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Working Paper 18-052

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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. Combining firm-specific measures of upstream and downstream exposure, we construct firm-specific exogenous credit supply shocks and estimate their direct and indirect effects on real activity. Credit supply shocks have sizable direct and downstream propagation effects on investment and output throughout the period but no significant impact on employment during the expansion period. Downstream propagation effects are comparable or even larger in magnitude than direct effects. The results corroborate the importance of network effects in quantifying the real effects of credit shocks and show that real effects vary during booms and contractions.

JEL Codes: E44, G21, L25. Keywords: bank-lending channel, employment, investment, output, matched employer-employee, input-output linkages.

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1 Introduction

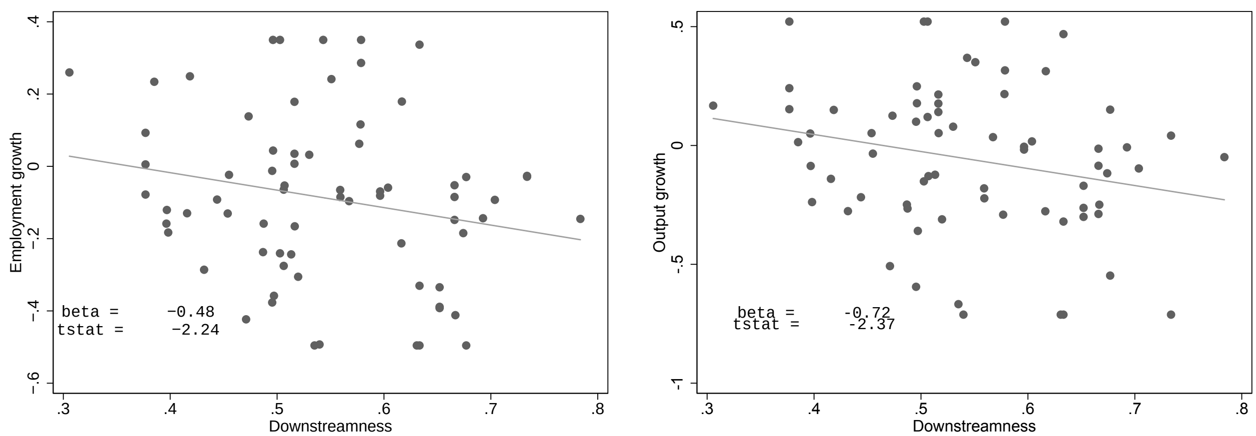
In this paper we examine the real effects of the bank lending channel and how bank-lending shocks permeate the economy through upstream and downstream linkages. Credit shocks matter if they have real effects on the economy. We show that bank credit supply shocks do affect, and indeed permeate the real economy through input and output relations, and we find their effects to differ between expansions and recessions.

We first analyze the direct real effects on employment, output, and investment of credit supply shocks for close to the total population of Spanish firms for 2003-2013. We identify bank-specific credit supply shocks for each year in the sample through differences in credit growth between banks lending to the same firm (bank lending channel at the firm-loan level; Khwaja and Mian (2008), Jimenez, Mian, Peydro, and Saurina (2014), Amiti and Weinstein (Forthcoming)) and matched employer-employee techniques (Abowd, Kramarz, and Margolis (1999)). We regress annual employment and output growth as well as investment rates on the estimated bank supply shocks at the firm-level, controlling for demand factors. Our micro data replicates to a nearly complete picture of the Spanish economy, while the time period, which includes the expansion (2003-2007), the global financial crisis (2008-2009), and the post-crisis recession (2010-2013), enables the study of the real effects of idiosyncratic credit shocks during crisis and non-crisis episodes.

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. We thus proceed to compare direct and indirect propagation effects of bank-lending shocks related to input-output relations. We combine the Spanish Input-Output structure and firm-specific measures of upstream and downstream exposure. Based on di Giovanni, Levchenko, and Mejean (2018) we measure whether firms that buy inputs from industries in which firms affected by the shocks operate are indirectly affected (downstream effects). Similarly, we also measure whether firms that sell goods to industries whose firms were affected by the shocks are indirectly affected (upstream effects).

We find that both the estimated direct effect and propagation effect on real variables are sizable. Our estimates imply that a one standard deviation increase in firms' credit supply generates increases of 0.28 pp., 0.10 pp., and 0.79 pp. in the change of employment, output and investment, respectively. Similarly, 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. Bank credit supply shocks, however,

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).

exhibit different effects over time, being much stronger during the 2008-2009 credit collapse. We find no significant direct effects of credit supply shocks on employment before the financial crisis while investment displays similar reactions throughout the entire period. Also, for employment, estimated downstream effects are not significant before the crisis.

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., firms' ability, or lack thereof, to borrow from alternative sources).[1] Even after identifying the shocks, the intricate, real consequences may vary across different types of firms involving direct and indirect effects via buyer-supplier (input-output) relations. Thus far, little empirical work has analyzed this channel. Effects, moreover, may differ during expansions and contractions. Albeit mixed overall, evidence of real effects is more consistently found when analyzing financial crises which differ from other episodes.[2] The exercise is very demanding, requiring firm-level data linking credit informa-

[1]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.

[2]The literature has used the Global Financial Crisis, notable for its speed, severity, and international span, to identify supply effects. As documented by Reinhart and Rogoff (2009), downturns associated with financial crises

tion to outcome variables (employment, investment, output, etc.). Common methodologies that involve storing a large number of fixed effect dummies are not well suited to handling large data sets, while working with smaller subsamples raises aggregation concerns. To overcome these challenges we proceed as follows, making several contributions to the literature.

To disentangle the bank-lending from the firm-borrowing channel, we exploit firm-loan-bank relations and use matched employer-employee techniques that enable us to identify multiple time-varying firm, and bank, fixed effects (see Abowd, Kramarz, and Margolis (1999)). This methodology, as explained below, 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.[3] The inclusion of firm-year fixed effects, possible because firms borrow from different banks, enables us to account for time-varying demand factors. Combining matched employer-employee estimation techniques with the Amiti and Weinstein (Forthcoming) identification strategy, we estimate more than 2,000 bank-year credit supply shocks and more than six million firm-year credit demand shocks. These shocks enable us to analyze the evolution of the bank lending channel beyond financial crises episodes traditionally used in the literature.

As mentioned, we apply this methodology to a data set that documents credit relations for the quasi-census of Spanish firms, nearly two million per year. The data set merges loan-level data on credit in the domestic banking sector from the Central Credit Register (CIR) of Banco de España with administrative data on firm-level characteristics from the Spanish Commercial Registry for 2003-2013, yielding approximately eighteen million bank-firm-year observations.

We validate our bank-supply-shocks in several ways. First, we divide the sample into healthy and weak banks, as in Bentolila, Jansen, and Jimenez (Forthcoming). We find that weak banks experienced greater supply shocks until 2006 and lesser 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. Using loan application information, available in the credit registry dataset, we show this to be the case. Finally, following Amiti and Weinstein (Forthcoming), we compute the R-square and show banks' predicted credit growth to explain banks' actual credit growth.

We find the effects of bank supply shocks to be large and significant at the loan-level: a one standard deviation increase is associated with a 5.1 pp. increase in credit growth. These estimates are very stable throughout the whole period. At the firm level, we analyze the change in credit for a

differ from other recessions. We discuss related work in the literature review subsection.

