On the Direct and Indirect Real Effects of Credit Supply Shocks

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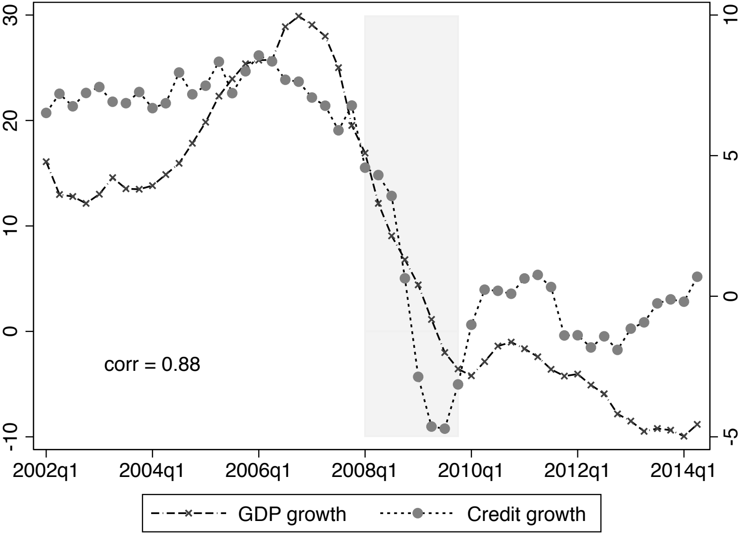
Dublin, December 2018

Credit and output growth in Spain



Estimate the relationship between credit and real outcomes: Challenges

- Identifying plausible exogenous shocks
  - Bank lending-channel (or the bank-specific shock)
  - Firm borrowing-channel (or firm's ability to borrow from alternative channels)
- Quantifying aggregate real effects
  - Expansions/contractions; Direct/indirect effects
- Data and methodological requirements: large datasets

Methodology and Approach (I)

- Exploit novel dataset covering Spain's universe of bank-firm credit relations over 2003-2013 + matched administrative data
  - Micro data replicates to a nearly complete picture of the Spanish economy
  - Evidence expansion, financial crisis, recession
- Exploit firm-loan-bank relations to disentangle the bank-lending channel from the firm-borrowing channel
  - Identify bank-specific credit supply shocks for each year through differences in credit growth between banks lending to the same firm
  - Around 75% of firms in Spain borrow from more than one bank

Findings (I)

- One standard deviation in the size of bank credit supply shock:
  - Loan level: increases credit growth by 5.1 pp. (sizeable and stable)
  - Firm level: increases credit growth by 3.2 pp. (higher effect during the crisis)
- Regressing annual employment growth, output growth, and investment rates on the estimated bank supply shocks
  - Sizeable direct effects on the real economy: 0.3 pp. employment, 0.1 pp. output, 0.8 pp. investment

Methodology and Approach (II): Indirect effects

- Compare direct and indirect propagation effects of bank shocks related to firms' input-output relations
- Spanish input-output structure and firm-specific measures of upstream and downstream exposure
  - Downstream effects: whether firms that buy inputs from industries in which firms affected by the shock operate are indirectly affected
  - Upstream effects: whether firms that sell goods to industries whose firms were affected by the shock are indirectly affected

Findings (II): Indirect effects

- Propagation through IO linkages sizeable (downstream effects)
- Effects differ expansion/financial crisis/recession
  - Significant employment and output effects during financial crisis
  - No significant employment effects before the financial crisis
- Channels
  - Trade credit
  - Price effects through GE

Related literature

- Bank lending channel literature:
  - Khwaja and Mian (2008), Jimenez et al. (2014), Bentolila et al. (2016), Chodorow-Reich (2014), Cingano et al. (2015).
  - Closest: Amiti and Weinstein (2016).
- Networks/propagation literature:
  - Mostly theoretical.
  - Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012), Bigio and Lao (2017).
  - Acemoglu, Akcigit, Kerr (2015), Barrot and Sauvagnat (2016), Boehm, Flaaen, and Nayar (2016).
  - Costello (2017), Jacobson and Schedvin (2015).

