sluggish recovery but still under recession of the Spanish economy.[10]

As mentioned, Figure 3 shows a strong correlation between bank credit and real variables during these periods. As noted in the introduction, an investigation of the link between credit shocks and real variables, however, poses several challenges. Crucial steps taken to address these challenges are discussed in the next sections.

3 Identification Strategy and Empirical Models

In this section, we first estimate bank-specific credit supply shocks by exploiting the richness of our dataset. We also discuss various ways in which we validate the estimated shocks in 3.1.1 and 3.1.2. Armed with the identified credit supply shocks, Section 3.2 presents the empirical model considered to estimate the real effects of credit shocks, both direct and indirect. Note also that Appendices A and B quantify the impact of bank lending shocks on credit at the loan- and firm-level, respectively.

3.1 Estimating Bank-Specific Credit Supply Shocks

Consider the following decomposition of credit growth between bank i and firm j in year t:

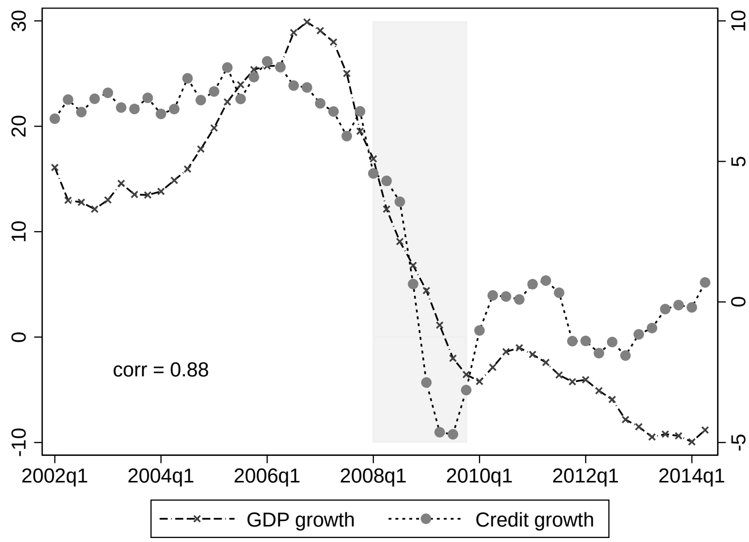
$$\Delta \ln c_{ijt} = \delta_{it} + \lambda_{jt} + \epsilon_{ijt} \tag{1}$$

where c_{ijt} refers to the yearly average of outstanding credit of firm j with bank i in year t. δ_{it} and λ_{jt} can be interpreted as supply and demand shocks, respectively, and δ_{it} captures bank-specific effects

[9]Measured at a higher industry-level of disaggregation, we can show that input-output tables in Spain have remained quite stable over time.

[10]Financial crises tend to be characterized by deep recession and slow recovery (Reinhart and Rogoff (2009)). The evolution of the Spanish economy broadly fits this pattern.

Figure 3: Credit and output growth in Spain



Notes. Credit (on the left-scale) refers to bank credit to non-financial corporations taken from Banco de España and output (on the right scale) refers to nominal GDP taken from the National Statistics Institute (INE). The shaded area represents the *financial crisis* (2008-2009) period.

identified through differences in credit growth between banks lending to the same firm.[11]

Imagine one firm and two banks in year $t-1$. If the firm's credit grows more between $t-1$ and t with the first bank, we assume credit supply of the first bank to be larger than that of the second bank. This is because demand factors are held constant by the inclusion of firm-specific effects (λ_{jt}). This identification strategy resembles that of the bank lending channel by Khwaja and Mian (2008), but instead of considering observed bank supply shocks (e.g., liquidity shocks), we consider unobserved shocks estimated by means of bank-specific effects. Finally, ϵ_{ijt} captures other shocks to the bank-firm relationship assumed to be orthogonal to the bank and firm effects. Note that this identification scheme implies reliance on multi-bank firms, which represent approximately 75% of the bank-firm-year relationships in our sample.

We resort to matched employer-employee techniques (see Abowd, Kramarz, and Margolis (1999)) in order to estimate the model.[12] Given the sparsity of typical matrices involved in the estimation

[11]Since the credit registry data has a monthly frequency, we could estimate equation (1) with quarterly or even monthly data. Using annual data allows us to have have more firms per bank and better estimate the bank effects. However, using quarterly/monthly data, allows to better control for demand shocks because firm effects are allowed to vary within a year. With this trade-off in mind, we have finally decided to use annual data in order to merge the estimated effects with the dataset on firm-level characteristics available at a yearly frequency.

[12]Consistent with the matched employer-employee methods, banks and firms in our data correspond to firms and workers in typical matched employer-employee panels. Also, for each firm in our data we have the number of banks as the time dimension in standard matched employer employee datasets.

of high-dimensional fixed effects, the methods used in this literature consider an efficient storage of these matrices in compressed form so that the "FEiLSDVj" approach —combining fixed-effects (FE) and the least-squares dummy variable (LSDV)— is feasible with standard computers (see for instance Cornelissen (2008)).[13]

Turning to identification, the bank- and firm-effects are identified only in relative terms within each *group*.[14] A *group* is understood to be a set of banks and firms connected such that that the *group* contains all firms that have a credit relationship with any of the banks, and all banks that provide credit to at least one firm in the *group*. In contrast, a *group* of banks and firms is not connected to a second *group* if no bank in the first group provides credit to any firm in the second *group*, nor any firm in the first *group* has a credit relationship with a bank, in the second *group*. In practice, we identify 11 groups in our data using the algorithm in Abowd, Creecy, and Kramarz (2002). Each *group* corresponds to a calendar year in our data because all firms and banks are connected within a year but there are neither banks nor firms connected across years. Therefore, the estimated shocks depend not only on this bank's credit supply evolution but also on the credit supply of the omitted category/bank. In section 5.2, we present a methodology for interpreting the evolution of the effects. In Appendix C we also discuss an approach that allows identifying a time varying indicator of aggregate credit supply. This methodology estimates bank-specific time trends but does not identify bank-year fixed effects required to isolate time-varying credit supply shocks.

3.1.1 Threats to Identification

A concern when using equation (1) is that it does not allow for bank-firm-time interactions. As noted by Jimenez, Mian, Peydro, and Saurina (2014) and Paravisini, Rappoport, and Schnabl (2017), these interactions may be relevant in the context of bank-lending specialization. That is, an implicit assumption in this strategy is that firms' credit demand is the same for all lenders, and thus firm-time fixed effects (λ_{jt}) account for demand effects. However, in our case, three points alleviate this concern.

First, Amiti and Weinstein (2018) show that the bank-time fixed effects estimated from equation (1) are identical to those resulting from a specification accounting for bank-firm-time-specific factors (see Amiti and Weinstein (2018) for a formal proof). As they explain, although bank-firm interac-

[13] A common approach for estimating the model in (1) is to include the bank effects as dummy variables and to sweep out the firm effects by the within transformation, typically labeled "FEiLSDVj" because it combines the fixed-effects (FE) and the least-squares dummy variable (LSDV) methods. The dimension of our dataset contains 24,490,973 bank-firm-year observations and 2,820 bank-years. Assuming that one cell of the data matrix consumes 8 bytes, storing the matrix of bank dummies would consume 552 GB, making the problem computationally intractable. This is the case when working in high-precision mode in STATA.

[14] To be more concrete, we fix the omitted category to be BBVA, so that individual bank dummies can be interpreted relative to BBVA.

tions enable us to understand a particular firm's demand, bank and firm shocks can be consistently estimated from equation (1). Intuitively, the effect of bank-firm-year factors is only identifiable if some component is orthogonal to the bank- and firm-year fixed effects, and this orthogonal variation is precisely the one identified in our bank-year fixed effects.

Second, our estimates, as demonstrated in Amiti and Weinstein (2018), remain broadly unaltered when accounting for idiosyncratic bank-firm-year factors in equation (1), as discussed in Appendix A for the effects on credit as well as in the robustness section 4.3 for the effects on real outcomes. Along these lines, specialization in housing by some banks may be a source of concern in the presence of firm attachment to those banks given the housing boom and bust cycle experienced by the Spanish economy. However, our findings are robust to the exclusion of construction and real estate firms from the sample (see also Section 4.3).

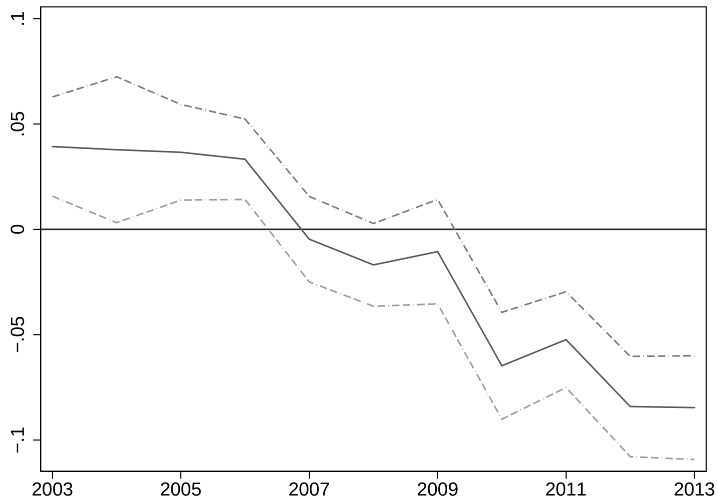
Third, at the frequency of our analysis, the variation in maturity at the bank-firm level in our data is mostly explained by variation across firms for a given bank (59%) while the variation across banks for a given firm explains very little (7%) of the total variation. We interpret this pattern as an indication that firms' loans characteristics are similar across banks, at least in terms of maturity, so the assumption of firms' constant credit demand across banks is not sharply at odds with our data.

3.1.2 Validating the Bank-specific Credit Supply Shocks

We provide further validation of the estimated credit supply shocks. First, in order to assess the plausibility of the $\hat{\delta}_{it}$ estimates, we divide our sample into healthy and weak banks, as in Bentolila, Jansen, and Jimenez (2018). Figure 4 shows the time evolution of the average difference in credit supply shocks between healthy and weak banks as identified by the bank dummies ($\hat{\delta}_{it}$). Weak banks had higher supply shocks until 2006 and lower ones afterwards, which coincides with the narrative in Bentolila, Jansen, and Jimenez (2018). We interpret this evolution as clear evidence in favor of the plausibility of our estimated bank supply shocks.

We also validate our estimates as follows. If our identified bank-specific credit shocks capture supply factors, a bank with a larger dummy ($\hat{\delta}_{it}$) should grant more loans to the same firm. Loan application data enables us to test this hypothesis. We regress a loan granting dummy on the estimated bank shocks and a set of firm fixed effects to account for demand factors. As mentioned above, the identification of our bank-year dummies relied on multi-bank firms. However, the firms used in this validation exercise cannot have any credit exposure to the banks in the regression used to estimate the bank-year shocks as otherwise they would not be observed in the loan application data. The bank-firm pairs exploited in this exercise are thus not used in the identification of the bank dummies in (1). In particular, for each year from 2003 to 2013, we run the following regression:

Figure 4: Average difference in bank supply shocks (weak - healthy)



Notes. This plot is based on year-by-year regressions of the estimated bank-level shocks on a constant and a dummy that takes value of one if the bank is classified as "weak" in Bentolila, Jansen, and Jimenez (2018). For each year, we plot the coefficient on the weak bank dummy, which estimates the average difference in supply shocks by type of bank (weak or healthy).

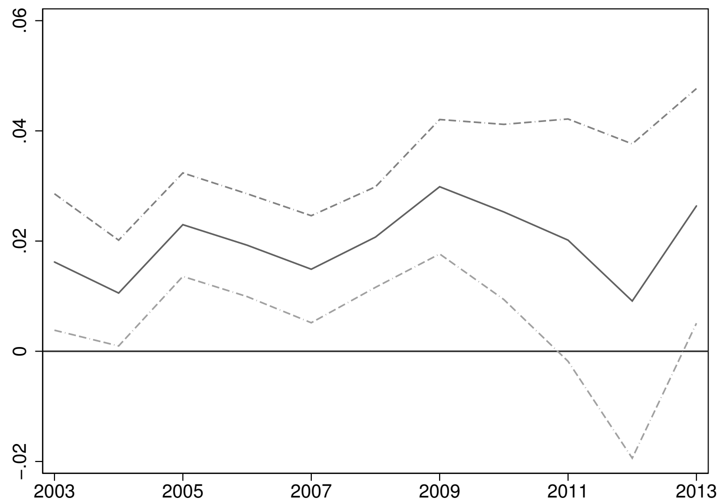
$$\text{Loan granted}_{ij} = \gamma\hat{\delta}_i + \lambda_j + \epsilon_{ij} \tag{2}$$

where Loan granted$_{ij}$ is a dummy variable taking the value 1 if firm j has at least one loan granted by bank i (conditional on having applied for a loan) and zero if no loans originated from loan applications from firm j to bank i. $\hat{\delta}_i$ refers to our estimated bank supply shock for bank i, and λ_j captures firm-specific effects to account for demand. The γ parameter captures the effect of credit supply shocks on the probability of loan acceptance. A positive and significant estimate can be interpreted as evidence that our bank dummies capture credit supply. Intuitively, a firm applying to two different banks—with no previous credit relationship with the firm—has a higher probability of securing the loan from the bank with the larger bank dummy if γ is positive. Figure 5 plots the estimated γ coefficient for each year. The effect of the bank-specific shocks is positive and significant in all years, which we interpret as further evidence of the validity of our identified bank supply shocks.