[3]Given the sparsity of typical matrices involved in estimating high-dimensional fixed effects, the use of efficient algorithms for matrix inversion and storage is fundamental to the matched employer-employee techniques used here (see, for example, Cornelissen (2008)).

particular firm considering the supply shocks estimated for all banks with relationships to this firm. We also find sizable effects at the firm level: a one standard deviation increase in credit supply shocks generates an increase of 3.2 pp. in firm credit growth. This effect, smaller than that estimated at the loan level, indicates that firms, in particular multi-bank firms, are able to partially offset bank supply shocks. Also, in line with the effects on real outcomes, we find that the estimated effects on credit growth are higher during the financial crisis, when it is more difficult for firms to offset a credit shock by resorting to other banks. We perform several robustness tests of our findings. To ensure that the estimated bank supply shocks are not driven by few observations, we restrict our sample of multi-bank firms to those with at least 5 banks per year. In order to account for bank-firm idiosyncratic factors, we control for lagged exposure between bank i and firm j in the estimation of bank supply shocks. We also consider different subsamples for shock identification and real effects estimation further confirming that the methodology consistently estimates bank and firm shocks.

With our estimated credit supply shocks at hand, we investigate the aggregate effects of financial shocks by using a general equilibrium model with buyer-supplier relations under the presence of financial frictions, as in Bigio and La'o (2017). In particular, we aggregate our firm-level shocks to the industry level, in a way that makes them comparable over time. We then plug these shocks into the model and examine how the identified credit shocks permeate the economy. 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. The implied growth in employment between 2011 and 2012, during the recession period, was -2.38 pp. (actual growth was -6.98%), -1.20 pp. attributable to direct, and -1.18 pp. to propagation, effects.

We further use the model to investigate the relative importance of each sector in accounting for the aggregate effects. In particular, we focus on the financial crisis period and 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, real estate is also intensively used by other sectors. In fact, our model predicts that around 50% of the 0.24% loss is explained by propagation of the shock to other sectors. We also find that shocking other central sectors like electricity services or wholesale would also generate large output losses.

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 (Forthcoming).

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), and 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. Methodologically, our paper is closest to Amiti and Weinstein (Forthcoming). 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). Our data covering the quasi-population of Spanish firms, aggregation bias is less of a concern.[4] We further contribute to this literature by quantifying the propagation of the credit supply shocks through input-output linkages.

A series of recent papers have investigated the aggregate effects of shocks that propagate through the economy's IO network, such as Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). 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. A series of papers in the literature have exploited natural disasters as exogenous shocks, finding IO 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). In recent work, Dewachter, Tielens, and Hove (2017), using mostly single bank-firm relations in Belgium, exploiting value added information, analyze the propagation effects of shocks. 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. Our paper quantifies the effects of a well identified shock, that is, firm-level credit supply shocks, and investigates the direct and indirect effects on other firms through connections in the production network. More concretely, we follow di Giovanni, Levchenko, and Mejean (2018) in using industry-level IO tables together with firm-level information on expenditure shares to construct measures of firms' exposure to downstream and upstream shocks.[5] On the other hand, our paper builds on a recent contribution 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

[4] Amiti and Weinstein (Forthcoming) 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).

[5] Alfaro, Antrás, Chor, and Conconi (Forthcoming) use input-output relations to establish upstream and downstream relations.

network. We use credit registry data to identify financial shocks at the firm level. We then aggregate these shocks at the industry-level 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. Section 4 presents the direct real effects of the bank lending shocks. Section 5 discusses our estimates for downstream and upstream propagation effects of the credit shocks. Section 6 describes the methodology and framework to quantify the aggregate effects of the credit shocks. Section 7 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.

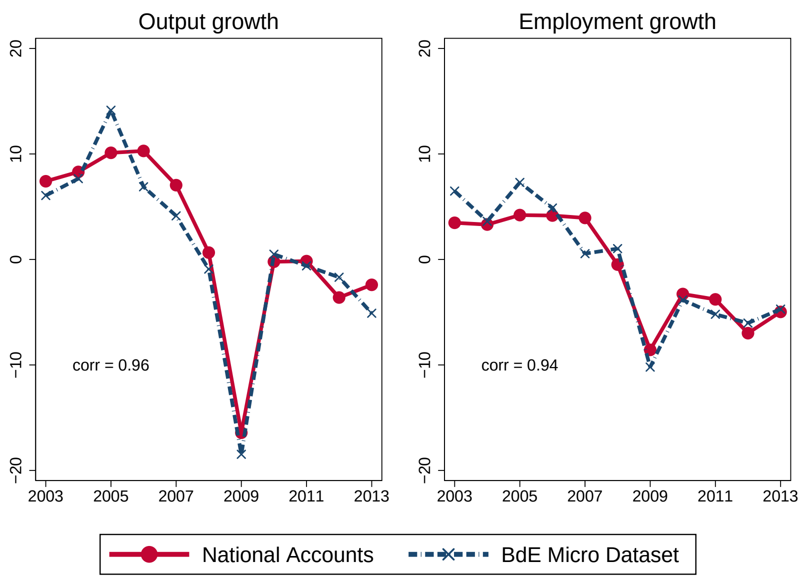
The CIR identifies the parties involved in each loan, enabling us to match loan-level data from CIR with administrative data on firm-level characteristics. While the CIR data are available at the monthly frequency, firm-level characteristics are only available on a yearly basis. Therefore, we collapse 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 3.1.1

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.[6] 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.

[6]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.

Input-Output Tables We use the Input-Output tables provided by INE and constructed at the 64-industry-level of disaggregation (see Table A.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 the paper.[7] 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.[8]

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.

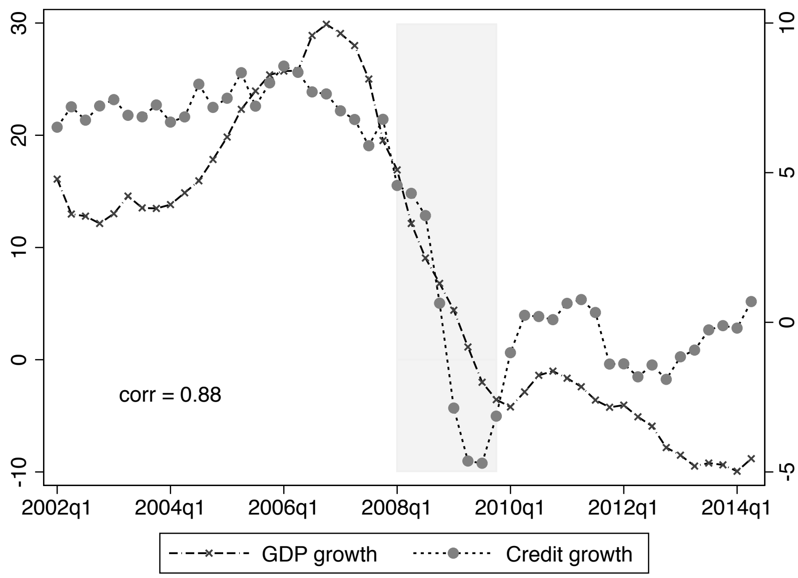
3 The Bank Lending Channel

In this section we analyze the bank lending channel. In subsection 3.1, we estimate bank-specific credit supply shocks by exploiting the richness of our dataset, in which in each period, we observe different banks lending to the same firm and different firms borrowing from the same bank. We also describe various ways in which we validate the estimated shocks in 3.1.1. In subsection 3.2, we quantify the bank-lending channel at the bank-firm (loan) level. In subsection 3.3, we quantify the bank-lending channel at the firm level by aggregating all loans across banks within each firm.

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

[8] As documented by Reinhart and Rogoff (2009), financial crises tend to be characterized by deep recession and slow recovery. 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.

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 identified through differences in credit growth between banks lending to the same firm.[9]

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

[9]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.

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.[10] Given the sparsity of typical matrices involved in the estimation 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)).[11]

Turning to identification, the bank- and firm-effects are identified only in relative terms within each *group*.[12] 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 6, we present a methodology for interpreting the evolution of the effects. In Appendix B 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.

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

[10]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.

[11]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.