Roadmap

- **Data**.
- Identification and validation of credit supply shocks.
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Data (I) — CIR (credit registry data)

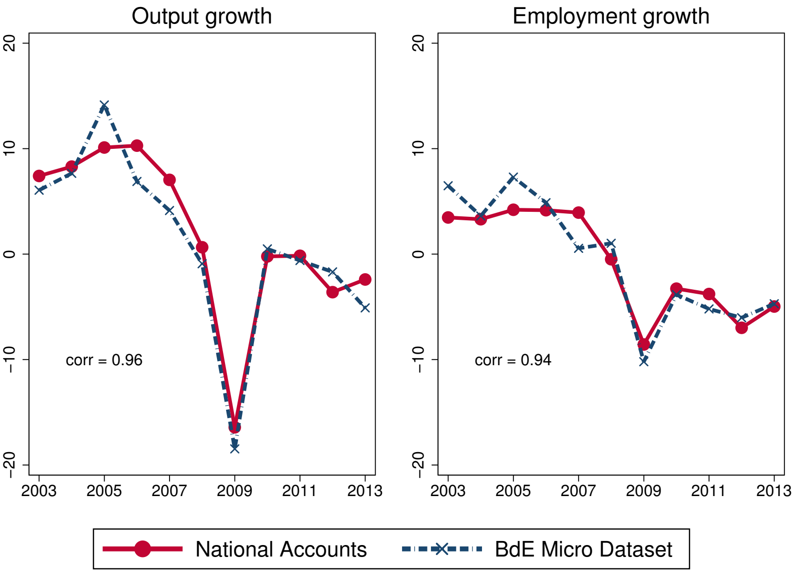
- The Central Credit Register (CIR) is maintained by the Bank of Spain in its role as primary banking supervisory agency.
- It contains detailed monthly information on all outstanding loans over 6,000 euros to non-financial firms granted by all banks operating in Spain.
- Annual bank-firm credit exposure 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
  - 1,743,933 firms
  - 22,461,333 **bank-firm-year** observations (our so-called outstanding loans).

Data (II) — SABI-CBI (firm-level data)

[Firm size distribution]

- We use administrative data on firm-level characteristics taken from the Spanish Commercial Registry
- The so-called SABI-CBI data set combines two different samples taken from the Commercial Registry raw data:
  - The "Central de Balances Integrada (CBI)" from the Bank of Spain.
  - The "Informa" dataset commercialized by Bureau van Dijk under the denomination of SABI, the Portuguese and Spanish input for the Amadeus and Orbis datasets.
- We end up with a **firm-year** database covering:
  - 12 years from 2002 to 2013
  - 1,645,324 firms
  - 10,857,224 *firm-year observations.*

SABI-CBI dataset



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Identification of bank-specific credit supply shocks (I)

- We consider the following decomposition of outstanding credit growth between bank i and firm j in year t:

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

- δ_{it} and λ_{jt} can be interpreted as supply and demand respectively

- δ_{it} captures bank-specific effects that are identified through differences in credit growth between banks lending to the same firm

  - Example: Imagine one firm borrowing from banks A and B in $t-1$
  - Imagine the change in credit between $t-1$ and t is larger with the bank A than with the bank B
  - We interpret this as the credit supply of bank A having increased more than that of bank B

- We run this regression by relying only on multi-bank firms (75% of firms)

Identification of bank-specific credit supply shocks (II)

- We rely on multi-bank firms
  - Matched employer-employee techniques: Abowd, Kramarz, Margolis (1999)
  - Applied to Japanese banks: Amiti and Weinstein (forthcoming)
- Bank- and firm-effects identified in relative terms within each group
  - A group: set of banks and firms connected within a year

Identification of bank-specific credit supply shocks (III)

Main threat to identification:

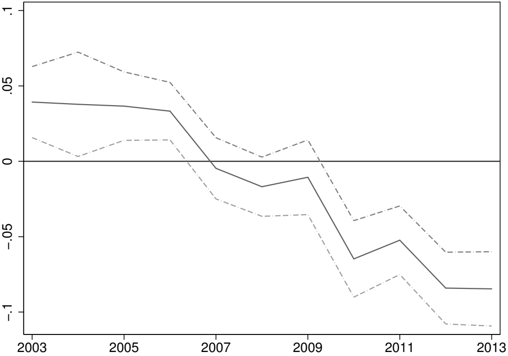
- λ_{jt} account for demand effects (firm's credit demand constant across lenders)
- Concern: Bank-firm level interaction may be relevant (ex: bank lending specialization)
- We alleviate this concern by:
  1. Controlling for factors at the firm-bank level
  2. Excluding construction and real state firms from the sample
  3. Showing that firm's loan characteristics (e.g: maturity) are similar within firms across banks
  4. Implementing a number of checks

Check # 1: Weak banks vs Healthy banks

- We divide our sample of 218 banks into "healthy" and "weak"
- We follow the definition by Bentolila et al (2016)
  - Bank classified as weak if bailed out by the Spanish government in 2011-2012
- 33 banks in total
- Out of which 32 were savings banks (*cajas de ahorros*)
- We check whether the dummy "weak" helps in predicting our estimated $\hat{\delta}_{it}$

Check # 1: Weak banks vs Healthy banks

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



Notes. This plot is based on year-by-year regressions of the bank-level dummies on a constant and a dummy for weak banks as identified in Bentolila et al (2016). 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).**

Check # 2: Probability of loan granting

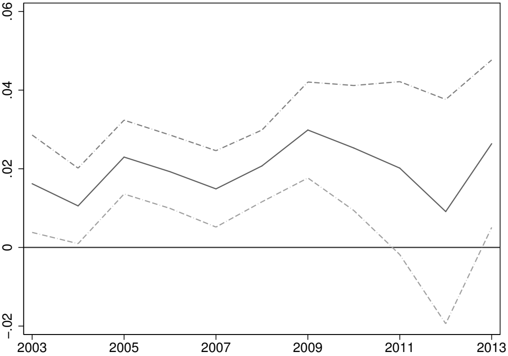
- In credit registry data, we can also observe loan applications involving new bank-firm relationships
- This means that we observe when a firm applies for a loan to a bank with which was not connected before
- We can also measure whether the loan was granted or not
- Then, in a **given year** we can run the following regression:

$$\text{Loan\_Granted}_{ij} = \gamma\hat{\delta}_i + \lambda_j + u_{ij}$$

  - Loan Granted_{ij} is a dummy that takes value of 1 if the bank i has granted at least one loan to firm j (conditional on the application taking place)
  - $\hat{\delta}_i$ is our estimated bank-supply shock for bank i
  - γ captures the effect of our estimated supply shocks on the probability of a loan being granted

Check # 2: Probability of loan granting

Figure: 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. In particular, the γ parameter plotted here estimates the effect of the bank dummies on the probability of acceptance of a loan request. Standard errors are clustered at the bank level.

Check # 3: Actual vs. predicted bank's credit growth

- Explore how well our predicted bank's credit growth explains the bank's actual credit growth.
- Compute predicted bank's credit growth in two steps:

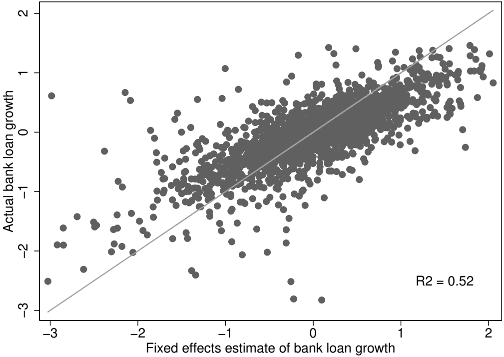
$$\Delta \hat{\ln} c_{ijt} = \hat{\delta}_{it} + \hat{\lambda}_{jt} \tag{1}$$

$$\Delta \hat{\ln} c_{it} = \sum_j \frac{c_{ijt-1}}{\sum_j c_{ijt-1}} \Delta \hat{\ln} c_{ijt} \tag{2}$$