Following Amiti and Weinstein (2018), we further explore how well our predicted bank's credit growth explains the bank's actual credit growth. Specifically, we compute the R-squared of a regression of the banks' actual credit growth ($\Delta \ln c_{it}$) on the bank's credit growth predicted by our model ($\Delta \hat{\ln} c_{it}$).[15] The R^2 for the entire 2003-2013 period is 52%, which indicates that the estimated bank-

[15]We construct $\Delta \hat{\ln} c_{it}$ as a weighted average of the change in credit at the bank-firm (loan) level, where weights

Figure 5: Effect of the bank shocks on loan granting



Notes. This plot is based on year-by-year regressions of the loan granted dummy on the bank-level dummies and a set of firm fixed effects. The γ parameter plotted estimates the effect of the bank dummies on the probability of acceptance of a loan request. Standard errors are clustered at the bank level.

and firm-specific effects explains a significant fraction of the variation in bank lending as illustrated in Figure 6. Note that Figure 6 refers to the intensive margin without including new lending relationships from both credit growth variables, $\Delta \ln c_{it}$ and $\Delta \hat{\ln} c_{it}$. Indeed, the R-squared drops to 30% when including the extensive margin in actual credit growth. All in all, the estimated R^2s are relatively large in both cases.[16]

3.2 Empirical Specifications

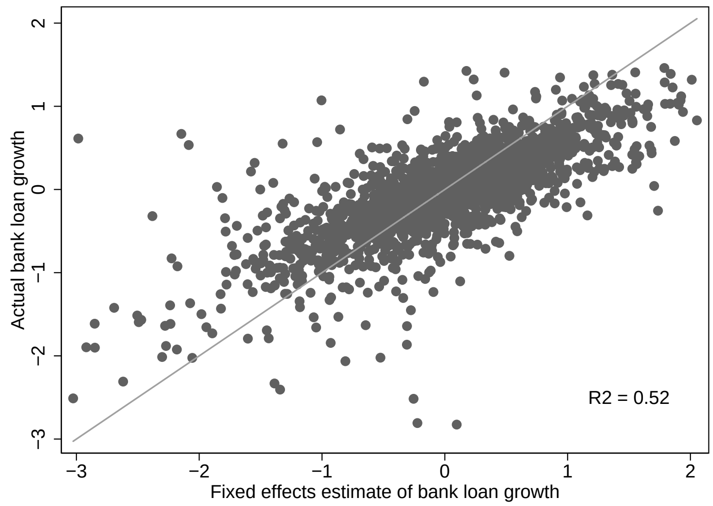
We now discuss the specification used to estimate the real effects of the identified credit supply shocks. To estimate the effects of the bank lending channel on real outcomes, we match the credit registry information with annual, firm-level administrative data on different firm characteristics. We consider the effects of credit supply on firms' annual employment and output growth as well as investment as follows:

$$Y_{jt} = \theta \overline{\delta}_{jt} + \pi X_{jt} + \nu_{jt} \tag{3}$$

are computed as the amount of credit extended to firm j by bank i as a fraction of total credit granted by bank i (computed in $t-1$): $\Delta \hat{\ln} c_{it} = \sum_j \frac{c_{ijt-1}}{\sum_j c_{ijt-1}} \Delta \hat{\ln} c_{ijt}$ where $\Delta \hat{\ln} c_{ijt} = \hat{\delta}_{it} + \hat{\lambda}_{jt}$.

[16] In any case, they are significantly lower than those in Amiti and Weinstein (2018), which are equal to one by construction.

Figure 6: Explanatory power of our estimated shocks



Notes. This graph plots the relationship between the bank's actual credit growth ($\Delta \ln c_{it}$) (y-axis) and that predicted by our estimates ($\Delta \hat{\ln} c_{it}$) (x-axis). $\Delta \hat{\ln} c_{it}$ is constructed as a weighted average of the change in credit at the bank-firm (loan) level, where weights are computed as the amount of credit extended to firm j by bank i as a fraction of total credit granted by bank i (computed in $t-1$): $\Delta \hat{\ln} c_{it} = \sum_j \frac{c_{ijt-1}}{\sum_j c_{ijt-1}} \Delta \hat{\ln} c_{ijt}$ where $\Delta \hat{\ln} c_{ijt} = \hat{\delta}_{it} + \hat{\lambda}_{jt}$.

where Y_{jt} refers to annual employment growth (in terms of log differences of number of employees), annual output growth (in terms of log differences of Euros), or investment (capital stock in year t minus capital stock in year $t-1$ as a share of total capital stock in t) of firm j in year t.[17] Also, X_{jt} represents a vector of firm-specific characteristics including the firm-specific credit demand shocks ($\hat{\lambda}_{jt}$) as well as size dummies, lagged loan-to-assets ratio, and lagged productivity. Finally, we also include a set of sector $\times$ year dummies.[18]

Finally, $\overline{\delta}_j$ represents a firm-specific credit supply shock constructed as a weighted average of the supply shocks estimated for all banks in a relationship with firm j. The weights are given by the share of credit of each bank with this firm in the previous period:

$$\overline{\delta}_{jt} = \sum_i \frac{c_{ij,t-1}}{\sum_i c_{ij,t-1}} \hat{\delta}_{it} \tag{4}$$

Crucially, firms not directly hit by a credit supply shock may be affected through buyer-supplier relations. For instance, if a supplier of firm j is hit by a negative credit supply shock, the reaction

[17]Results considering $\Delta \ln(1+E_j)$ and $(E_j - E_{j,-1})/(0.5 \times (E_j + E_{j,-1}))$ as dependent variables remain unaltered. These alternative definitions are considered by Bentolila, Jansen, and Jimenez (2018) and Chodorow-Reich (2014), respectively.

[18]Note that our main findings remain robust when separately including sector and year fixed effects (to conserve space these estimates are left unreported).

of this supplier may also affect production of firm j. Indeed, the negative association between employment growth and downstreamness depicted in Figure 1, as mentioned in the introduction, resembles this pattern.[19]

We exploit our firm-level information combined with input-output linkages relations to study the propagation effects of our identified bank-credit supply shocks. Specifically, following di Giovanni, Levchenko, and Mejean (2018), we combine firm-specific measures of usage intensity of material inputs and domestic sales with the sector-level Input-Output matrix, as in Alfaro, Antràs, Chor and Conconi (2017).[20] We use IO relations for Spain for both propagation downstream (i.e., shocks from suppliers) and upstream (i.e., shocks from customers). In practice, we include two additional regressors in the empirical model in (3) to capture the indirect effects of credit shocks through input-output relations.

Provided credit supply shocks have direct real effects (see below), if a negative credit supply shock hits firms operating in a given industry, the production in this industry will decrease. Viewed through the lens of standard general equilibrium models with IO linkages, the fall in production will be associated with an increase in the price of the directly affected industry. Customer firms will then be forced to decrease production. $DOWN_{jt,s}$, a proxy for this effect, measures the indirect shock received by firm j operating in sector s from its suppliers (downstream propagation). In addition, when a negative credit supply shock hits firms operating in a given industry, their revenue and, hence, their demand for intermediate goods, is likely to go down. This will affect their supplier industries, which will be forced to scale down production. $UP_{jt,s}$ proxies for this indirect shock received by firm j operating in sector s from its customers (upstream propagation).

To be more concrete, we define these proxies as follows:

$$DOWN_{jt,s} = \omega_{jt}^{IN} \sum_{p} IO_{ps} \Delta_{jt,p} \tag{5}$$

$$UP_{jt,s} = \omega_{jt}^{DO} \sum_{p} IO_{sp} \Delta_{jt,p} \tag{6}$$

where s and p index sectors, and firm j belongs to sector s. $\Delta_{jt,p}$ is the credit supply shock hitting sector p computed as a weighted average of firm-specific shocks ($\overline{\delta}_{jt}$) using credit exposure as weights. Note that this shock is firm-specific because firm j is excluded from the computation of sector-specific

[19]Employment losses during the global financial crisis were larger in those industries more dependent on suppliers (higher downstreamness). This type of indirect effects of credit supply shocks can operate through different channels, from purchases/sales of intermediate inputs by the directly hit firms to changes in factor and goods prices.

[20]di Giovanni, Levchenko, and Mejean (2018) construct proxies for indirect linkages between French firms and foreign countries inspired by the propagation terms in Acemoglu, Akcigit, and Kerr (2016). Alfaro, Antràs, Chor, and Conconi (forthcoming) use input-output linkages to establish upstream and downstream relations.

shocks in the case that $s = p$. IO_{ps} is the domestic direct requirement coefficient of the 2010 Spanish Input-Output matrix, defined as the share of spending on domestically-produced sector p inputs for production in sector s. Finally, ω^{IN}_{jt} refers to total input usage intensity of firm j in year t, defined as the total material input spending divided by material input spending plus wage bill and ω^{DO}_{jt} domestic sales intensity, defined as the domestic market share of firm j's sales, that is total sales minus exports divided by total sales.

Armed with these indirect credit supply shocks, we estimate the following empirical model:

$$Y_{jt} = \theta\bar{\delta}_{jt} + \theta_D DOWN_{jt,s} + \theta_U UP_{jt,s} + \pi X_{jt} + \nu_{jt} \tag{7}$$

where all elements are defined as in equations (3), (5), and (6).[21]

4 Results

In this Section, we first present the baseline results for direct and indirect real effects of credit shocks (subsection 4.1). Then, we show the estimated effects for different subperiods in subsection 4.2 and discuss several robustness exercises in subsection 4.3.

4.1 Baseline Estimates

Table 1 presents our baseline estimates for the direct and indirect effects for the 2003-2013 period on employment growth, output growth, and investment.

Direct Effects: Table 1 (columns (1)-(3)) reports the results of estimating equation (3) for the 2003-2013 sample. Column (1) reports the results using employment changes of firm j in year t as the left hand side variable Y_{jt}. Columns (2) and (3) use output changes and investment instead.

We find positive and statistically significant effects of credit supply shocks across all specifications, and all estimated coefficients are significant at 1%. Our estimated coefficients are also economically sizable. Let us focus first on discussing the magnitude of the estimated coefficients for employment. Our estimates from columns (1) imply that a one standard deviation increase in the firm's credit supply shock is associated with increases in firm employment growth of around 0.29 percentage points. These number represents approximately 93% of the average firm-level annual employment

[21] It is worth highlighting that our main conclusions are robust when (1) separately including sector and year fixed effects instead of sector × year as in our baseline specification and (2) including the shares of domestic sales (not interacted) as a control. For the crisis period (2007-09), the estimated direct and indirect downstream effects are 0.477 (se 0.156) and 0.665 (se 0.257) in the former case, and 0.475 (se 0.165) and 0.852 (se 0.490) in the latter.

Table 1: Direct and Indirect real effects of credit shocks

	Direct			Direct + Indirect		
	Employment	Output	Investment	Employment	Output	Investment
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Shock	0.292***	0.103***	0.802***	0.284***	0.107***	0.798***
(s.e.)	(0.097)	(0.030)	(0.069)	(0.098)	(0.029)	(0.075)
DOWN				0.301**	0.354***	0.690***
(s.e.)				(0.119)	(0.069)	(0.174)
UP				0.061	0.209***	0.174
(s.e.)				(0.120)	(0.077)	(0.209)
# obs	4,064,376	3,873,003	3,938,238	3,827,042	3,744,353	3,737,540
# banks	216	216	216			
# firms	812,067	779,500	782,872			
R2	0.050	0.057	0.028	0.053	0.067	0.030
Sample firms	All	All	All	All	All	All
Fixed effects	sector × year	sector × year	sector × year	sector × year	sector × year	sector × year

Notes. This table reports the effect of credit supply shocks on employment (columns (1) and (4)), output (columns (2) and (5)), and investment (columns (3) and (6)) estimated using equation (3) (direct effects, columns (1)-(3)) and equation (7) (indirect effects, columns (4)-(6)) for the 2003-2013 period. The dependent variables are employment growth in %, output growth in %, and investment as a share of capital stock. *Credit Shock* refers to the firm-specific credit supply shock estimated in equation (4), normalized to have zero mean and unit variance. DOWN and UP have been constructed according to equations (5) and (6) respectively. All regressions include the following control variables: firm-specific credit demand shocks ($\hat{\lambda}_{jt}$), size dummies, lagged loan-to-assets ratio, and lagged productivity. We denote significance at 10%, 5%, and 1% with *, **, and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

growth rate of 0.31% over the 2003-2013 period.[22]

With respect to output, the estimated coefficients reported in column (2) implies that a one standard deviation increase in firm credit supply shock is associated with an average increase in firm output growth of around 0.10 pp., approximately 20% of the observed firm-level annual value added growth of 0.5% over the same period.

When looking at investment, the estimated coefficients reported in column (3) implies that a one standard deviation increase in firm credit supply shock is associated with an increase in firm investment of 0.80 pp. This number represents 10% of the average observed investment rate over the 2003-2013 period. Finally, it is worth highlighting that these effects are quantitatively and statistically significant for small- and medium-sized firms while effects for larger firms are not statistically significant.[23]

[22]Average firm-level annual growth refers to the simple average of the change of a variable as measured in our final sample of firms for a particular period. These are the variables that we refer to when comparing the size of our estimates throughout this section.

[23]Appendix G reports the real effects estimated for firms of different size.

Indirect Effects: We also find strong evidence of the propagation of real effects of firms' credit supply shocks (Table 1, columns (4)-(6)). In fact, we find, depending on the specifications, that the coefficients associated with our measure of downstream propagation, $DOWN_{jt,s}$, are similar or larger in magnitude than the estimated coefficients for direct effects. We find mixed evidence for the case of upstream propagation, $UP_{jt,s}$, with our estimated coefficients having different signs and significance depending on the left hand side variable used.[24]

Regarding employment regressions, the estimated coefficients for the direct credit shock and indirect downstream propagation shock ($DOWN$) are similar in magnitude. In particular, these estimates imply that an increase of one standard deviation in the $DOWN$ variable is associated with an increase of approximately 0.30 pp. in the change in employment, which compares with the estimated 0.28 pp. for the direct effect. These numbers represent approximately 96% and 91% of the actual average annual change in firm-level employment over the same period (0.31%). We find an insignificant effect for the indirect upstream propagation shock (UP).