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

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, Amiti and Weinstein (Forthcoming) 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 (Forthcoming) for a formal proof). As they explain, although bank-firm interactions enable to understand particular firm's demand, bank and firm shocks can be consistently estimated from equation (1). Indeed, in the robustness section, we show our results remain unaltered when accounting for lagged bank-firm idiosyncratic factors in equation (1). Moreover, 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.

3.1.1 Validating the Bank-specific Credit Supply Shocks

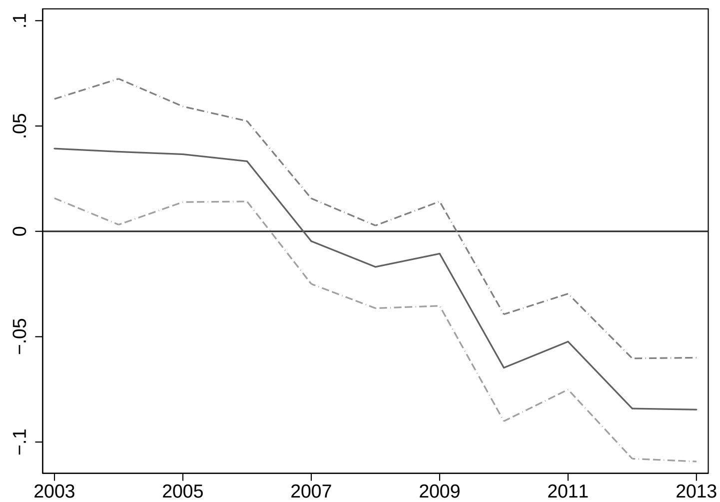
We provide further validation of the estimated credit supply shocks. First, in order to assess the plausibility of the $\hat{\delta}_{it}$ estimates, we divide our sample into healthy and weak banks, as in Bentolila, Jansen, and Jimenez (Forthcoming). Figure 4 shows the time evolution of the average 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 afterwards, which coincides with the narrative in Bentolila, Jansen, and Jimenez (Forthcoming). 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:

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

where Loan granted$_{ij}$ is a dummy variable taking the value 1 if firm j has at least one loan granted by

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



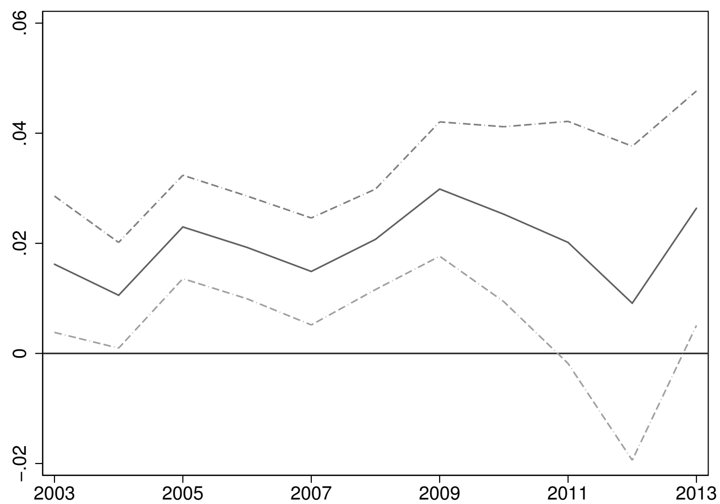
Notes. This plot is based on year-by-year regressions of the estimated bank-level shocks on a constant and a dummy that takes value of one if the bank is classified as "weak" in Bentolila, Jansen, and Jimenez (Forthcoming). For each year, we plot the coefficient on the weak bank dummy, which estimates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

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 (Forthcoming), we further explore how well our predicted banks' credit growth explains the banks' actual credit growth. Specifically, we compute the R-squared of a regression of the bank's actual credit growth ($\Delta \ln c_{it}$) on the bank's credit growth predicted by our model ($\Delta \hat{\ln} c_{it}$).[13] The R^2 for the entire 2003-2013 period is 52%, which indicates that the estimated bank- 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

[13]We construct $\Delta \hat{\ln} c_{it}$ 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 $\Delta \hat{\ln} c_{ijt} = \hat{\delta}_{it} + \hat{\lambda}_{jt}$.

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.

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.[14]

3.2 Loan-Level Effects

We first 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:

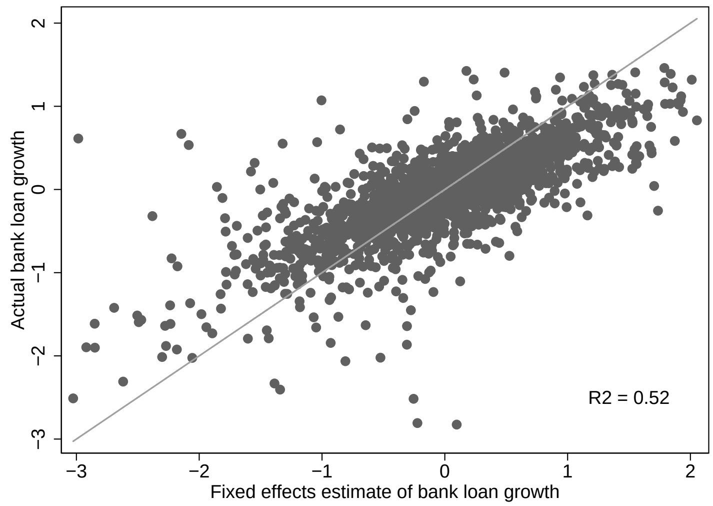
$$\Delta \ln c_{ijt} = \beta \hat{\hat{\delta}}_{it} + \eta_{jt} + v_{ijt} \tag{3}$$

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,[15] 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

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

[15]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.

Figure 6: Explanatory power of our estimated shocks



Notes. This graph plots the relationship between the banks' 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 $\Delta \hat{\ln} c_{ijt} = \hat{\delta}_{it} + \hat{\lambda}_{jt}$.

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,[16] we can also estimate the evolution of the bank lending channel over time.

Note that equation (3) 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:[17]

$$\Delta \ln c_{ijt} = \beta \hat{\delta}_{it} + \gamma \hat{\lambda}_{jt} + v_{ijt} \tag{4}$$

Table 1 reports the estimates of the bank lending channel at the bank-firm (loan) level. Column (1) presents the results of estimating equation (3) using the entire period (2003-2013). We find a

[16]Since our regressor of interest is estimated in a first step, standard errors in equation (3) 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.

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

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 (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 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 (3) for a sample of multibank firms. Columns (2) are (3) are based on equation (4), 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 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 C.2 in Appendix C presents the year-by-year estimates of the loan-level effect.

3.3 Firm-Level Effects

The bank lending channel appears to be quantitatively and statistically important given the loan-level estimates reported in section 3.2. 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:

$$\Delta \ln c_{jt} = \beta^F \overline{\delta}_{jt} + \gamma^F \hat{\lambda}_{jt} + u_{jt} \tag{5}$$

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:

$$\overline{\delta}_{jt} = \sum_i \frac{c_{ij,t-1}}{\sum_i c_{ij,t-1}} \hat{\delta}_{it} \tag{6}$$

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 (3) 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 2 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 C.2 in Appendix C presents the year-by-year estimates of this effect.

Interestingly enough, the magnitude of the bank lending channel at the firm level varies significantly over the cycle (see Table 2) while it does not vary at the loan level (Table 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 2: 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 (5). 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 (6), 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 (5) 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.

4 Direct Real Effects of Credit Shocks

We now turn to analyzing 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:

$$Y_{jt} = \theta\bar{\delta}_{jt} + \pi X_{jt} + \nu_{jt} \tag{7}$$

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.[18] $\bar{\delta}_{jt}$ is the bank supply shocks at the firm level defined in equation (6), and 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.