- We then regress $\Delta \ln c_{it}$ against $\Delta \hat{\ln} c_{it}$

Check # 3: Actual vs. predicted bank's credit growth

Figure: Explanatory power of our estimated shocks



Notes. This figure plots the relationship between changes in credit predicted by our shocks and the actual changes in credit.

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The bank lending channel at the **loan** level

- For multi-bank firms we estimate:

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

  where:

  - $\hat{\delta}_{it}$: estimated bank-specific supply shock
  - β: "bank-lending channel"
  - η_{jt}: firm-year firm FE to account for demand side

- For all firms we estimate:

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

  where:

  - $\hat{\lambda}_{jt}$: above-estimated time varying firm demand effects
  - For only-one bank firms this is computed as:

$$\hat{\lambda}_{jt} = \Delta \ln c_{ijt} - \hat{\delta}_{it}$$

The bank lending channel at the **loan** level

[Yearly]

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

	2003-2013		
	(1)	(2)	(3)
Bank_shock	5.058***	5.218***	5.272***
(s.e.)	(0.083)	(0.031)	(0.021)
# obs	12,216,375	12,216,375	17,954,745
# banks	221	221	221
# firms	700,722	700,722	1,511,767
R2	0.350	0.349	0.522
Fixed effects	firm $\times$ year	$\hat{\lambda}_{jt}$	$\hat{\lambda}_{jt}$
Sample firms	Multibank	Multibank	All

Notes. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors clustered at the bank level are reported in parentheses.

The bank lending channel at the **firm** level

- We estimate the following regression:

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

  where

  - $\overline{\delta}_{jt} = \sum_i \frac{c_{ij,t-1}}{\sum_i c_{ij,t-1}} \hat{\delta}_{it}$
  - β^F represents "bank-lending channel" at the firm level

The bank lending channel at the **firm** level

[Yearly]

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

	2003-2013	
	(1)	(2)
Bank_shock	1.158**	3.207***
(s.e.)	(0.515)	(0.278)
# obs	4,424,519	8,743,459
# banks	220	220
#?firms	924,441	1,481,377
R2	0.330	0.501
Sample firms	Multibank	All

Notes. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

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Direct real effects of credit supply shocks

- We estimate the following equation:

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

where Y_{jt} refers to either

- employment growth (in terms of $\log$ differences of number of employees)
- output growth (in terms of $\log$ differences of value added)
- investment (capital stock in t minus capital stock in $t-1$ as a share of total capital stock in t).

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.

Direct real effects of credit supply shocks

Table: Real direct effects of credit shocks — 2003-2013

	employment		output		investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Bank_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. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

Direct real effects by period — employment

Table: Real direct effects of credit shocks by period — employment

	2003-2007		2008-2009		2010-2013	
	(1)	(2)	(3)	(4)	(5)	(6)
Bank_shock	0.251	0.201	0.503***	0.502**	0.243**	0.151
(s.e)	(0.153)	(0.179)	(0.149)	(0.206)	(0.111)	(0.156)
# obs	1,823,859	1,102,347	810,335	482,597	1,430,182	851,233
R2	0.042	0.047	0.055	0.069	0.035	0.045
Sample firms	All	Multibank	All	Multibank	All	Multibank
Fixed effects	sector × year	sector × year	sector × year	sector × year	sector × year	sector × year