Turning to output regressions, the coefficients associated with the two indirect propagation shocks are significant at 1%. In fact, the indirect effects dominate the direct effects in terms of magnitude. The downstream (upstream) effect is 0.35 (0.21), which is significantly larger than the direct effect of 0.10 pp.

Finally, in the case of investment regressions, the indirect downstream shock is significant at the 1% level. As in the employment case, the direct and indirect downstream effects are relatively similar in magnitude, 0.80 pp. and 0.69 pp. respectively. These effects represent around 10% and 9% of the actual average investment rate over the period.

4.2 Expansion, Financial Crisis, and Recession

As mentioned above, an advantage of our methodology is that it enables us to estimate year-by-year supply shocks. We now investigate how the real direct and indirect effects of firms' credit supply shocks change with the state of the macroeconomy. To that end, we break down our sample into three periods. Tables 2 and 3 report our estimated direct and indirect effects for employment, output, and investment.[25]

Employment: We find that aggregate economic conditions contribute to the understanding of the effects of credit supply shocks on employment. For example, the estimated effect is not significant in the regressions run for the *expansion* period of 2003-2007, but is positive and significant in the

[24] Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016) show theoretically that negative upstream propagation effects are possible under low substitution elasticities between labor and intermediate inputs.

[25] Note also that Appendix E reports the year-by-year estimates.

regressions run for the *financial crisis* of 2008-2009.[26] In particular, our estimates suggest that an increase of one standard deviation in the credit supply shock is associated with an increase in the employment growth rate of 0.5 pp. (column (2)). The average annual change in firm-level employment for the 2008-2009 period was -2.17%, which implies that the estimated effect represents 18% of the mean change in absolute value. We also find a significant effect in the regressions run for the *recession* period (2010-2013), whose results are reported in column (3). The estimated effect implies that an increase of one standard deviation in the credit supply shock is associated with an increase in firm's employment growth of approximately 0.24 pp. which represents around 10% of the actual change over the period in absolute value (-2.24%).

Turning to indirect effects in Table 3, the effects of credit shocks are not significant either when focusing on the *expansion* period (2003-2007). Note that the insignificant effect on employment of the direct shock was present before when not including the indirect shocks (column (1) of Table 2). In fact, the estimated coefficients for the direct shock are similar across the two specifications (0.251 vs 0.218). For the *financial crisis* 2008-2009 period, we find the effect of the indirect downstream propagation shock ($DOWN$) to be particularly strong relative to the direct shock (see column (2) in Table 3). The estimates imply that an increase of one standard deviation in the $DOWN$ variable is associated with an increase of approximately of 0.69 pp in the change in employment, which represents close to 27% of the absolute value of the average annual change in employment over the period (-2.76%). The magnitude of the estimated effect for the direct shock is significantly smaller at 0.48 pp, which represents approximately 17% of the absolute value of the average annual change. The effect of the indirect upstream propagation shock remains insignificant. Running the regressions for the 2010-2013 period, the effect for the $DOWN$ variable is insignificant. Additionally, we find a negative and marginally significant effect of the upstream propagation shock (UP) of -0.23 pp.

Output: The effects of credit supply shocks on output are always significant. However, the effect is particularly strong during the *financial crisis* of 2008-2009: an increase of one standard deviation in the shock implies an increase in output growth of 0.15 pp. (column (5)), approximately 9% of the absolute value of the actual change in output over the period (-1.75%). The estimated effects for the *expansion* period (2003-2007) are significantly smaller (0.06 pp.) representing close to 3% of the actual annual growth over the period (2.12%).

Turning to the indirect effects in Table 3, we find that the effects of the downstream and upstream propagation shocks are only strongly significant during the *financial crisis* 2008-09 period. In particular, the estimated effects are 0.64 pp. and 0.46 pp, respectively. These two values represent around

[26] The estimated effect is also not significant when restricting the analysis to multi-bank firms (coefficient of 0.201, s.e. 0.179) during the expansion.

Table 2: Direct real effects of credit shocks by period

	Employment			Output			Investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	2003-07	2008-09	2010-13	2003-07	2008-09	2010-13	2003-07	2008-09	2010-13
Credit Shock	0.251	0.503***	0.243**	0.060**	0.152***	0.109***	0.821***	0.625***	0.711***
(s.e.)	(0.153)	(0.149)	(0.111)	(0.028)	(0.032)	(0.024)	(0.173)	(0.087)	(0.080)
# obs	1,823,859	810,335	1,430,182	1,765,665	764,699	1,342,639	1,763,184	783,316	1,391,738
R2	0.042	0.055	0.035	0.040	0.075	0.042	0.034	0.016	0.011

Notes. This table reports the effect of credit supply on employment, output and investment for the 2003-2007 period (columns (1), (4), (7)), 2008-2009 (columns (2), (5), (8)), and 2010-2013 (columns (3), (6), (9)) estimated from equation (3). Dependent variable is employment growth in % in columns (1)-(3); output growth in columns (4)-(6); and investment in columns (7)-(9). *Credit Shock* refers to the firm-specific credit supply shock estimated in equation (4), normalized to have zero mean and unit variance. All regressions include a set of industry $\times$ year fixed effects as well as the following control variables: firm-specific credit demand shocks ($\hat{\lambda}_{jt}$), size dummies, lagged loan-to-assets ratio, and lagged productivity. We denote significance at 10%, 5%, and 1% with *, **, and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

Table 3: Indirect real effects of credit shocks by period

	Employment			Output			Investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	2003-07	2008-09	2010-13	2003-07	2008-09	2010-13	2003-07	2008-09	2010-13
Credit Shock	0.218	0.482***	0.255**	0.069**	0.155***	0.108***	0.845***	0.576***	0.708***
(s.e.)	(0.151)	(0.156)	(0.111)	(0.027)	(0.031)	(0.020)	(0.177)	(0.101)	(0.085)
DOWN	-0.077	0.697***	0.129	0.204*	0.646***	0.184	0.266	1.263***	0.110
(s.e.)	(0.076)	(0.258)	(0.392)	(0.106)	(0.166)	(0.251)	(0.281)	(0.320)	(0.552)
UP	0.062	-0.187	-0.233*	0.086	0.459***	-0.014	0.403**	0.085	-0.402
(s.e.)	(0.078)	(0.291)	(0.123)	(0.086)	(0.141)	(0.125)	(0.172)	(0.352)	(0.401)
# obs	1,727,803	759,170	1,340,069	1,704,934	739,238	1,300,181	1,687,930	739,729	1,309,881
R2	0.040	0.059	0.036	0.051	0.086	0.049	0.036	0.018	0.012

Notes. This table reports the effect of credit supply on employment, output and investment for the 2003-2007 period (columns (1), (4), (7)), 2008-2009 (columns (2), (5), (8)), and 2010-2013 (columns (3), (6), (9)) estimated from equation (7). Dependent variable is employment growth in % in columns (1)-(3); output growth in columns (4)-(6); and investment in columns (7)-(9). *Credit Shock* refers to the firm-specific credit supply shock estimated in equation (4), normalized to have zero mean and unit variance. DOWN and UP have been constructed according to equations (5) and (6) respectively. All regressions include a set of industry $\times$ year fixed effects as well as the following control variables: firm-specific credit demand shocks ($\hat{\lambda}_{jt}$), size dummies, lagged loan-to-assets ratio, and lagged productivity. We denote significance at 10%, 5%, and 1% with *, **, and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

36% and 26% of the observed average annual growth rate of -1.75% over the period, in comparison to an estimated effect of the direct shock of 0.15 pp., which represents approximately 9% of the actual change.

Investment: Turning to investment, we find that the estimated coefficients are significant at 1% across all specifications. In terms of magnitude, we find that a one standard deviation increase in credit supply shock generates an increase in investment rates that varies from 0.6 pp. to 0.8 pp. The magnitude of the effect varies across the different periods. For the *expansion* period (2003-2007), the estimated effect represents approximately 6% of the actual average investment rate of 12.89% over the period. The estimated effect represents around 12% of the average investment rate of 5.11% during the *financial crisis*. During the *recession* period (2010-2013), the effect more than doubled the average investment rate of 0.59% observed in the data over the same period.

When focusing on the indirect effects in Table 3, the downstream effect is stronger than the direct effect in the *financial crisis*. The estimated effect for the former is 1.26 pp. which compares to the 0.57 pp. for the latter. These numbers represent approximately 24% and 11% of the observed average investment rate.

Summary: Over the entire sample period 2003-2013, indirect credit shocks through IO propagation have a significant effect on the evolution of firm-level employment, output and investment. This effect is driven by the *financial crisis* period (2008-2009), where the downstream propagation effect systematically dominates the direct effect of credit shocks in magnitude. Note also that the difference in the coefficients estimated for employment and value added for the *boom* period (2003-2007) and the *financial crisis* period (2008-2009) are statistically significant with p-values below 0.1, both for the direct and the downstream indirect effects. For the case of investment, coefficients are different only for the downstream indirect effect. However, the differences in the estimates for the *financial crisis* (2008-2009) and the *recession* (2010-2013) are not statistically significant. Finally, evidence of the importance of the upstream propagation shock is mixed, in terms of both the significance and size of the effect.

4.3 Robustness Checks

Appendix F reports a battery of exercises that confirm our main findings to be robust along several dimensions.

As discussed in Section 3, Amiti and Weinstein (2018) show that the bank-time fixed effects estimated from equation (1) are identical to those resulting from a specification accounting for bank-firm-time-specific factor. In Table F.2, we show this to be the case. We first include in equation

(1) the lagged exposure between bank i and firm j in order to account for bank-firm idiosyncratic factors (see table F.1). As expected from the findings in Amiti and Weinstein (2018), the results are not affected by inclusion of these bank-firm-specific factors (see Table F.2).

To further alleviate concerns, we split our sample in two subsamples, one for bank shock estimation, the other for the regressions. Concretely, we randomly divide firms' fiscal IDs into two subsamples of equal size. Firms used in the identification of the bank credit shocks are thus not included in the subsequent regressions on real outcomes. The aim of this exercise is to ensure exogeneity of the bank shocks with respect to firms' decisions as relationship lending is fully absent in these results. This robustness exercise resembles the Bartik (1991) identification strategy popularized by Blanchard and Katz (1992) in which local employment growth is predicted by interacting local industry employment shares with national industry employment growth rates.[27] Analogously, we combine bank fixed effects identified from a group of firms with the firm-bank shares of a different group of firms. Table F.3 in Appendix F shows our baseline results to remain unaltered when considering these exercises thereby corroborating the exogeneity of our baseline bank credit shocks.

As an additional robustness, we restrict our sample of multibank firms for bank shock identification to those with at least 5 banks per year, to ensure that results are not driven by a handful of firms whose fixed-effects estimates can be noisy consequent to being identified by too few observations. Table F.4 illustrates the main conclusions to be robust to this exercise. In Table F.5 we exclude construction and real estate firms from our sample to ensure that the Spanish boom-bust housing cycle is not driving our results. In the presence of bank specialization in real estate, construction firms may turn to specific banks for credit (housing banks) during the boom and to non-housing banks during the bust. Then, credit demand would also determine our so-called bank supply shocks. The estimates in Table F.5 indicate that our findings remain present when considering a sample of non-housing loans (i.e. excluding construction and real estate firms).

Finally, Appendix G reports the real effects estimated for firms of different size. Overall the main patterns are quantitatively and statistically significant for small- and medium-size firms while effects for larger firms are not statistically significant.[28]

5 Channels

In the previous section, we estimated the direct and indirect relationship between credit supply shocks and real variables to be statistically significant and economically sizable in particular during

[27] Indeed, the "China shock" instrument of Autor, Dorn, and Hanson (2013) is also based on the same idea as it interacts local industry composition with the growth of Chinese imports to European countries.

[28] Note also that industries that rely on larger number of suppliers are not industries characterized by greater number of larger firms with the relation between the share of large firms and downstreamnes being flat.

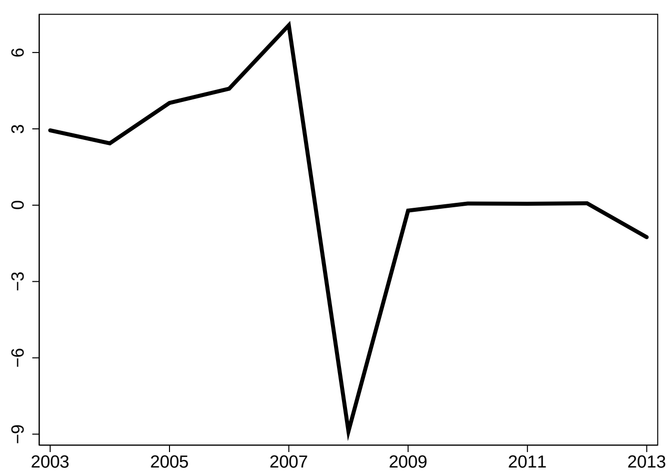
the financial crisis. Firms, conditional on their own credit supply shock, are also affected through buyer-supplier relations. To be more concrete, we found that credit shocks affect real outcomes of the firms directly hit and of their customers, i.e. downstream propagation.

In this section, we consider two different mechanisms that may rationalize these reduced form findings. On the one hand, liquidity shocks can be propagated in the economy via trade credits (Kiyotaki and Moore (1997)).

On the other hand, a negative credit shock to a particular supplier/industry may induce an increase in the price of its product and thus affect the customers' optimal decision in general equilibrium (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)). We first show that the trade credit channel explains part but not the whole downstream propagation effect. We then show some evidence that is consistent with the price adjustment in general equilibrium and calibrate a model similar to Bigio and La'o (2017) that allows us to quantify the extent of that channel.