4.1 Entire Sample (2003-2013)

Table 3 reports the results of estimating equation (7) for the 2003-2013 sample. Columns (1) and (2) report the results using employment changes of firm j in year t as the left hand side variable Y_{jt}. Columns (3)-(4) and (5)-(6) use output changes and investment instead. Columns (1), (3), and (5) refer to specifications in which we focus only on multi-bank firms, columns (2), (4), and (6) include all firms.

We find positive and statistically significant effects of credit supply shocks across all specifications.

[18] 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 (Forthcoming) and Chodorow-Reich (2014), respectively.

With the exception of the effect on employment when using multi-bank firms (column (1)), 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) and (2) imply that a one standard deviation increase in the firm's credit supply shock is associated with increases in firm employment growth of 0.22 pp. and 0.29 pp., respectively. These numbers represent approximately 71% and 93% of the average firm-level annual employment growth rate of 0.31% over the 2003-2013 period.[19]

With respect to output, the estimated coefficients reported in columns (3) and (4) imply that a one standard deviation increase in firm credit supply shock is associated with an average increase in firm output growth of around 0.14 pp. and 0.10 pp., respectively, approximately 27% and 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 columns (5) and (6) imply that a one standard deviation increase in firm credit supply shock is associated with an increase in firm investment of 1.00 pp. and 0.80 pp., respectively. These numbers represent 13% and 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-size firms while effects for larger firms are not statistically significant.[20]

Table 3: Direct real effects of credit shocks — 2003-2013

	employment		output		investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Shock	0.222*	0.292***	0.138***	0.103***	1.004***	0.802***
(s.e.)	(0.127)	(0.097)	(0.029)	(0.030)	(0.160)	(0.069)
# obs	2,436,177	4,064,376	2,339,456	3,873,003	2,390,583	3,938,238
# banks	216	216	216	216	216	216
# firms	560,954	812,067	542,191	779,500	546,913	782,872
R2	0.060	0.050	0.063	0.057	0.032	0.028
Sample firms	Multibank	All	Multibank	All	Multibank	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 (2)), output (columns (3) and (4)), and investment (columns (5) and (6)) estimated using equation (7) 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 (6), normalized to have zero mean and unit variance. 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.

[19] 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 sections 4 and 5.

[20] Appendix F reports the real effects estimated for firms of different size.

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 effects of firms' credit supply shocks change with the state of the macroeconomy. To that end, we break down our sample into three periods. Table 4 reports our estimated results for employment, output, and investment.

Employment We find aggregate economic conditions to 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 regressions run for the *financial crisis* of 2008-2009.[21] 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) reported in column (7). 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%).

Table 4: 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 (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 (6), 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.

[21] 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.

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%).

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.

5 Indirect Real Effects of Credit Shocks

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 of this supplier may also affect production of firm j. Indeed, the negative association between employment growth and downstreamness depicted in Figure 1 resembles this pattern. 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 in general equilibrium (see Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)).

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, Antrás, Chor and Conconi (2017).[22] We use IO relations for Spain for both propagation downstream (i.e., shocks

[22] 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, Antrás, Chor, and Conconi (forthcoming) use input-output linkages to establish upstream and downstream relations.

from suppliers) and upstream (i.e., shocks from customers). In practice, we include two additional regressors in our empirical specification in (7) to capture the indirect effects of credit shocks through input-output relations.

We have shown in the previous section that credit supply shocks have direct real effects. This implies that, 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).

Following di Giovanni, Levchenko, and Mejean (2018), we define these proxies as follows:

$$DOWN_{jt,s} = \omega_{jt}^{IN} \sum_p IO_{ps} \Delta_{jt,p} \tag{8}$$

$$UP_{jt,s} = \omega_{jt}^{DO} \sum_p IO_{sp} \Delta_{jt,p} \tag{9}$$

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 ($\bar{\delta}_{jt}$) using credit exposure as weights. (This shock is firm-specific because firm j is excluded from the computation of sector-specific 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_{jt}^{IN} 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_{jt}^{DO} 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 model:

$$Y_{jt} = \theta \bar{\delta}_{jt} + \theta_D DOWN_{jt,s} + \theta_U UP_{jt,s} + \pi X_{jt} + \nu_{jt} \tag{10}$$

where all elements are defined as in equations (7), (8), and (9).

5.1 Propagation Results

Tables 5, 6, and 7 show the results of running regressions from specification (10) using change in employment, change in output, and investment as the left hand side variables Y_{jt}. We find strong evidence to the propagation of real effects of firms' credit supply shocks. 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. The effects are particularly strong for the *financial crisis* 2008-2009 period. We find mixed evidence for the case of upstream propagation, $UP_{jt,s}$, our estimated coefficients having different signs and significance depending on the left hand side variable use and period.[23]

Table 5: Indirect effects — employment

	(1) 2003-2013	(2) 2003-2007	(3) 2008-2009	(4) 2010-2013
Credit Shock	0.284***	0.218	0.482***	0.255**
(s.e.)	(0.098)	(0.151)	(0.156)	(0.111)
DOWN	0.301**	-0.077	0.697***	0.129
(s.e.)	(0.119)	(0.076)	(0.258)	(0.392)
UP	0.061	0.062	-0.187	-0.233*
(s.e.)	(0.120)	(0.078)	(0.291)	(0.123)
# obs	3827042	1727803	759170	1340069
R2	0.053	0.040	0.059	0.036
Fixed effects	sector × year	sector × year	sector × year	sector × year

Notes. This table reports the effects of credit supply shocks on employment over the 2003-2013 period and 2003-07, 2008-09, and 2010-13 sub-periods estimated from equation (10). Credit Shock refers to the firm-specific credit supply shock estimated in equation (6), normalized to have zero mean and unit variance. DOWN and UP have been constructed according to equations (8) and (9) respectively. 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.

Employment Running the specification for the entire sample period yields estimated coefficients for the direct credit shock and indirect downstream propagation shock ($DOWN$) that 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 (see column (1) of Table 5). These

[23]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.

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). When focusing on the *expansion* period (2003-2007), the effects of credit shocks are not significant (see column 2 of Table 5). Note that the insignificant effect on employment of the direct shock was present before when not including the indirect shocks (column (1) of Table 4). In fact, the estimated coefficients for the direct shock are similar across the two specifications (0.222 vs 0.284).

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 3 in table 5). 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 significant effect of the upstream propagation shock (UP) of -0.23 pp.

Table 6: Indirect effects — output

	(1) 2003-2013	(2) 2003-2007	(3) 2008-2009	(4) 2010-2013
Credit Shock	0.107***	0.069**	0.155***	0.108***
(s.e.)	(0.029)	(0.027)	(0.031)	(0.020)
DOWN	0.354***	0.204*	0.646***	0.184
(s.e.)	(0.069)	(0.106)	(0.166)	(0.251)
UP	0.209***	0.086	0.459***	-0.014
(s.e.)	(0.077)	(0.086)	(0.141)	(0.125)
# obs	3744353	1704934	739238	1300181
R2	0.067	0.051	0.086	0.049
Fixed effects	sector × year	sector × year	sector × year	sector × year

Notes. This table reports the effects of credit supply shocks on output over the 2003-2013 period,and the 2003-2007, 2008-2009, and 2010-2013 sub-periods estimated using equation (10). Credit Shock refers to the firm-specific credit supply shock estimated in equation (6), normalized to have zero mean and unit variance. DOWN and UP have been constructed according to equations (8) and (9) respectively. 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.