Notes. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

Direct real effects by period — output

Table: Real direct effects of credit shocks by period — output

	2003-2007		2008-2009		2010-2013	
	(1)	(2)	(3)	(4)	(5)	(6)
Bank_shock	0.060**	0.085***	0.152***	0.201***	0.109***	0.150***
(s.e)	(0.028)	(0.025)	(0.032)	(0.038)	(0.024)	(0.029)
# obs	1,765,665	1,074,736	764,699	459,036	1,342,639	805,684
R2	0.040	0.041	0.075	0.079	0.042	0.046
Sample firms	All	Multibank	All	Multibank	All	Multibank
Fixed effects	sector × year	sector × year	sector × year	sector × year	sector × year	sector × year

Notes. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

Direct real effects by period — investment

Table: Real direct effects of credit shocks by period — investment

	2003-2007		2008-2009		2010-2013	
	(1)	(2)	(3)	(4)	(5)	(6)
Bank_shock	0.821***	1.065***	0.625***	0.678***	0.711***	0.931***
(s.e)	(0.173)	(0.294)	(0.087)	(0.187)	(0.080)	(0.169)
# obs	1,763,184	1,079,532	783,316	473,468	1,391,738	837,583
R2	0.034	0.033	0.016	0.016	0.011	0.012
Sample firms	All	Multibank	All	Multibank	All	Multibank
Fixed effects	sector × year	sector × year	sector × year	sector × year	sector × year	sector × year

Notes. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors clustered at the main bank level are reported in parentheses.

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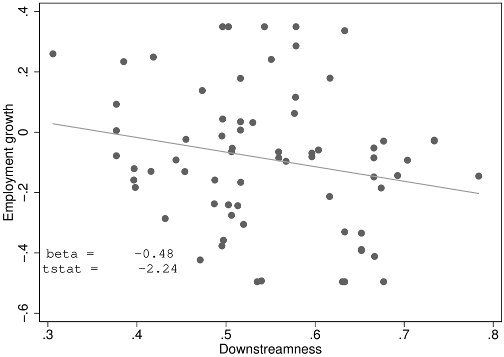
Downstreamness and employment growth by industry



Notes. Output/Employment growth refers to the change in real value added/employment by industry over the 2006-2010 period. Downstreamness refers the ratio of aggregate final direct use of industry's output to aggregate use of industry's output as an input. 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).

Indirect real effects of credit supply shocks (I)

- Firms not directly hit by a credit shock may also 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.
- We exploit firm level information combined with input-output linkages to study the propagation effects of our identified bank-credit supply shocks.
- Based on di Giovanni et al. (2017), we include two additional regressors in our empirical specification:
  - Downstream propagation (i.e. shocks from suppliers).
  - Upstream propagation (i.e. shocks from customers).

Indirect real effects of credit supply shocks (II)

- $DOWN_{jt,s}$ measures the indirect shock received by firm j operating in sector s from its suppliers (downstream propagation).
- $UP_{jt,s}$ measures the indirect shock received by firm j operating in sector s from its customers (upstream propagation).

$$
\begin{aligned}
DOWN_{jt,s} &= \omega_{jt}^{IN} \sum_p IO_{ps} \Delta_{jt,p} \\
UP_{jt,s} &= \omega_{jt}^{DO} \sum_p IO_{sp} \Delta_{jt,p}
\end{aligned}
$$

- s and p index sectors, and firm j belongs to sector s.
- $\Delta_{jt,p}$ is the credit supply shock hitting sector p.
- IO_{ps} is the share of spending by sector s on sector p inputs.
- ω_{jt}^{IN} refers to total input usage intensity of firm j in year t .
- ω_{jt}^{DO} is the domestic sales intensity.

Indirect effects of credit supply shocks on employment

	(1) 2003-2013	(2) 2003-2007	(3) 2008-2009	(4) 2010-2013
Bank_shock	0.284***	0.218	0.482***	0.255**
	(0.098)	(0.151)	(0.156)	(0.111)
DOWN	0.301**	-0.077	0.697***	0.129
	(0.119)	(0.076)	(0.258)	(0.392)
UP	0.061	0.062	-0.187	-0.233*
	(0.120)	(0.078)	(0.291)	(0.123)
# obs	3,827,042	1,727,803	759,170	1,340,069
R2	0.053	0.040	0.059	0.036
Sample firms	All	All	All	All
Fixed effects	sector × year	sector × year	sector × year	sector × year

Notes. All regressions include the following control variables: firm-specific credit demand shocks ($\hat{\lambda}_{jt}$), lagged loan-to-assets ratio, and lagged productivity. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors multi-clustered at the main bank and sector level are reported in parentheses.