5.1 The Role of Trade Credit

Figure 7: Evolution of accounts payable growth (%) over time



Notes. This figure plots the evolution of average growth of accounts payable from our sample of Spanish firms.

While bank lending generally represents the main source of firms financing, trade credit is also important. This type of credit is extended by suppliers to their clients in the form of the delay of the payment for the delivered goods by the supplier. Costello (2017) documents that firms more exposed to a large decline in bank lending reduced the trade credit extended to their customers resulting in negative effects on their real outcomes. This mechanism would thus rationalize our estimated downstream effects.[29]

Fortunately enough, we have information on accounts payable from the firms balance-sheet information in our data. The evolution over time of trade credit received by customer firms from their supplier firms is precisely measured by this item of the balance-sheet. Figure 7 shows a large drop in the average growth in accounts payable in 2008, which confirms that the negative bank lending shock implied by the global financial crisis was indeed reflected in the form of a reduction in extended trade credit. Also, according to our data, only around 10% of the firms in our sample do not receive trade credit from their suppliers (zero accounts payable), and the average share of accounts payable over total credit is 47.6%.

In order to explore the role of trade credit in explaining our findings on downstream propagation of credit supply shocks, we include an additional control variable (the growth of accounts payable by firm j) in our baseline specification from equation (7). The estimated coefficient on the $DOWN_{jt,s}$ regressor would capture the effect of suppliers credit shock on firm j's outcomes beyond the trade credit channel.

Table 4 shows the results.[30] When compared to the baseline estimates, the magnitude of the downstream propagation in 2008-2009 is significantly lower once we account for trade credit. For instance, the 1.26 effect for investment is reduced to 0.81 when controlling for the change in accounts payable (trade credit). Additionally, the effect of accounts payable is always statistically significant and large, which corroborates the findings in Costello (2017) that trade credit shocks affect real outcomes of customer firms (buyers).[31] However, our estimated effect of the suppliers credit shock ($DOWN_{jt,s}$) is even larger than that of the trade credit effect. Therefore, we conclude that some additional mechanism must be at work in order to explain the downstream propagation of credit shocks.

5.2 The Role of Price Adjustments and Propagation in General Equilibrium

The recent work by Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), Acemoglu, Akcigit, and Kerr (2016), building on earlier work by Long and Plosser (1983), emphasize the role of input-output linkages in propagating sectoral shocks to the macroeconomy. The intuition is the following:

[29] Alternatively, trade credit may also explain upstream propagation of financial shocks if debtor (customer) failure triggers supplier's losses through both credit losses and demand shrinkage (see for instance Jacobson and Schedvin (2015)). However, we focus here in downstream propagation because our evidence for upstream effects is rather mixed.

[30] We focus in the 2008-2009 sub-period because accounts payable are only available for a small subsample of around 10,000 firms in 2003-2007. This is so because firms were not obliged to report this information to the Mercantile Registries before 2008.

[31] Costello (2017) scales receivables by total sales and finds an estimated coefficient of -0.003 (s.e. 0.001) compared to -0.395 (s.e. 0.096) when not considering demand effects.

Table 4: Indirect effects — the role of trade credit

	Employment		Output		Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
	2003-2013	2008-2009	2003-2013	2008-2009	2003-2013	2008-2009
Bank shock	0.20**	0.39***	0.08***	0.09***	0.61***	0.37***
	(0.08)	(0.10)	(0.02)	(0.02)	(0.06)	(0.07)
DOWN	0.47*	0.59*	0.41***	0.55***	0.66***	0.81***
	(0.24)	(0.34)	(0.11)	(0.17)	(0.17)	(0.22)
UP	0.28	0.28	0.14	0.27*	0.14	0.32
	(0.30)	(0.42)	(0.12)	(0.14)	(0.32)	(0.36)
Trade credit	0.33***	0.37***	0.12***	0.22***	0.89***	0.75***
	(0.05)	(0.07)	(0.04)	(0.08)	(0.18)	(0.24)
# obs	1,175,489	225,549	1,149,871	221,186	1,152,278	221,140
R2	0.04	0.04	0.06	0.09	0.01	0.01
Fixed effects	sector × year	sector × year	sector × year	sector × year	sector × year	sector × year

Notes. All regressions include the following control variables: firm-specific credit demand shocks ($\hat{\lambda}_{jt}$), lagged loan-to-assets ratio, and lagged productivity. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors multi-clustered at the main bank and sector level are reported in parentheses. Trade credit refers to the growth of accounts payable of the firm, i.e., the growth of trade credit received from the firms' suppliers. All regressors are normalized to have zero mean and unit variance.

imagine that a negative supply shock affects an industry producing good i. Its output decreases, which implies an increase in the price of the good i. Industries that use good i as an intermediate input now decrease their demand for that good, and as a consequence their production goes down and their price goes up. This affects industries that use their goods as inputs an so on and so forth. The total effect to an economy is then the overall direct and indirect effects of the initial negative supply shock. Our estimates are consistent with this type of propagation.

5.2.1 Price Adjustments

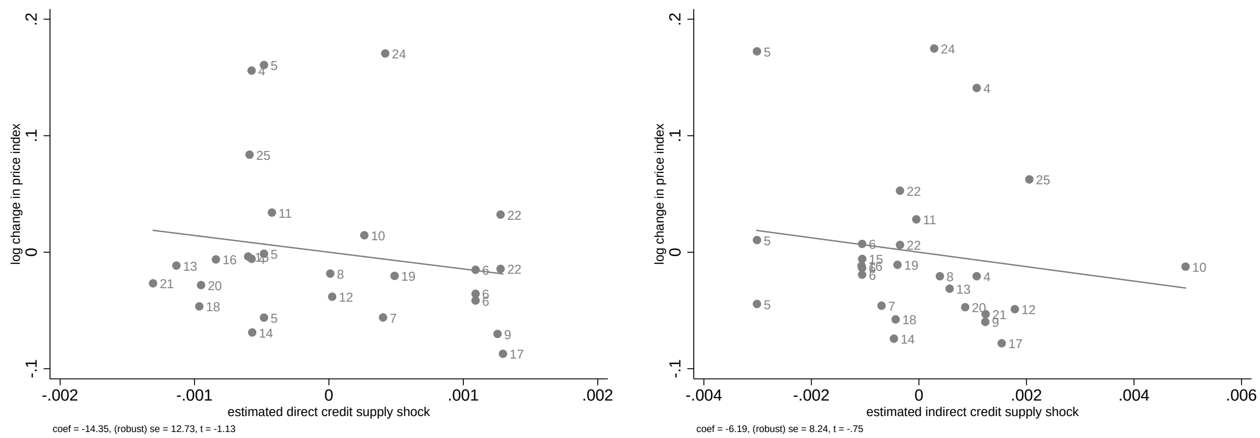
In order to check if this mechanism is at work in our estimates, we construct changes in prices across different industries between 2007 and 2010 and correlate them with our estimated shocks credit supply for the year 2007.[32] To compute changes in prices, we calculate the growth rate of industrial price indexes reported by the Spanish *National Statistical Institute* over that period. We then run a regression of the computed changes in prices against our direct "credit shock" and the indirect "downstream shock" as defined in equation (5).

Figure 8 shows the partial correlations implied from running such regression. The left panel shows the correlation between the log change in price and the direct shock. The right panel shows the correlation with the indirect downstream shock. We find that both the direct and indirect shocks are negatively related to the change in prices. First, the price in a given industry increases when

[32] Price indexes are provided only for a limited number of industries. In particular, price indexes are not reported for service industries.

the industry faces a direct negative shock. Second, the price of that industry also increases when supplier industries face a negative shock. Notice that these relationships are not robustly statistically significant, so one has to take them with a grain of salt.

Figure 8: Change in industrial price indexes and credit supply shocks



Notes. This figure shows the partial correlation between the log change in industrial price indexes between 2007 and 2010 and our estimated direct and indirect credit supply shocks in 2007. The partial correlation has been computed from running a regression of the log change in prices against the two types of shocks. The source of the price indexes is *Indice the Precios Industriales, INE.*

5.2.2 Propagation: Aggregate Effects and Counterfactuals

In order to provide further evidence on the strength of this mechanism, we plug our estimated shocks into a general equilibrium model that enables us to quantify the aggregate industry- and macro-level effects of the credit supply shocks estimated above. As already mentioned, we use the model recently developed by Bigio and La'o (2017), which delivers input-output propagation of shocks that affect firms' access to finance (see Appendix H).

To quantify the aggregate propagation effects through price adjustments in general equilibrium, we consider a two-step strategy. First, we calibrate the model to the Spanish economy for the year 2003. Second, we discipline the over time changes in the financial friction parameters using our estimated real effects of credit shocks at the industry level. With respect to the calibration for 2003, we proceed as follows: (i) we take the parameter governing decreasing returns to scale in every industry and the parameters governing the household labor supply from outside the model; (ii) then we calibrate the remaining parameters to match important statistics of the Spanish economy (see Appendix (I) for details).

The parameters governing the IO structure of the economy are inferred using the Spanish IO *direct* *requirement matrix*. Information provided in this matrix enables us to measure, in each industry, the expenditure on each intermediate good as a fraction of total expenditure on intermediate goods. For the "initial" level of financial frictions, that is, financial frictions in 2003, we target the ratio of industries' expenditures to revenue. In the model, this is given by the degree of financial frictions and the parameter governing decreasing returns to scale. Given our predetermined value for the decreasing returns to scale parameter, we can easily recover the parameter that governs the degree of financial frictions for each industry. Labor share in each industry is pinned down by matching the industries' expenditures in labor as a fraction of total expenses on inputs. Finally, we identify the different industries' shares in the household's utility function by matching the final consumption expenditure shares measured in the data.

Turning to the second step, we use our reduced form estimates of the direct real effects of credit supply shocks to discipline the changes in financial frictions that we plug into the model. We find values for the parameter governing the financial frictions in each industry (i.e. the parameter influencing the collateral constraint) such that a *horizontal economy* version of the model is able to generate the changes in employment implied by our reduced form estimates of the direct real effects described below. This is, if there were no indirect effects at work, our economy would deliver the same effects on employment as the direct effects implied by our reduced form estimates.[33]

For instance, we identify the changes in financial frictions (i.e. credit supply shocks) for the year 2004 by employing a horizontal economy version of the model that generates changes in employment between 2003 and 2004 that correspond to those estimated from our predicted direct real effects. With new values for the parameters governing financial frictions in 2004, we can proceed in similar manner for the years 2005-2013.

Aggregate Effects We first analyze the quantitative importance of the propagation effects by "shocking" all the industries of the economy at once. We use the "estimated" financial frictions parameters for each year to solve the full economy with IO linkages and thereby quantify the propagation effects of credit supply shocks.

Figure 9 presents the aggregate effects of our estimated financial shocks on output in the Spanish economy. The figure contains two panels. In the left panel, we plot the total effect (*direct+network*) in output in percentage changes implied by the model against that observed in the data for each year. We find a strong correlation between the two variables, which is driven by the fact that the shocks we plug into our model strongly correlate with the real direct effects that we estimate year by year.

[33]Instead, Bigio and La'o (2017) proxy financial frictions using sectoral credit spreads (difference in yields between various corporate (private) debt instruments and government securities of comparable maturity not accounted for by default risk) from Gilchrist and Zakrajsek (2012).

The full model accounts for significant fractions of the observed increases in output over the *boom* period (2003-2007), although it tends to under-predict the changes.[34] For instance, the change in output predicted by the model is 2.02% between 2005 and 2006, which is around 62% of the 3.23% observed in the data. This means that even with the network channel at work, the model is not able to replicate the big increases in output observed in the Spanish economy during the boom.

For the *financial crisis* (2008-2009), the model over-estimates the fall in output. For example, the model (data) predicts a fall in output of -3.18% (-0.39%) between 2008 and 2009. Moreover, for the *recession* period (2010-2013), the model predicts negative changes in output, while the changes are positive in the data. For example, the model (data) predicts a fall in output of -2.16% (0.70%) between 2010 and 2011. The reason for this is that we are identifying changes in financial frictions by matching the observed changes in employment, which are negative during this part of the sample. Hence, and not surprisingly, the model is not able to replicate the fact that output started recovering earlier than employment in the Spanish economy.