Output The coefficients for output associated with the two indirect propagation shocks are significant at 1% when the regression is run for both the entire period (2003-2013) and when we focus on the *financial crisis* period (2008-09). In these two specifications, in fact, the indirect effects dominate the direct effects in terms of magnitude. The downstream (upstream) effect for the whole period is 0.35 (0.21), which is significantly larger than the direct effect of 0.10 pp. Turning to the *financial crisis* 2008-09 period, we find that the effects of the downstream and upstream propagation shocks were 0.64 pp. and 0.46 pp. respectively. These two values represent around 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.

Table 7: Indirect effects — investment

	(1) 2003-2013	(2) 2003-2007	(3) 2008-2009	(4) 2010-2013
Credit Shock	0.798***	0.845***	0.576***	0.708***
(s.e.)	(0.075)	(0.177)	(0.101)	(0.085)
DOWN	0.690***	0.266	1.263***	0.110
(s.e.)	(0.174)	(0.281)	(0.320)	(0.552)
UP	0.174	0.403**	0.085	-0.402
(s.e.)	(0.209)	(0.172)	(0.352)	(0.401)
# obs	3737540	1687930	739729	1309881
R2	0.030	0.036	0.018	0.012
Fixed effects	sector × year	sector × year	sector × year	sector × year

Notes. This table reports the effects of credit supply shocks on investment over the 2003-2013 period and the 2003-2007, 2008-2009, and 2010-2013 sub-periods estimated from equation (10). Credit Shock refers to the firm-specific credit supply shock estimated in equation (6), normalized to have zero mean and unit variance. DOWN and UP have been constructed according to equations (8) and (9) respectively. 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.

Investment The estimates of the direct shock to investment are significant at 1% across all specifications. The indirect downstream shock is significant when focusing on the entire period and during the *financial crisis*. The indirect upstream shock is only significant in the *expansion* (2003-2007) specification. As in the employment case, the direct and indirect downstream effects are relatively similar in magnitude when looking at the whole period (2003-2013), 0.79 pp. and 0.69 pp. respectively. These effects represent around 10% and 9% of the actual average investment rate over the period. When focusing on the *financial crisis*, the indirect downstream effect is stronger than the direct effect. 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.

Table 8: Summary and magnitude of the estimated effects

	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)	0.284***	0.482***	0.107***	0.155**	0.798***	0.576***
$\lvert\theta$/mean annual growth (%)$\rvert$	0.91	0.17	0.21	0.09	0.10	0.11
DOWN coefficient (θ_D)	0.301***	0.697***	0.354***	0.646**	0.690***	1.263***
$\lvert\theta_D$/mean annual growth (%)$\rvert$	0.96	0.28	0.70	0.37	0.09	0.25
UP coefficient (θ_U)	0.061	-0.187	0.209***	0.459***	0.174	0.085
$\lvert\theta_U$/mean annual growth (%)$\rvert$	0.19	0.60	0.41	0.26	0.02	0.02

Notes. This table presents a summary of the estimated effects reported in tables 6, 7 and 5. We focus on the effects estimated for the entire period (2003-2013) and the *financial crisis* (2008-2009) period. *Mean annual growth (%)* refers to the simple average annual growth rate of the variable as measured in our final sample of firms for a particular period. *Credit Shock coefficient (θ)*, *DOWN coefficient (θ_D)*, and *UP coefficient (θ_U)* are the estimated coefficients reported in Tables 6, 7, and 5. We denote significance at 10%, 5%, and 1% with *, **, and ***, respectively. $\lvert\theta$/mean annual growth (%)$\rvert$ is simply the absolute value of the estimated coefficient divided by the mean annual growth (%).

Summary Table 8 summarizes our main findings while Appendix D reports the year-by-year estimates. 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 dominated 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.

5.2 Robustness Checks

Appendix E reports a battery of exercises that confirm our main findings to be robust along several dimensions. We first 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.[24] Table E.2 in Appendix E shows our baseline results to remain unaltered when considering these exercises thereby corroborating the exogeneity of our baseline bank credit shocks.

Second, 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 E.3 illustrates the main conclusions to be robust to this exercise.

Third, we include in equation (1) the lagged exposure between bank i and firm j in order to account for bank-firm idiosyncratic factors. As expected from the the findings in Amiti and Weinstein (Forthcoming), the results are not affected by inclusion of these bank-firm-specific factors (see Table E.4).

Finally, Appendix F 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.[25]

6 From Micro to Macro: Aggregate Effects of Credit Shocks

In previous sections we estimated the direct and indirect relationship between credit supply shocks and real variables to be statistically significant and economically sizable. In this section, we quantify the aggregate effects of bank credit supply shocks on output and employment. For that purpose, we use a general equilibrium model with financial frictions and input-output linkages to quantify the propagation effects of the credit supply shocks identified from the data.[26]

[24]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. 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. Analogously, we combine bank fixed effects identified from a group of firms with the firm-bank shares of a different group of firms.

[25]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.

[26]Our empirical methodology identifies relative bank credit supply shocks within a given year. In the jargon of the matched employer-employee literature this means that we can only identify the relative effects of a connected group

Our quantitative strategy is as follows: we first estimate employment effects of credit shocks that are comparable over time. To this end, we consider an IV strategy that serves to identify the elasticity between credit and employment at the firm level; then, we aggregate to the industry level the employment effects of credit shocks estimated at the firm level. We use these direct effects estimated from the data to calibrate our model.

Armed with calibrated parameters, we first quantify the aggregate effects of the implied financial shocks, and use the model to measure the relative importance of the direct vs propagation effect. We then use the model to quantify the role of individual sectors in generating the aggregate effects. We next describe the model, the calibration strategy, and the identified aggregate effects.

6.1 A Quantitative Model

We use a general equilibrium model that enables us to quantify the aggregate industry- and macro-level effects of the credit supply shocks estimated above and compare the evolution of the effects over time. To this end, we employ a framework in which supply shocks to a given industry directly affect its output and indirectly affect the output of related industries. We quantify the propagation effects predicted by the model by plugging in our estimated shocks aggregated at the industry level. In particular, we build on the model recently developed by Bigio and La'o (2017). We explain the main features of the model in the text in what follows while presenting a more detailed description in Appendix G.

Productive Structure: There are n industries, and a representative firm operating in each industry i competing in monopolistic competition.[27] Firms have access to a decreasing returns to scale Cobb-Douglas production function in which labor and intermediate goods are used as inputs. How intensively firms in a given industry use goods produced in their own and other industries is determined by the input-output structure of the economy.

Financial Frictions: Each firm must borrow the total cost of inputs expenditures (wages plus intermediate good costs) before initiating production. How much a firm can borrow is limited to a fraction of its revenue, which is sector specific. Under some circumstances, firms would like to borrow in excess of the limit and hence will be financially constrained.[28] In this case, the firm's marginal revenue will be higher than the firm's marginal cost.

Households: A representative household maximizes utility over consumption of a composite good and the amount of labor supplied in the market. The composite consumption good is the result of

of banks and firms (see Abowd, Creecy, and Kramarz (2002)).

[27]The concepts of firm and industry are thus interchangeable in the model.

[28]In particular, firms will be financially constrained whenever the fraction they can borrow is less than the parameter that governs the decreasing returns to scale. See Appendix G for details.

aggregating across the n goods in the economy. To simplify the analysis, we assume a Cobb-Douglas aggregator. The household solves the problem of choosing how much to consume of each good and how much to work subject to its budget constraint.

6.2 Calibration and Predicted Real Effects

To quantify the aggregate propagation effects, we consider a two-step strategy. First, we calibrate the model to the Spanish economy for the year 2003 following Bigio and La'o (2017). Second, we discipline the 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 (G) for details).

The parameters governing the IO structure of the economy are from 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 a 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 for each industry.

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 (i.e. the parameter influencing the collateral constraint) in each industry that yield a *horizontal economy* version of the model able to generate the changes in employment implied by our reduced form estimates of the direct real effects described below.