In the right panel, we plot the direct effect against the network effect, both as implied by the model. As we can observe, the size of the network effects is significantly larger in magnitude than that of the direct effect. Following Bigio and La'o (2017), we construct a measure of the importance of the network propagation effects in our calibration, the *network multiplier*. In particular, we calculate the ratio of the total (*direct+network*) effects on output to the effects implied by a horizontal (*direct*). We find this multiplier to be very stable over the years, and ranging between 4.5 and 5.[35]

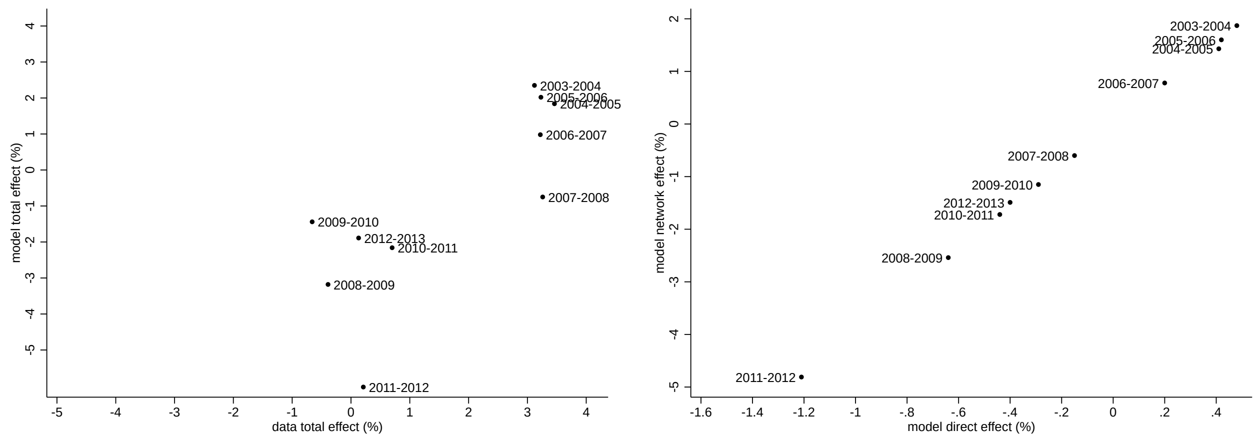
Counterfactuals We now quantify the aggregate effects of shocking one industry at a time. This exercise allows us to analyze the relative importance of different sectors in accounting for the aggregate effects. We focus on the *financial crisis* (2008-2009), which is the period in which the estimated credit supply shocks are largest. Our starting point is the calibrated economy for 2008. We compute a number of counterfactual economies in which we shock each of the 62 different industries at a time. We then compare the implied level of output of these economies with that of the 2008 economy. We decompose this effect into the direct effect and the propagation effect. The right panel of Figure 10 shows the results of this exercise. Each dot represents a different counterfactual economy in which we only shock the labeled industry. The left panel shows shows the IO direct requirement matrix of the Spanish economy.

We find that the shock that generates the largest output loss is the one that affects the *Real*

[34] Changes in the data here refer to the change in aggregate real value added as measured in Spanish National accounts. Notice that these changes are different from those used for the quantification of the reduced form estimates, which refer to simple average growth rates across the firms present in our sample.

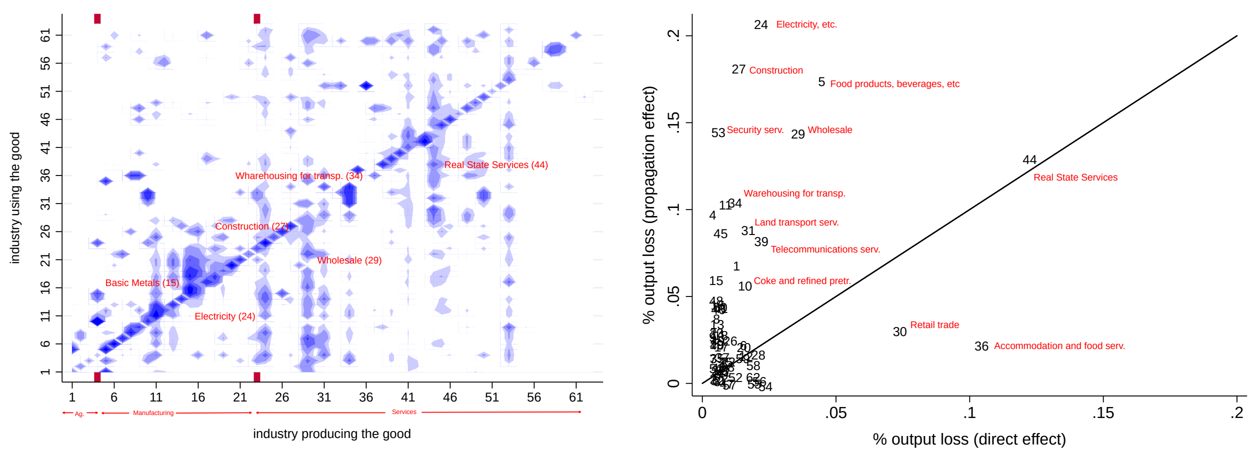
[35] In their calibration for the US, Bigio and La'o (2017) network multipliers that are smaller, ranging between 1.7 and 2.4. These differences may be due to the different calibration strategies, the use of different parameter values and differences between the IO structure in the US and Spain.

Figure 9: Aggregate effects of credit supply shocks on output



Notes. Left panel of this figure shows the relationship between the total output loss as measured in the data (x-axis) and that implied by the model. Right panel shows the relationship between the output losses implied by the direct effects (x-axis) and that implied by the network indirect effects (y-axis), both as measured in the model.

Figure 10: IO structure (left panel) and output losses of isolated industry specific shocks (right panel)



Notes. The left panel shows the IO structure of the Spanish economy for the year 2010 (direct requirement matrix). Element $\{i, j\}$ represents the amount of euros spent by industry i in goods from industry j as a fraction of gross output in industry i. A contour plot method is used, showing only those shares greater than 1%, 2%, 5%, 10% and 20%. Source: INE. The right panel shows the output loss due to the direct (x-axis) and propagation effect (y-axis) between 2008 and 2009 of applying our industry-specific shocks one by one.

Estate (44) sector. The implied output loss is around 0.24%, of which 0.11% is explained by the direct effect and 0.13% by the propagation effect. There are several reasons why the counterfactual economy in which we shock only this sector is the one that produces the largest output loss. First, this sector accounted for a high share of the Spanish economy in 2008 (around 13%). Second, our estimated credit supply shock in that year was the highest among all industries. And third, this sector is one of the most connected to others through the IO network. In particular, it is a sector whose output is produced intensively by many other sectors.

Perhaps more interestingly, we find that shocking central sectors in the IO structure of the economy implies large output losses even if the shocks are not particularly high. Take for instance the sectors for which the negative direct effect on output is between 0 and 0.5. Across these sectors, however, there is significant variation in the estimated propagation effects, which translates into large differences of the implied total output loss. Some examples of sectors in which the propagation effect is much larger than the direct effect are *Electricity,etc (24)*, *Construction (27)* and *Wholesale (29)*. Shocking each of these sectors at a time would imply aggregate output losses of 0.22%, 0.19% and 0.17% respectively. Out of these total effects, 0.20, 0.18, and 0.14 are accounted for by the propagation effect. These results show the importance of IO linkages in explaining the aggregate effects of a credit supply shock to a given industry.

6 Concluding Remarks

In this paper, we study the direct and indirect real effects of the bank lending channel. Using the quasi-census of firms' loans and economic activity for Spain and input-output linkages, we analyze the real effects of bank-lending shocks during the period of 2003-2013. This period allows us to study firms' responses to different shocks during times of boom (expansion) and contraction (financial crisis and recession).

We bring to this analysis new methods from the matched employer-employee literature, which accommodate handling large data sets, combined with a methodology that enables analyzing the evolution of credit shocks over time. Specifically, we construct firm-specific, exogenous credit supply shocks and estimate their direct effects on firm credit, employment, output, and investment over a decade. We find sizable effects of credit supply shocks on real outcomes, particularly during the Global Financial Crisis.

Combining the Spanish Input-Output structure and firm-specific measures of upstream and downstream exposure, we find the estimated bank credit supply shocks to have strong downstream propagation effects, especially during the the Global Financial Crisis. The massive reduction in trade credit extended by suppliers as well as price adjustments in general equilibrium seem to explain the downstream propagation of credit shocks.

Our results show that credit supply shocks affect the real economy through sizable direct and indirect effects that affect investment and output primarily. Loan, firm, direct, and indirect effects are quantitatively important during the financial crisis but the impact cannot be generalized to other episodes. Overall, our results corroborate the importance of network effects in quantifying the real effects of credit shocks. In terms of the channels, we find evidence which is consistent with both trade credit and general equilibrium adjustments being quantitatively relevant.

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A Bank Lending Channel at the Loan-Level

We estimate the magnitude of the so-called bank lending channel at the bank-firm (loan) level. In particular, quantifying the bank lending channel amounts to estimating the β coefficient in the following model:

$$\Delta \ln c_{ijt} = \beta \hat{\delta}_{it} + \eta_{jt} + v_{ijt} \tag{8}$$

where $\Delta \ln c_{ij}$ refers to the credit growth between bank i and firm j in year t, $\hat{\delta}_{it}$ represents the estimated bank-specific supply shock,[36] and η_{jt} accounts for firm-year demand shocks. The lending channel corresponds to the parameter β. Crucially, the availability of firms borrowing from different banks enables us to include in the regression time-varying firm-fixed effects (η_{jt}) to control for the demand side (see Khwaja and Mian (2008)). Bank supply shocks δ_{it} are proxied by exogenous changes in deposits in Khwaja and Mian (2008), or access to securitization in Jimenez, Mian, Peydro, and Saurina (2014). In our case, we exploit the bank supply shocks estimated above (see section 3.1), standardized to have zero mean and unit variance. In contrast to previous literature, because we have estimated bank credit supply shocks for each year,[37] we can also estimate the evolution of the bank lending channel over time.

Note that equation (8) can only be estimated for the sample of multibank firms given the inclusion of firm-year fixed effects. However, the availability of time-varying firm fixed effects ($\hat{\lambda}_{jt}$) estimated in section 3.1 enables us to estimate the bank lending channel parameter in the sample of all firms as follows:[38]

$$\Delta \ln c_{ijt} = \beta \hat{\delta}_{it} + \gamma \hat{\lambda}_{jt} + v_{ijt} \tag{9}$$

Table A.1 reports the estimates of the bank lending channel at the bank-firm (loan) level. Column (1) presents the results of estimating equation (8) using the entire period (2003-2013). We find a positive and significant effect: conditional on firm fixed effects, higher estimated bank shocks imply higher growth in credit at the bank-firm level. In terms of magnitude, our estimates imply that a one standard deviation increase in the credit supply shock of bank i generates a 5.1 pp. increase in credit growth between bank i and firm j. It is worth mentioning that when we re-estimate column

[36]The shocks are standardized to have zero mean and unit variance in order to ease interpretation and enhance comparability across specifications (and time periods) of the estimated effects magnitudes. Note that without such standardization the estimated β should be equal to 1.

[37]Since our regressor of interest is estimated in a first step, standard errors in equation (8) should be adjusted in order to account for the sampling error from the first step. However, the adjustment factor in linear models resembles the traditional sandwich formula that depends on the variance of the estimated parameters in the first step (see Murphy and Topel (1985)). Give the huge sample sizes we are using in the first step, the correction factor for the second step tends to have a negligible effect on our second-step inferences because the first-step variance is close to zero.

[38]Note that firm-specific shocks are recovered for firms without multiple bank relationships by subtracting the bank-specific component $\hat{\lambda}_{jt} = \Delta \ln c_{ijt} - \hat{\delta}_{it}$.

(1) without firm-specific effects on the same sample of multibank firms, the bank lending channel is less important, the effect dropping from 5.1 pp. to 4.2 pp. This reduction indicates that banks' supply and firms' loan demand shocks are negatively correlated in the cross-section as also found by Khwaja and Mian (2008).

Table A.1: Estimates of the bank lending channel at the loan-level

	2003-2013			2003-2007	2008-2009	2010-2013
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Shock	5.058***	5.218***	5.272***	5.401***	5.320***	5.181***
(s.e.)	(0.088)	(0.037)	(0.025)	(0.021)	(0.062)	(0.063)
# obs	12,216,375	12,216,375	17,954,745	7,624,590	3,682,414	5,124,886
# banks	221	221	221	209	192	192
# firms	700,722	700,722	1,511,767	1,183,558	1,049,208	1,019,567
R2	0.350	0.349	0.522	0.543	0.503	0.484
Fixed effects	firm × year	$\hat{\lambda}_{jt}$	$\hat{\lambda}_{jt}$	$\hat{\lambda}_{jt}$	$\hat{\lambda}_{jt}$	$\hat{\lambda}_{jt}$
Sample firms	Multibank	Multibank	All	All	All	All

Notes. This table reports the estimates of the bank lending channel parameter at the loan level (β). Column (1) is based on equation (8) for a sample of multibank firms. Columns (2) are (3) are based on equation (9), controlling for the firm-year estimated fixed effects. The dependent variable is credit growth between firm j and bank i. *Credit Shock* refers to the bank-specific credit supply shock ($\hat{\delta}_{it}$) estimated in equation (1), normalized to have zero mean and unit variance. We denote significance at 10%, 5%, and 1% by *, **, and ***, respectively. Standard errors clustered at the bank level are reported in parentheses.

Column (2) of Table A.1 repeats the estimation of column (1) but substitutes our firm-year effects ($\hat{\lambda}_{jt}$) estimated in section 3.1 for the firm-year dummies. As expected, the estimates of the bank lending channel remain very similar as both approaches are equivalent (see Cingano, Manaresi, and Sette (2016)). In column (3), we repeat the estimation for the sample including all firms, not only multibank firms, which is possible because of the availability of firm-specific effects ($\hat{\lambda}_{jt}$) for all firms in the sample. Finally, columns (4)-(6) show the magnitude of the bank lending channel at the loan-level to be stable over time. Figure D.1 in Appendix D presents the year-by-year estimates of the loan-level effect. Finally, all the figures in Table A.1 remain very stable when controlling for bank-firm idiosyncratic factors in the indentification of bank supply shocks (see discussion in Robustness Section 4.3 and Table F.1 in the Appendix).

B Bank Lending Channel at the Firm-Level

The bank lending channel appears to be quantitatively and statistically important given the loan-level estimates reported in section A. Moreover, the magnitude of the effect is similar for multibank and single bank firms. However, firms may be able to undo a negative bank supply shock by resorting to other banks, especially in the case of multibank firms. If this is the case, a large drop in the credit of a client firm with a bank affected by a negative supply shock would not capture the actual effect of credit supply on annual credit growth. In order to obtain such an estimate, we consider the following regression at the firm level:

$$\Delta \ln c_{jt} = \beta^F \overline{\delta}_{jt} + \gamma^F \hat{\lambda}_{jt} + u_{jt} \tag{10}$$

where $\overline{\delta}_j$ represents a firm-specific credit supply shock constructed as a weighted average of the supply shocks estimated for all banks in a relationship with firm j. The weights are given by the share of credit of each bank with this firm in the previous period:

$$\overline{\delta}_{jt} = \sum_i \frac{c_{ij,t-1}}{\sum_i c_{ij,t-1}} \hat{\delta}_{it} \tag{11}$$

Given this specification, the bank lending channel at the firm-level can be estimated from β^F, as in Khwaja and Mian (2008) and Jimenez, Mian, Peydro, and Saurina (2014). As in the loan-level case, however, we can obtain time-varying estimates of the bank lending channel.

We also account for demand shocks at the firm-level. In the case of loan-level data, the inclusion of firm unobserved heterogeneity is possible due to the circumstance of firms borrowing from different banks. This approach is no longer possible when using firm-level data. Under these circumstances, Khwaja and Mian (2008) and Jimenez, Mian, Peydro, and Saurina (2014) take recourse to the correlation between supply and demand effects implied by differences between the OLS and FE estimates at the loan-level to correct the biased OLS estimate of β^F. In particular, they exploit the fact that differences between the OLS and FE estimates at the loan-level in equation (8) provide a quantification of the covariance between δ_{it} and η_{jt} given the formula for omitted variable bias. In our case, we include, in the firm-level regression, the firm-level demand shocks ($\hat{\lambda}_{jt}$) estimated in section 3.1 by means of matched employer-employee techniques. Both approaches are equivalent but including the estimated demand shocks enables us to easily compute appropriate standard errors (see Cingano, Manaresi, and Sette (2016)).

Table B.1 reports the estimates of the bank lending channel at the firm-level. The effect is positive and significant. The magnitude is smaller than that estimated at the loan-level, which indicates that firms are able to partially offset bank supply shocks. Not surprisingly, multibank firms can better undo bank shocks: a one standard deviation increase in the credit supply of firm j generates an overall increase of 3.2 pp. in credit growth (see column (2)), whereas the effect is 1.1 pp. in the case of multibank firms, as reported in column (1). Turning to the evolution of the bank lending channel at the firm-level, columns (3)-(5) illustrate that the effect of bank shocks on firm credit growth is significantly larger during the 2008-2009 financial crisis. In particular, a one standard deviation increase in credit supply generates a 4.8 pp. increase in credit growth during those years (average firm credit growth during 2008-2009 was -6.2%), which is significantly larger than the effect during 2003-2007 and 2010-2013. Figure D.1 in Appendix D presents the year-by-year estimates of this effect. Note also that these estimates are robust to the inclusion of bank-firm controls as well as the exclusion of construction and real estate firms from the sample (see Section 4.3 for more details these robustness exercises in the case of real outcomes).

Interestingly enough, the magnitude of the bank lending channel at the firm-level varies significantly over the cycle (see Table B.1) while it does not vary at the loan-level (Table A.1). Since loan-level effects are very similar across the different subperiods, the larger effects at the firm-level during the financial crisis points to a more limited capacity of firms to substitute credit across banks during this period. This finding may also be at the root of the larger real effects of credit shocks during the global financial crisis discussed below.

Table B.1: Estimates of the bank lending channel at the firm-level

	2003-2013		2003-2007	2008-2009	2010-2013
	(1)	(2)	(3)	(4)	(5)
Credit Shock	1.158**	3.207***	3.414***	4.846***	2.162***
(s.e.)	(0.515)	(0.278)	(0.197)	(0.483)	(0.564)
# obs	4,424,519	8,743,459	4,122,017	1,920,723	2,700,719
# banks	220	220	208	191	193
# firms	924,441	1,481,377	1,183,558	1,049,208	1,019,567
R2	0.330	0.501	0.525	0.521	0.412
Sample firms	Multibank	All	All	All	All

Notes. This table reports the estimates of the bank lending channel parameter at the firm level (β^F) estimated from equation (10). The dependent variable is the credit growth of firm j in year t. *Credit Shock* refers to the firm-specific credit supply shock ($\hat{\delta}_{jt}$) estimated in equation (4), normalized to have zero mean and unit variance. All specifications include a set of firm-year effects ($\hat{\lambda}_{jt}$). We denote significance at 10%, 5%, and 1% with *, **, and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

Finally, it is worth mentioning that including firm-year demand shocks in the model has a crucial effect on the estimates. Re-estimating the model in (10) by OLS without firm-level effects ($\hat{\lambda}_{jt}$), the 2003-2013 estimate of β^F drops from 3.2 pp. to 0.7 pp., indicating that banks' supply and firms' loan demand shocks are negatively correlated in the cross-section, as found in the loan-level case.

In terms of comparisons with the literature, although Jimenez, Mian, Peydro, and Saurina (2014) find credit supply shocks to have had no significant effects on credit growth at the firm-level between

2004 and 2007, both results are not strictly comparable given differences in the nature of the bank supply shocks and data sample. On one hand, they analyze supply shocks identified through greater access to securitization of real estate assets. The sample in Jimenez, Mian, Peydro, and Saurina (2014) covers loans in excess of €60,000, mainly corresponding to larger multibank firms that may be better able to undo bank supply shocks by borrowing from other banks as our estimates suggest.

C A Time-varying Credit Supply Indicator

The aggregate estimates reported in section 3 clearly suggest a positive credit supply shock during the boom period (2004-2007) and a negative one afterwards. In this appendix, we present an alternative approach and estimate a time-varying indicator of credit supply that confirms this pattern. Intuitively, we use the loan-level data to estimate bank-specific time trends of credit supply after accounting for demand shocks (i.e., firm fixed effects). The resulting bank-specific time trends can then be aggregated to construct an aggregate indicator of credit supply over time.

Consider the following model:

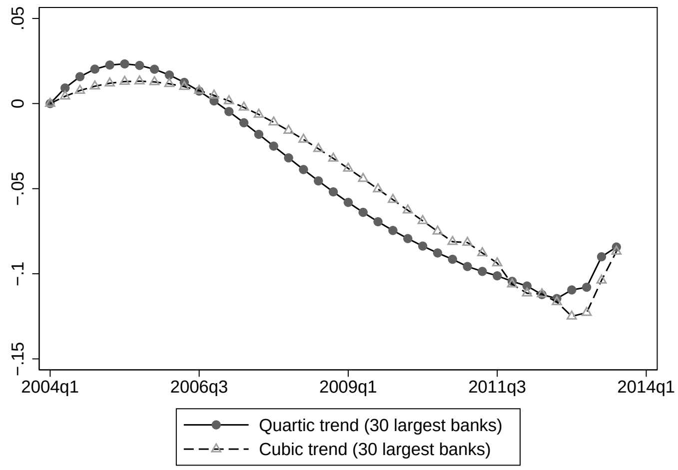
$$\Delta \ln c_{ijt} = \mu_{jt} + \zeta_i + K_i' \times T + \xi_{ijq} \tag{12}$$

where $\Delta \ln c_{ijt}$ refers to credit growth between bank i and firm j in quarter t, $K_i' \times T$ captures a bank-specific time trend intended to identify the evolution of bank-specific credit supply. For our baseline quartic trend, we define $K_i = (\kappa_{1,i}, \kappa_{2,i}, \kappa_{3,i}, \kappa_{4,i})'$ and $T = (t, t^2, t^3, t^4)$. Bank-specific time trends in credit supply can be estimated as $\hat{K}_i' \times T$.

The identification of bank-specific credit supply time trends is based on the inclusion of firm-quarter effects (μ_{jt}) that account for time-varying demand shocks as well as time invariant bank-specific effects (ζ_i) that account for constant heterogeneity in supply factors at the bank level. Note that we use now quarterly data to get a better identification of the time trends that are now the focus of our analysis. Matched employer-employee techniques employed above enable to accommodate the firm-quarter (μ_{jt}) and bank dummies (ζ_i). However, the bank-specific time trends also represent a challenge from a computational perspective given the use of quarterly data, which multiplies by a factor of four the number of annual observations.[39] We therefore restrict the analysis to the 30 largest banks in the sample, which account for 88% of total credit.

[39]This is because each bank-specific time trend must be stored as an additional set of variables to be included in the regression. For instance, in the case of a quartic trend, quarterly loan-level data up to 2013 includes approximately 70 million bank-firm-quarter observations. The inclusion of a quartic trend for each bank in the sample implies that $180 \times 4 = 720$ variables must be included in the regression in addition to the firm-quarter and bank dummies handled by the FEiLSDVj approach. This estimation requires around 350 GB of memory which makes the problem computationally intractable.

Figure C.1: Aggregate credit supply over time



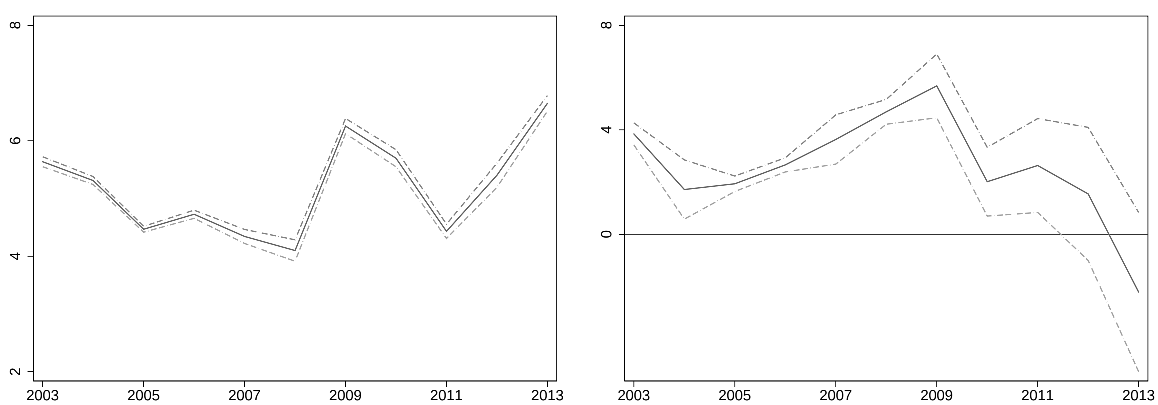
Notes. This figure plots the aggregate credit supply indicator that result from averaging the bank-specific trends given by $\hat{K}_i' \times T$. Quartic and cubic trend are plotted. The value in the first quarter is normalized to 0.

Figure C.1 plots the indicators of credit supply when considering cubic and quartic time trends. Interestingly, credit supply in both cases indicate an increase during 2004-2007, and a dramatic reduction starting in 2008. This pattern fully coincides with our aggregate quantification in section 5.2.2. These exercises illustrate that the type of trend (cubic or quartic) does not alter the aggregate pattern of credit supply over time.

D Annual Estimates of the Bank Lending Channel

The left panel in Figure D.1 plots year-by-year estimates of the bank lending channel at the loan-level. Despite including only multibank firms, our sample consists, on average of 1,632,249 loans in each year. Therefore, the coefficients are very precisely estimated (note that standard errors are multi-clustered at the bank and firm level—see Cameron, Gelbach, and Miller (2011)). The magnitude of the bank lending channel is sizable: an increase of one standard deviation in bank supply generates an average increase of 5.2 percentage points in the growth of each bank-firm credit ($\Delta \ln c_{ij}$). The highest average bank-firm credit growth is 6.25% in 2007. Moreover, Figure D.1 also points to an increase in the relevance of the bank lending channel during the crisis.

Figure D.1: Time-varying estimates of the bank lending channel at the loan- and firm-level



Notes. The left panel plots the β estimates from year-by-year regressions using equation (8). Standard errors used to construct the confidence bands are multi-clustered at the bank and firm level. The right panel plots the β^F estimates from year-by-year regressions given by equation (10), which identify the bank lending channel at the firm level.

The right panel in Figure D.1 plots time-varying estimates of the bank lending channel at the firm level. In this case, our sample comprises, on average, 870,734 firms per year. The magnitude of the bank lending channel is still sizable at the firm level: an increase of one standard deviation in bank supply generates an average increase of 2.6 percentage points in credit growth at the firm level ($\Delta \ln c_j$). The highest firm-level credit growth in our data is 5.9% in 2006, underscoring that the bank lending channel still operates at the firm level.