To be more concrete, 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 to generate changes in employment between 2003 and 2004 that correspond to those estimated from our predicted real effects as described below. With new values for the parameters governing financial frictions in 2004, we can proceed in similar manner for the years 2005-2013. Conceptually, we are identifying financial shocks by matching (with a version of the model in which propagation effects are absent) the *direct effect* on employment estimated from the data as we next describe.

Predicted Real Effects To estimate the employment effects of credit shocks that are comparable over time and used in the calibration, 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.

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:

$$\begin{aligned} \Delta \ln E_j &= \phi \Delta \ln c_j + \pi_{IV} X_j + u_j \\ \Delta \ln c_j &= \psi \overline{\delta}_j + \Phi_{IV} X_j + v_j \end{aligned} \tag{11}$$

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 (6), 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 (5). Moreover, the reduced form effect in (7) 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 (11). More specifically, we first estimate the firm-level credit growth due to the bank supply shocks:

$$\widetilde{\Delta \ln c_j} = \hat{\psi} \overline{\delta}_j \tag{12}$$

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:

$$\widetilde{\Delta \ln E_j} = \Delta \ln E_j - \hat{\phi} \widetilde{\Delta \ln c_j} \tag{13}$$

where E_j refers to employment of firm j, and $\hat{\phi}$ refers to the estimate obtained from (11).

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

$$\widetilde{\Delta \ln E} = \sum_j \varphi_j \widetilde{\Delta \ln E_j} \tag{14}$$

$$\Delta \ln E = \sum_j \varphi_j \Delta \ln E_j \tag{15}$$

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.

6.3 Aggregate Effects Across Periods

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. Table 9 presents the aggregate effects of our estimated financial shocks on employment and real output in the Spanish economy. The table presents, for each year from 2004-2013, three series for employment and real output: (i) the *direct* effect of our estimated shocks as predicted by the horizontal economy model, i.e., the model without input-output linkages; (ii) the *direct+network* effect as predicted by the full model, and (iii) actual growth as measured in the data.

The full model accounts for significant fractions of the observed increases in output and employment over the *boom* period (2003-2007). For instance, the change in employment between 2005 and 2006 predicted by the full model is 0.85%, which represents approximately 20% of the observed 4.16% change in the data.[29] In terms of output, for the same year, the change predicted by the model is 2.02%, which is around 62% of the 3.23% observed in the data. For the *financial crisis* (2008-2009), the model tends to under-estimate the observed employment decline and over-estimate that in output. For example, the model (data) predicts a decline in employment of 1.34% (8.57%) between 2008 and 2009. In the case of output, the model (data) predicts a fall of -3.18% (-0.39%). For the *recession* period (2010-2013), the model predicts negative changes in output, the changes being positive in the data. The reason for this is that we are identifying changes in financial frictions by matching the observed changes in employment, which are negative. Given negative changes in

[29] "Observed changed in the data" refers to the change in aggregate employment and 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.

Table 9: Aggregate effects of credit supply shocks on employment and output

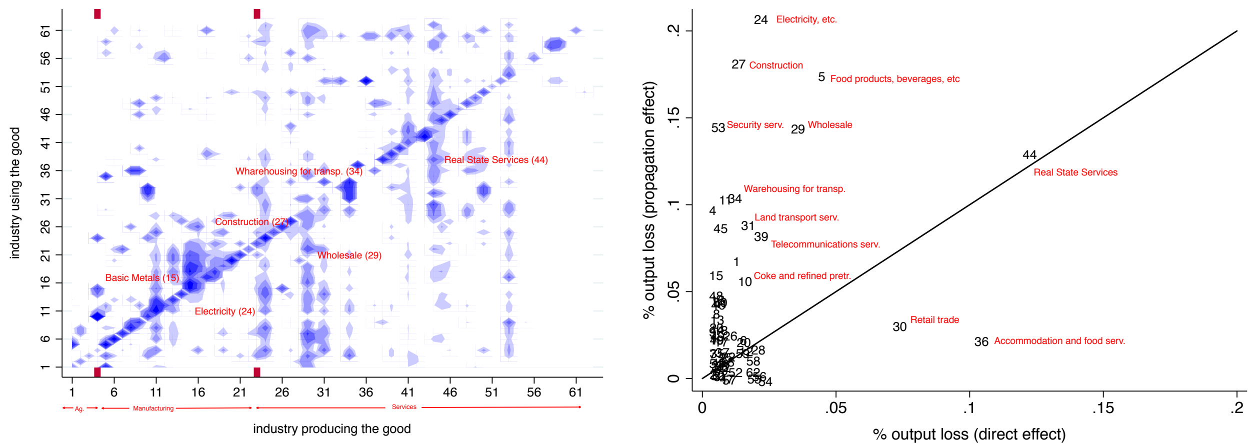
Year	Direct Effect (model)	Network Effect (model)	Total Effect (model)	Actual growth (data)
Panel A: Employment growth				
2003-2004	0.47	0.49	0.96	3.31
2004-2005	0.37	0.37	0.74	4.20
2005-2006	0.41	0.44	0.85	4.16
2006-2007	0.20	0.22	0.42	3.93
2007-2008	-0.15	-0.17	-0.32	-0.49
2008-2009	-0.64	-0.70	-1.34	-8.57
2009-2010	-0.29	-0.31	-0.60	-3.28
2010-2011	-0.44	-0.44	-0.88	-3.78
2011-2012	-1.20	1.18	-2.38	-6.98
2012-2013	-0.39	0.34	-0.73	-4.97
Panel B: Real output growth				
2003-2004	0.48	1.87	2.35	3.12
2004-2005	0.41	1.43	1.84	3.46
2005-2006	0.42	1.60	2.02	3.23
2006-2007	0.20	0.78	0.98	3.22
2007-2008	-0.15	-0.60	-0.75	3.26
2008-2009	-0.64	-2.54	-3.18	-0.39
2009-2010	-0.29	-1.15	-1.44	-0.66
2010-2011	-0.44	-1.72	-2.16	0.70
2011-2012	-1.21	-4.81	-6.03	0.21
2012-2013	-0.40	-1.49	-1.89	0.13

Notes. Table shows the growth of employment and output predicted by the model between years. The first column (*Direct Effect*) reports the predicted change by the horizontal economy version of the model in which IO linkages are absent. The second column (*Network*) effect reports the change predicted by the full model minus the change predicted by the horizontal economy model. The third column reports the change predicted by the full model. The fourth column presents the actual change as measured in the Spanish National accounts (source: National Statistical Institute).

employment, the model generates negative changes in output. as mentioned, Appendix B presents a time varying indicator of credit supply that is consistent with the evolution over time resulting from the model.

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 7 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.

Figure 7: 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.

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

7 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. Effects during the expansion differ. For example, direct effects on employment are not significant while investment reacts to credit supply shocks over the entire period. 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, larger in magnitude than the direct effects.

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. More generally, our estimates show that the real effects of bank-lending shocks vary substantially during booms and busts.

References

Abowd, J., J. Creecy, and F. Kramarz (2002): "Computing person and firm effects using linked longitudinal employer–employee data," *Technical Report U.S. Census Bureau*.

Abowd, J., F. Kramarz, and D. Margolis (1999): "High wage workers and high wage firms," *Econometrica*, 67, 251–333.

Acemoglu, D., U. Akcigit, and W. Kerr (2016): *Networks and the Macroeconomy: An Empirical Exploration*, vol. 30. NBER Macro Annual 2015.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012): "The Networks Origins of Aggregate Fluctuations," *Econometrica*, 80(5), 1977–2016.

Adrian, T., P. Colla, and H. S. Shin (2012): "Which Financial Frictions? Parsing the Evidence from the Financial Crisis of 2007-09," *NBER Macroeconomics Annual*, 27, 159–214.

Alfaro, L., P. Antrás, D. Chor, and P. Conconi (Forthcoming): "Internalizing Global Value Chains: A Firm-Level Analysis," *Journal of Political Economy*.

Almunia, M., D. Lopez-Rodriguez, and E. Moral-Benito (2018): "Evaluating the Macro-Representativeness of a Firm-Level Database: An Application for the Spanish Economy," *Occasional Paper Banco de España 1802*.

Amiti, M., and D. E. Weinstein (Forthcoming): "How Much do Idiosyncratic Bank Shocks Affect Investment? Evidence from Matched Bank-Firm Loan Data," *Journal of Political Economy*.

Autor, D., D. Dorn, and G. Hanson (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103(6), 2121–2168.

Barrot, J.-N., and J. Sauvagnat (2016): "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks," *Quarterly Journal of Economics*, 131(3), 1543–1592.

Bartik, T. (1991): "Who Benefits from State and Local Economic Development Policies?," *W.E. Upjohn Institute*.

Bentolila, S., M. Jansen, and G. Jimenez (Forthcoming): "When Credit Dries up: Job Losses in the Great Recession," *Journal of the European Economic Association*.

Bigio, S., and J. La'o (2017): "Distortions in Production Networks," *Working Paper*.

Blanchard, O., and L. Katz (1992): "Regional Evolutions," *Brookings Papers on Economic Activity*, 1, 1–75.

Blattner, L., L. Farihan, and F. Rebelo (2017): "When Losses Turn Into Loans: The Cost of Undercapitalized Banks," *Working Paper*.

Boehm, C., A. Flaaen, and N. Pandalai-Nayar (2016): "The Role of Global Supply Chains in the Transmission of Shocks: Firm-Level Evidence from the 2011 Tohoku Earthquake," *Working Paper*.

Cameron, C., J. Gelbach, and D. Miller (2011): "Robust Inference With Multiway Clustering," *Journal of Business & Economic Statistics*, 29(2), 238–249.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2016): "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," *Working Paper*.

Chodorow-Reich, G. (2014): "The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-9 Financial Crisis," *The Quarterly Journal of Economics*, 129(1), 1–59.

Cingano, F., F. Manaresi, and E. Sette (2016): "Does credit crunch investments down? New evidence on the real effects of the bank-lending channel," *The Review of Financial Studies*, 29(10), 2737–2773.

Cornelissen, T. (2008): "The Stata command felsdvreg to fit a linear model with two high-dimensional fixed effects," *Stata Journal*, 8, 170–189.

Dewachter, H., J. Tielens, and J. V. Hove (2017): "Credit Supply Shock Propagation and Amplification in the Real Economy: Firm–Level Evidence," *Working Paper*.

di Giovanni, J., A. Levchenko, and I. Mejean (2018): "The Micro Origins of International Business Cycle Comovement," *American Economic Review*, 108, 82–108.

Giannetti, M., and F. Saidi (2017): "Shock Propagation and Banking Structure," *Working Paper*.

Greenstone, M., A. Mas, and H.-L. Nguyen (2015): "Do Credit Market Shocks Affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and 'Normal' Economic Times," *Working Paper*.

Huber, K. (Forthcoming): "Disentangling the Effects of a Banking Crisis: Evidence from German Firms and Counties," *American Economic Review*.

Jimenez, G., A. Mian, J.-L. Peydro, and J. Saurina (2014): "The Real Effects of the Bank Lending Channel," *Working Paper*.

Kashyap, A. K., J. C. Stein, and D. W. Wilcox (1993): "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance," *American Economic Review*, 83(1), 78–98.

Khwaja, A., and A. Mian (2008): "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, 98(4), 1413–1442.

Klein, M. W., J. Peek, and E. S. Rosengren (2002): "Troubled Banks, Impaired Foreign Direct Investment: The Role of Relative Access to Credit," *American Economic Review*, 92(3).

Midrigan, V., and D. Xu (2014): "Finance and Misallocation: Evidence from Plant Level Data," *American Economic Review*, 2(104), 422–58.

Murphy, K., and R. Topel (1985): "Estimation and Inference in two Step Econometrics Model," *Journal of Business and Economic Statistics*, 3(4), 370–379.

Paravisini, D., V. Rappoport, and P. Schnabl (2017): "Specialization in Bank Lending: Evidence from Exporting Firms," *mimeo*.

Reinhart, C. M., and K. S. Rogoff (2009): *This Time Is Different: Eight Centuries of Financial Folly*. Princeton University Press, Princeton, New Jersey.

A Additional Tables and Figures

Table A.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

B 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 negative 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:

$$\Delta \ln c_{ijt} = \mu_{jt} + \zeta_i + K_i' \times T + \xi_{ijq} \tag{16}$$

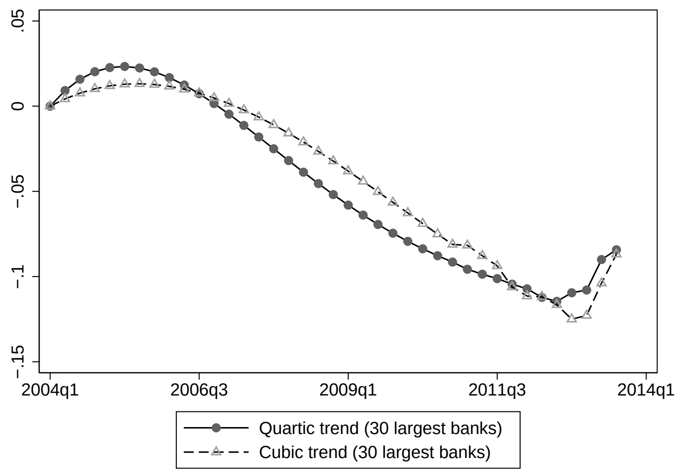
where $\Delta \ln c_{ijt}$ refers to credit growth between bank i and firm j in quarter t, $K_i' \times T$ captures a bank-specific time trend intended to identify the evolution of bank-specific credit supply. For our baseline quartic trend, we define $K_i = (\kappa_{1,i}, \kappa_{2,i}, \kappa_{3,i}, \kappa_{4,i})'$ 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.[30] We therefore restrict the analysis to the 30 largest banks in the sample, which account for 88% of total credit.

Figure B.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 6.3. These exercises illustrate that the type of trend (cubic or quartic) does not alter the aggregate pattern of credit supply over time.

[30]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 B.1: Aggregate credit supply over time



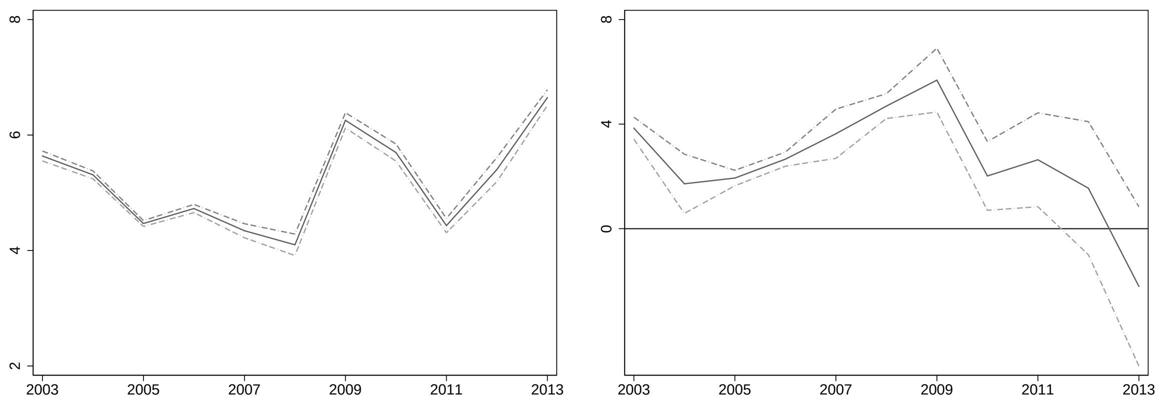
Notes. This figure plots the aggregate credit supply indicator that result from averaging the bank-specific trends given by $\hat{K}_i' \times T$. Quartic and cubic trend are plotted. The value in the first quarter is normalized to 0.