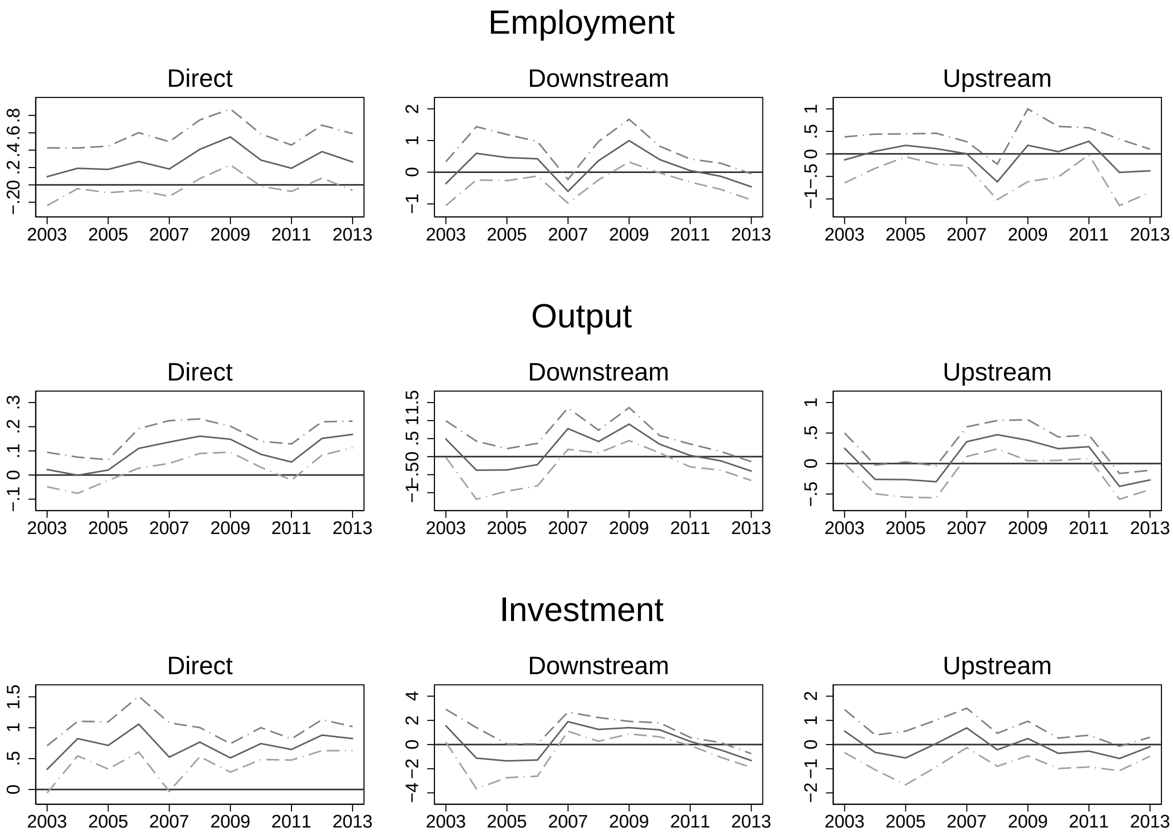
E Annual Estimates of Real Effects

Figure E.1 plots the estimated direct and indirect effects of credit supply shocks on firm growth in terms of employment (upper panel), output (middle panel), and investment (bottom panel). We find a positive and statistically significant direct effect of credit supply shocks on employment growth at the firm level for all years in our sample. However, note that the statistical significance is only marginal during the years 2004-2007. An increase of one standard deviation in bank supply generates an average increase of 0.3 percentage points in annual employment growth at the firm level while annual employment growth in our sample is, on average, 2.9%. These estimates confirm the larger real effects of the credit channel during the 2008-2009 credit collapse. Downstream effects are only positive and significant during 2008-2009 as reported in the main text while upstream effects are statistically indistinguishable from zero in all years. The magnitude of these propagation effects is larger than that of the direct effects.

The effects of firm-level credit supply shocks on output growth are positive and statistically significant on output growth for most years in the sample. A one standard deviation increase in the credit supply shock generates an average increase of 0.2 pp. in firm output growth, which accounts for 20% of the average output growth of 1.0% observed in the sample. Regarding propagation, there is a positive and significant downstream effect during 2007-2009. The effects are not significant before and after that period. In contrast to employment, there is a positive upstream effect during the global financial crisis.

The direct effects are larger and always significant in the case of investment, as reported in the main text. In line with the findings for employment and output, the magnitude of the indirect effects is also larger than that of the direct effects, but insignificant in the case of upstream propagation. The estimated downstream effects are larger and more precisely estimated around the global financial crisis in 2008-2009.

Figure E.1: Reduced-form effects of the bank lending channel on firm growth



Notes. This figure plots the estimated direct and indirect effects of credit supply shocks from year-by-year regressions. Specifically the figure plots the effect of a one standard deviation increase in the credit supply shock on annual employment and output growth as well as investment in percentage points. The estimation samples includes, on average, 347,913, 340,396 and 339,776 firms in each year. Standard errors used to construct the confidence bands are multi-clustered at the main bank and industry level.

F Robustness Checks

The following tables summarize the estimated effects of a series of robustness to the main analysis considering different samples for identification of the shocks and for estimation of the real effect, additional controls at the bank-firm-year level, and excluding construction and real estate firms. The tables report estimates for the entire period (2003-2013) and the *financial crisis* (2008-2009).

Table F.1: Robustness I — Estimates of the bank lending channel controlling for bank-firm characteristics

	2003-2013			2003-2007	2008-2009	2010-2013
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Shock	5.341***	5.201***	5.163***	5.225***	5.329***	5.276***
(s.e.)	(0.122)	(0.102)	(0.083)	(0.098)	(0.107)	(0.081)
# obs	12,216,375	12,216,375	17,954,745	7,624,590	3,682,414	5,124,886
# banks	221	221	221	209	192	192
# firms	700,722	700,722	1,511,767	1,183,558	1,049,208	1,019,567
R2	0.353	0.349	0.524	0.542	0.502	0.484
Fixed effects	firm × year	$\hat{\lambda}_{jt}$	$\hat{\lambda}_{jt}$	$\hat{\lambda}_{jt}$	$\hat{\lambda}_{jt}$	$\hat{\lambda}_{jt}$
Sample firms	Multibank	Multibank	All	All	All	All

Notes. This table reports the estimates of the bank lending channel parameter at the loan level (β) controlling for bank-firm idiosyncratic factors (lagged credit exposure) in the identification of the bank lending shocks. See notes to Table F.1 in the main text for more details.

G Results by Firm-Size

The richness of our sample and identified shocks enables us to run our specification from equation (7) for three size bins: 0-10, 10-500, ≥ 500. Table G.1 reports the regression outcomes. Our main result from these regressions is that the largest firms do not seem to be affected either directly or indirectly by the estimated credit supply shocks. In particular, when we run the regression for firms with more than 500 employees, the coefficients associated to credit supply shocks and downstream and upstream propagation of these shocks are not statistically significant. This is the case for both employment growth, output growth, and investment when the direct shock is considered. Turning to downstream propagation (shock from suppliers), the effect is only significant in the case of output growth for large firms while it is not significant in the case of employment growth and investment. Note, however, that the sample for larger firms is substantially smaller.

Table F.2: Robustness II — Shock identification including bank-firm controls in the regression.

	Employment		Output		Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
	2003-2013	2008-2009	2003-2013	2008-2009	2003-2013	2008-2009
mean annual growth (%)	0.312	-2.764	0.508	-1.755	7.572	5.111
Credit Shock coefficient (θ)	0.299***	0.568***	0.106***	0.167***	0.786***	0.632***
$\|\theta$/mean annual growth (%)$\|$	0.96	0.21	0.21	0.10	0.10	0.12
DOWN coefficient (θ_D)	0.276**	0.674**	0.408***	0.627***	0.875***	1.239***
$\|\theta_D$/ mean annual growth (%)$\|$	0.88	0.24	0.80	0.36	0.12	0.24
UP coefficient (θ_U)	0.055	-0.178	0.229***	0.447***	0.219	0.094
$\|\theta_U$/mean annual growth (%)$\|$	0.18	0.06	0.45	0.25	0.03	0.02

Notes. This table summarizes the estimated effects when including bank-firm controls in the shock identification regression. We focus on the estimates for the entire period (2003-2013) and the *financial crisis* (2008-2009). *Mean annual growth (%)* refers to the average annual growth rate of the variable as measured in the sample of firms in a particular period. *Credit Shock coefficient (θ)*, *DOWN coefficient (θ_D)*, and *UP coefficient (θ_U)* are the estimated coefficients reported in tables **??**, **??** and **??**. We denote significance at 10%, 5%, and 1% with *, **, and ***, respectively. $|\theta$/mean annual growth (%)$|$ is the absolute value of the estimated coefficient divided by the mean annual growth (%).

Table F.3: Robustness III — Different subsamples for shock identification and real effects estimation

	Employment		Output		Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
	2003-2013	2008-2009	2003-2013	2008-2009	2003-2013	2008-2009
mean annual growth (%)	0.312	-2.764	0.508	-1.755	7.572	5.111
Credit Shock coefficient (θ)	0.277**	0.594***	0.115***	0.175***	0.784***	0.617***
$\|\theta$/mean annual growth (%)$\|$	0.89	0.21	0.23	0.10	0.10	0.12
DOWN coefficient (θ_D)	0.316**	0.663**	0.344***	0.622***	0.662***	1.230***
$\|\theta_D$/ mean annual growth (%)$\|$	1.01	0.24	0.68	0.35	0.09	0.24
UP coefficient (θ_U)	0.065	-0.186	0.200**	0.458***	0.147	0.084
$\|\theta_U$/mean annual growth (%)$\|$	0.21	0.07	0.39	0.26	0.02	0.02

Notes. This table summarizes the estimated effects when considering different samples for identification of the shocks and for estimation of the real effects. We focus on the estimates for the entire period (2003-2013) and the *financial crisis* (2008-2009). *Mean annual growth (%)* refers to the average annual growth rate of the variable as measured in the sample of firms in a particular period. *Credit Shock coefficient (θ)*, *DOWN coefficient (θ_D)*, and *UP coefficient (θ_U)* are the estimated coefficients reported in tables **??**, **??** and **??**. We denote significance at 10%, 5%, and 1% with *, **, and ***, respectively. $|\theta$/mean annual growth (%)$|$ is the absolute value of the estimated coefficient divided by the mean annual growth (%).

Table F.4: Robustness IV — Sample of firms working with at least 5 banks per year

	Employment		Output		Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
	2003-2013	2008-2009	2003-2013	2008-2009	2003-2013	2008-2009
mean annual growth (%)	0.312	-2.764	0.508	-1.755	7.572	5.111
Credit Shock coefficient (θ)	0.143	0.513***	0.124***	0.175***	0.649***	0.587***
$\|\theta$/mean annual growth (%)$\|$	0.46	0.19	0.24	0.10	0.09	0.11
DOWN coefficient (θ_D)	0.286***	0.770***	0.197***	0.709***	0.132	1.399***
$\|\theta_D$/ mean annual growth (%)$\|$	0.92	0.28	0.39	0.40	0.02	0.27
UP coefficient (θ_U)	0.059	-0.191	0.097	0.514***	0.131	0.107
$\|\theta_U$/mean annual growth (%)$\|$	0.19	0.07	0.19	0.29	0.02	0.02

Notes. This table summarizes the estimated effects when restricting the sample to those firms with at least five banks per year. We focus on the estimates for the entire period (2003-2013) and the *financial crisis* (2008-2009). *Mean annual growth (%)* refers to the average annual growth rate of the variable as measured in our sample of firms in a particular period. *Credit Shock coefficient (θ)*, *DOWN coefficient (θ_D)*, and *UP coefficient (θ_U)* are the estimated coefficients reported in tables **??**, **??** and **??**. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. $|\theta$/mean annual growth (%)$|$ is the absolute value of the estimated coefficient divided by the mean annual growth (%).

Table F.5: Robustness V — Excluding construction and real estate firms.

	Employment		Output		Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
	2003-2013	2008-2009	2003-2013	2008-2009	2003-2013	2008-2009
mean annual growth (%)	2.382	1.179	0.686	-0.749	6.764	5.964
Credit Shock coefficient (θ)	0.306***	0.589***	0.119***	0.207***	0.927***	0.811***
$\|\theta$/mean annual growth (%)$\|$	0.13	0.50	0.17	0.28	0.14	0.14
DOWN coefficient (θ_D)	0.308*	0.659**	0.284***	0.454***	0.459***	0.681***
$\|\theta_D$/ mean annual growth (%)$\|$	0.13	0.56	0.41	0.61	0.07	0.11
UP coefficient (θ_U)	0.019	-0.309	0.151**	0.319***	0.144	0.123
$\|\theta_U$/mean annual growth (%)$\|$	0.01	0.26	0.22	0.43	0.02	0.02

Notes. This table summarizes the estimated effects when excluding construction and real estate firms both in the shock identification step and the network regressions. We focus on the estimates for the entire period (2003-2013) and the *financial crisis* (2008-2009). *Mean annual growth (%)* refers to the average annual growth rate of the variable as measured in the sample of firms in a particular period. *Credit Shock coefficient (θ)*, *DOWN coefficient (θ_D)*, and *UP coefficient (θ_U)* are the estimated coefficients reported in tables **??**, **??** and **??**. We denote significance at 10%, 5%, and 1% with *, **, and ***, respectively. $|\theta$/mean annual growth (%)$|$ is the absolute value of the estimated coefficient divided by the mean annual growth (%).

Table G.1: Real directs and indirect effects of credit shocks by firm size 2008-2009

	employment			output			investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	0-10	10-500	+500	0-10	10-500	+500	0-10	10-500	+500
Credit Shock	0.447***	0.638*	1.063	0.065***	0.305***	0.268	0.460***	0.438***	3.106
(s.e)	(0.133)	(0.319)	(0.894)	(0.013)	(0.049)	(1.247)	(0.098)	(0.148)	(2.807)
DOWN	1.016***	0.480	-1.028	0.515***	2.183***	4.407	1.497***	0.925**	0.061
(s.e)	(0.336)	(0.663)	(1.309)	(0.170)	(0.343)	(1.598)	(0.266)	(0.407)	(1.917)
UP	0.312	-0.219	1.455	0.328**	0.246	1.834	0.242	0.134	-0.212
(s.e)	(0.392)	(0.609)	(0.838)	(0.153)	(0.224)	(1.218)	(0.348)	(0.402)	(1.215)
# obs	289,327	98,522	1,036	279,098	97,389	1,015	280,285	97,939	1,050
R2	0.042	0.051	0.058	0.116	0.096	0.10	0.012	0.015	0.013
Sample firms	All	All	All	All	All	All	All	All	All
Fixed effects	sector × year	sector × year	sector × year	sector × year	sector × year	sector × year	sector × year	sector × year	sector × year

Notes. This table reports the direct and indirect effects of credit supply on employment, output, and investment over the 2008-2009 period, estimated using equation (7), for firms of different size. Columns (1), (4), and (7) refer to firms with between 0 and 10 employees. Columns (2), (5), and (8) refer to firms with between 10 and 500 employees, and columns (3), (6), and (9) to firms with more than 500 employees. *Credit Shock* refers to the firm-specific credit supply shock estimated in equation (4), normalized to have zero mean and unit variance. $DOWN_{jt,s}$ measures the indirect shock received by firm j operating in sector s from its suppliers (downstream propagation). $UP_{jt,s}$ proxies for the indirect shock received by firm j operating in sector s from its customers (upstream propagation). All regressions include the following control variables: firm-specific credit demand shocks ($\hat{\lambda}_{jt}$), lagged loan-to-assets ratio, and lagged productivity. We denote significance at 10%, 5%, and 1% with *, **, and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

H A Description of Bigio and La'o (2016)

Technology and market structure: There are n industries in the economy. In each of these industries $i = 1, ..., n$, there is a representative perfectly competitive firm that has access the following Cobb-Douglas production function:

$$y_i = \left[l_i^{\alpha_i} \left(\prod_{j=1}^{n} x_{ij}^{w_{ij}} \right)^{1-\alpha_i} \right]^{\eta_i} \tag{13}$$

where y_i is the amount of units produced in industry i, x_{ij} is the amount of goods produced in industry j used as inputs by industry i, l_i is the amount of labor used by industry i, $\eta_i \in (0,1)$ $\forall i$ governs the fraction of revenue devoted to cover input expenditures, i.e., labor plus intermediate goods, $\alpha_i \in (0,1)$ $\forall i$ determines the share of labor in total input expenditures. Finally, w_{ij} determines the share of intermediate good j in total expenditure in intermediate goods of industry i, with $\sum_{j=1}^{n} w_{ij} = 1$.