C Annual Estimates of the Bank Lending Channel

The left panel in Figure C.2 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 C.2 also points to an increase in the relevance of the bank lending channel during the crisis.

The right panel in Figure C.2 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.

Figure C.2: 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 (3). 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 (5), which identify the bank lending channel at the firm level.

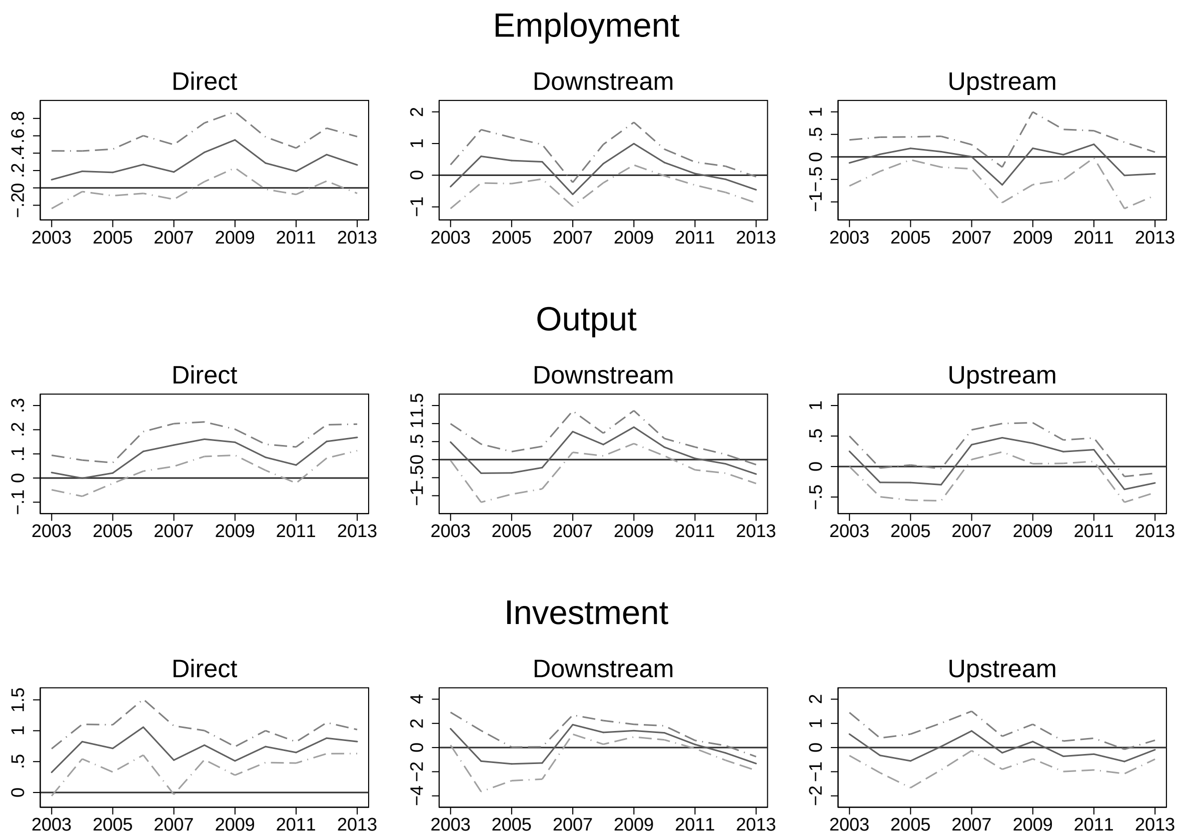
D Annual Estimates of Real Effects

Figure D.3 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

Figure D.3: 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.

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.

E 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 as well as additional controls. The tables report estimates for the entire period (2003-2013) and the *financial crisis* (2008-2009).

Table E.2: Robustness I — 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. Analogous to Table 8 in the main text, 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 6, 7 and 5. 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 E.3: Robustness II — 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. Analogous to Table 8 in the main text, 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 6, 7 and 5. 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 E.4: Robustness III — 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. Analogous to Table 8 in the main text, 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 6, 7 and 5. 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 (%).

F Results by Firm-Size

The richness of our sample and identified shocks enables us to run our specification from equation (10) for three size bins: 0-10, 10-500, ≥ 500. Table F.5 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.5: Real directs and indirect effects of credit shocks by firm size 2008-2009

	employment			output			investment		
	(1) 0-10	(2) 10-500	(3) +500	(4) 0-10	(5) 10-500	(6) +500	(7) 0-10	(8) 10-500	(9) +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 (10), 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 (6), 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.

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

Technology and market structur: 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:

$$y_i = \left[l_i^{\alpha_i} \left(\prod_{j=1}^{n} x_{ij}^{w_{ij}} \right)^{1-\alpha_i} \right]^{\eta_i} \tag{17}$$

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:

$$l_i + \sum_{j=1}^{n} p_j X_{ij} \leq \chi_i p_i y_i \tag{18}$$

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

$$u(C,l) = \frac{C^{1-\gamma}}{1-\gamma} - \frac{l^{1+\epsilon}}{1+\epsilon} \tag{19}$$

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:

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

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

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:

$$
\begin{aligned}
l_i &= \alpha E_i && (20)\\
p_j x_{ij} &= (1-\alpha_i) w_{ij} E_i && (21)
\end{aligned}
$$

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

$$E_i = \phi_i \eta_i R_i \qquad where \qquad \phi_i = min\{\frac{\chi_i}{\eta_i}, 1\} \tag{22}$$

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:

$$\frac{c_j p_j}{\bar{p} C} = v_j \tag{23}$$

$$\frac{C^{-\gamma}}{l^{\epsilon}} = \frac{\bar{p}}{w} \tag{24}$$

where $\bar{p} = \prod_{j=1}^{n} \left(\frac{p_j}{v_j}\right)^{v_j}$ is the ideal price index. Equation (23) implies that the household's consumption expenditure share on a particular good j is constant and given by the share parameter j. Equation (24) 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 (20), (21), and (22) are satisfied.
2. Households solve their optimization problem, i.e., equations (23) and (24) are satisfied.
3. Markets clear:

$$y_i = \sum_{j=1}^{n} x_{ji} + c_i \quad \forall i \tag{25}$$

$$l = \sum_{i=1}^{n} l_i \quad \forall i \tag{26}$$

Aggregate effects of financial frictions

$$\text{real GDP} = \underbrace{\bar{z}\ (\mathbf{z})\ \Phi\ (\phi)}_{\text{efficiency}} \underbrace{L^{\bar{\eta}}}_{\text{labor}} \tag{27}$$

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*.

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:

$$\frac{wl_i + \sum_{j=1}^{n} p_j x_{i,j}}{p_i y_i} = \phi_i \eta \quad \forall i \tag{28}$$

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:

$$\alpha_i = \frac{wl_i}{wl_i + \sum_{j=1}^{n} p_j x_{i,j}} \quad \forall i \tag{29}$$

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

$$v_i = \frac{p_i c_i}{\sum_{j=1}^{n} p_j c_j} \quad \forall i \tag{30}$$

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:

$$w_{i,j} = \frac{p_j x_{ij}}{\sum_{j=1}^{n} p_j x_{ij}} \quad \forall i, j \tag{31}$$