Financial constraints We assume the existence of working capital, which implies that firms must pay wages and the cost of intermediate goods before production takes place. Firms must borrow for this purpose. Financial markets are subject to some imperfection and thus firms can borrow up to a fraction χ_i of their revenue. A firm operating in industry i maximizes its profits subject to:

$$l_i + \sum_{j=1}^{n} p_j X_{ij} \leq \chi_i p_i y_i \tag{14}$$

Preferences Assume that the economy is populated by a representative household whose preferences are represented by the following utility function:

$$u(C,l) = \frac{C^{1-\gamma}}{1-\gamma} - \frac{l^{1+\epsilon}}{1+\epsilon} \tag{15}$$

where $C = \prod_{i=1}^{n} c_j^{v_j}$ with $v_j \in (0,1)$ and $\sum_{j=1}^{n} v_j = 1$ is the composite consumption good and l the amount of labor supplied by the household, $\gamma \geq 0$ captures the wealth effect on labor supply, whereas $\epsilon > 0$ captures the inverse of the substitution effect, i.e., the Frisch elasticity.

Firms' profit maximization A firm operating in industry i solves the following maximization problem:

$$\max_{l_i, x_{ij}, \forall j} \{p_i y_i - l_i - \sum_{j=1}^{n} p_j x_{ij}\}$$

$$\begin{aligned} \text{subject to:} \quad y_i &= \left[l_i^{\alpha_i} \left(\prod_{j=1}^{n} x_{ij}^{w_{ij}} \right)^{1-\alpha_i} \right]^{\eta_i} \\ l_i + \sum_{j=1}^{n} p_j x_{ij} &\leq \chi_i p_i y_i \end{aligned}$$

This problem can be solved in two stages. In the first stage, for a given level of firm's expenditure E_i, the firms decides how to allocate this expenditure across the different production factors. The solution of this problem is given by:

$$l_i = \alpha E_i \tag{16}$$

$$p_j x_{ij} = (1-\alpha_i) w_{ij} E_i \tag{17}$$

In the second stage, the firm decides the level of expenditure E_i, which must satisfy:

$$E_i = \phi_i \eta_i R_i \qquad where \qquad \phi_i = min\{\frac{\chi_i}{\eta_i}, 1\} \tag{18}$$

Note that under decreasing returns to scale, the firm would always like to borrow an amount equal to $\eta_i p_i y_i = \eta_i R_i$. When $\eta_i \leq \chi_i$, the firm will be able to borrow optimally. However, when $\eta_i > \chi_i$, the firm will borrow less than optimally.

Household's maximization problem The representative household maximizes the following problem:

$$\max_{C,l} \frac{C^{1-\gamma}}{1-\gamma} - \frac{l^{1+\epsilon}}{1+\epsilon}$$

$$\begin{aligned} \text{subject to:} \quad C &= \prod_{i=1}^{n} c_j^{v_j} \\ \sum_{j}^{n} p_j c_j &\leq wl + \sum_{i}^{n} \pi_i \end{aligned}$$

where wl measures the household's labor income and $\sum_i^n \pi_i$ the income from firms' profits. This problem can also be solved in two stages. In the first stage, given a total amount of consumption of the composite good, the household minimizes its associated expenditure across the different goods i. This stage implies an ideal price index for the composite good. Given this price index and the wage, the household decides how much to spend on total consumption and how much to work. The solution of this problem is given by:

$$\frac{c_j p_j}{\bar{p}C} = v_j \tag{19}$$

$$\frac{C^{-\gamma}}{l^{\epsilon}} = \frac{\bar{p}}{w} \tag{20}$$

where $\bar{p} = \prod_{j=1}^{n} \left(\frac{p_j}{v_j}\right)^{v_j}$ is the ideal price index. Equation (19) implies that the household's consumption expenditure share on a particular good j is constant and given by the share parameter j. Equation (20) implies that the marginal rate of substitution of consumption for leisure must be equal to the ratio of prices.

Equilibrium An equilibrium in this economy is defined as a set of prices $\{p_1, ..., p_n\}$ and allocations $\{l_1, ...; l_n\}$, $\{c_1, ..., c_n\}$ and $\{x_{i1}, ..., x_{in}\}$, $\forall i$, such that:

1. Firms solve their maximization problem, i.e., equations (16), (17), and (18) are satisfied.

2. Households solve their optimization problem, i.e., equations (19) and (20) are satisfied.

3. Markets clear:

$$y_i = \sum_{j=1}^{n} x_{ji} + c_i \quad \forall i \tag{21}$$

$$l = \sum_{i=1}^{n} l_i \quad \forall i \tag{22}$$

Aggregate effects of financial frictions

$$\text{real GDP} = \underbrace{\bar{z}\ (\mathbf{z})\ \Phi\ (\phi)}_{\text{efficiency}} \underbrace{L^{\bar{\eta}}}_{\text{labor}} \tag{23}$$

where $\bar{z}(\mathbf{z})\Phi(\phi)$ depends on sectoral productivities and financial frictions, L is the endogenous amount of labor in the economy, and $\bar{\eta}$ is a constant that reflects the decreasing returns in firms' technology. Bigio and La'o (2017) refer to the term $\bar{z}(\mathbf{z})\Phi(\phi)$ as the *efficiency wedge* and to the term $L^{\bar{\eta}}$ as the *labor wedge*.

I Calibration and Predicted Real Effects

Calibration: Details For our baseline results, we set $\eta = 0.99$ for all sectors i. We report results using a different value for η in the appendix. We further set to some predetermined values the parameters governing the household labor supply. In particular, following Bigio and La'o (2017), we set $\gamma = 0$ and $\epsilon = 2$.

We identify the 2003 level of financial frictions for each sector i (ϕ_i) by exploiting the fact that in the model the ratio of firms' expenditures to revenue satisfies:

$$\frac{wl_i + \sum_{j=1}^{n} p_j x_{i,j}}{p_i y_i} = \phi_i \eta \quad \forall i \tag{24}$$

Given our assumed value of η and data on sectoral gross output, labor and intermediate goods expenses measured from the input-output tables, we can obtain a value of ϕ for each industry. We identify the labor share in each sector i (α_i) in the production function by exploiting the fact that in the model firms' expenditure in labor as a fraction of total expenses in inputs satisfies:

$$\alpha_i = \frac{wl_i}{wl_i + \sum_{j=1}^{n} p_j x_{i,j}} \quad \forall i \tag{25}$$

Finally, we identify the industry shares in the Cobb-Douglas consumption aggregator by matching the final consumption expenditure shares:

$$v_i = \frac{p_i c_i}{\sum_{j=1}^{n} p_j c_j} \quad \forall i \tag{26}$$

provided by the IO tables. The parameters governing the IO structure of the economy use the information provided by the Spanish *direct requirement matrix*. In particular, with the information provided in this matrix we can measure, in each industry i, the expenditure on each intermediate good j as a fraction of total expenditure on intermediate goods:

$$w_{i,j} = \frac{p_j x_{ij}}{\sum_{j=1}^{n} p_j x_{ij}} \quad \forall i, j \tag{27}$$

Predicted Direct Effects To estimate the employment effects of credit shocks that are comparable over time, we compute the effects in employment at the firm-level that are predicted by the direct credit supply shocks and aggregate them to the industry-level. Armed with these direct effects estimated from the data, we quantify the real effects of the financial shocks over time according to the calibration strategy described in Section 5.2.2.

We first estimate the strength of the credit channel at the firm level by regressing employment firm growth on credit growth instrumented with our firm-specific credit supply shocks:

$$\begin{aligned} \Delta \ln E_j &= \phi \Delta \ln c_j + \pi_{IV} X_j + u_j \\ \Delta \ln c_j &= \psi \overline{\delta}_j + \Phi_{IV} X_j + v_j \end{aligned} \tag{28}$$

where $\Delta \ln c_j$ refers to the credit growth of firm j, $\overline{\delta}_j$ is the bank supply shocks at the firm level defined in equation (4), and X_j are firm level controls. The identification assumption is that bank credit supply ($\overline{\delta}_j$) affects firm growth only through its effect on credit. Note that the first stage is similar to the bank lending channel at the firm level estimated in (10). Moreover, the reduced form effect in (3) is equal to the bank lending channel multiplied by the pass-through of credit to firm growth: $\theta = \psi \times \phi$. We then estimate year-by-year counterfactual employment growth at the firm level in the absence of credit supply shocks using the estimates from (28). More specifically, we first estimate the firm-level credit growth due to the bank supply shocks:

$$\widetilde{\Delta \ln c}_j = \hat{\psi} \overline{\delta}_j \tag{29}$$

With the credit growth induced by supply factors ($\widetilde{\Delta \ln c}_j$), we can estimate the counterfactual employment growth that would have been observed in the absence of credit supply shocks as follows:

$$\widetilde{\Delta \ln E}_j = \Delta \ln E_j - \hat{\phi} \widetilde{\Delta \ln c}_j \tag{30}$$

where E_j refers to employment of firm j, and $\hat{\phi}$ refers to the estimate obtained from (28).

Firm-specific employment growth measures (both observed and counterfactual) can be aggregated as follows:

$$\widetilde{\Delta \ln E} = \sum_j \varphi_j \widetilde{\Delta \ln E_j} \tag{31}$$

$$\Delta \ln E = \sum_j \varphi_j \Delta \ln E_j \tag{32}$$

where φ_i refers to the employment weight of firm i in the previous year ($\varphi_i = \frac{E_{i(-1)}}{\sum_j E_{j(-1)}}$).

We apply this formula at the industry level to obtain sector-specific credit supply shocks in terms of employment. The estimated effects point to positive credit supply shocks over the 2003-2007 period for all the 64 (NACE rev2 classification) sectors. In contrast, the shocks appear to be negative in the 2008-2009 period.

J List of Industries

Table J.1: List of industries

Number	Industry
1	Crop and animal production, hunting and related service activities
2	Forestry and logging
3	Fishing and aquaculture
4	Mining and quarrying
5	Manufacture of food products, beverages and tobacco products
6	Manufacture of textiles, wearing apparel and leather products
7	Manufacture of wood and of products of wood and cork, except furniture
8	Manufacture of paper and paper products
9	Printing and reproduction of recorded media
10	Manufacture of coke and refined petroleum products
11	Manufacture of chemicals and chemical products
12	Manufacture of basic pharmaceutical products and pharmaceutical preparations
13	Manufacture of rubber and plastic products
14	Manufacture of other non-metallic mineral products
15	Manufacture of basic metals
16	Manufacture of fabricated metal products, except machinery and equipment
17	Manufacture of computer, electronic and optical products
18	Manufacture of electrical equipment
19	Manufacture of machinery and equipment n.e.c.
20	Manufacture of motor vehicles, trailers and semi-trailers
21	Manufacture of other transport equipment
22	Manufacture of furniture; other manufacturing
23	Repair and installation of machinery and equipment
24	Electricity, gas, steam and air conditioning supply
25	Water collection, treatment and supply
26	Sewerage; waste collection, treatment and disposal activities; materials recovery;
27	Construction
28	Wholesale and retail trade and repair of motor vehicles and motorcycles
29	Wholesale trade, except of motor vehicles and motorcycles
30	Retail trade, except of motor vehicles and motorcycles
31	Land transport and transport via pipelines
32	Water transport
33	Air transport
34	Warehousing and support activities for transportation
35	Postal and courier activities
36	Accommodation; food and beverage service activities
37	Publishing activities
38	Motion picture, video and television programme production, sound recording and music publishing activities
39	Telecommunications
40	Computer programming, consultancy and related activities; information service activities
41	Financial service activities, except insurance and pension funding
42	Insurance, reinsurance and pension funding, except compulsory social security
43	Activities auxiliary to financial services and insurance activities
44	Real estate activities
45	Legal and accounting activities; activities of head offices; management consultancy activities
46	Architectural and engineering activities; technical testing and analysis
47	Scientific research and development
48	Advertising and market research
49	Other professional, scientific and technical activities; veterinary activities
50	Rental and leasing activities
51	Employment activities
52	Travel agency, tour operator reservation service and related activities
53	Security and investigation activities; services to buildings and landscape activities; business support activities
54	Public administration and defence; compulsory social security
55	Education
56	Human health activities
57	Social work activities
58	Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling activities
59	Sports activities and amusement and recreation activities
60	Activities of membership organisations
61	Repair of computers and personal and household goods
62	Other personal service activities