Indirect effects of credit supply shocks on output

	(1) 2003-2013	(2) 2003-2007	(3) 2008-2009	(4) 2010-2013
Bank_shock	0.107***	0.069**	0.155***	0.108***
	(0.029)	(0.027)	(0.031)	(0.020)
DOWN	0.354***	0.204*	0.646***	0.184
	(0.069)	(0.106)	(0.166)	(0.251)
UP	0.209***	0.086	0.459***	-0.014
	(0.077)	(0.086)	(0.141)	(0.125)
# obs	3,744,353	1,704,934	739,238	1,300,181
R2	0.067	0.051	0.086	0.049
Sample firms	All	All	All	All
Fixed effects	sector $\times$ year	sector $\times$ year	sector $\times$ year	sector $\times$ year

Notes. All regressions include the following control variables: firm-specific credit demand shocks ($\hat{\lambda}_{jt}$), lagged loan-to-assets ratio, and lagged productivity. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors multi-clustered at the main bank and sector level are reported in parentheses.

Indirect effects of credit supply shocks on investment

	(1) 2003-2013	(2) 2003-2007	(3) 2008-2009	(4) 2010-2013
Bank_shock	0.798***	0.845***	0.576***	0.708***
	(0.075)	(0.177)	(0.101)	(0.085)
DOWN	0.690***	0.266	1.263***	0.110
	(0.174)	(0.281)	(0.320)	(0.552)
UP	0.174	0.403**	0.085	-0.402
	(0.209)	(0.172)	(0.352)	(0.401)
# obs	3,737,540	1,687,930	739,729	1,309,881
R2	0.030	0.036	0.018	0.012
Sample firms	All	All	All	All
Fixed effects	sector × year	sector × year	sector × year	sector × year

Notes. All regressions include the following control variables: firm-specific credit demand shocks ($\hat{\lambda}_{jt}$), lagged loan-to-assets ratio, and lagged productivity. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors multi-clustered at the main bank and sector level are reported in parentheses.

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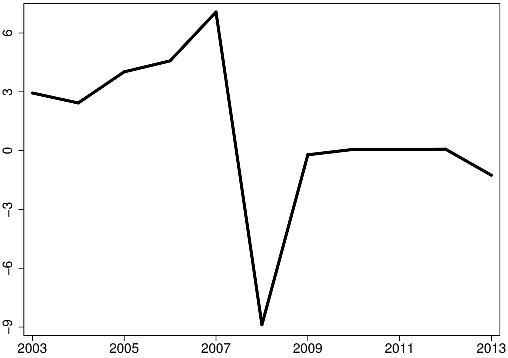
Channel 1: Trade Credit

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



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

Channel 1: Trade Credit

Table: Indirect effects — the role of trade credit

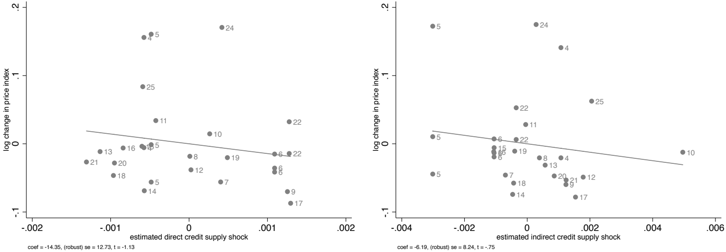
	Employment		Output		Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
	2003-2013	2008-2009	2003-2013	2008-2009	2003-2013	2008-2009
Bank shock	0.20**	0.39***	0.08***	0.09***	0.61***	0.37***
	(0.08)	(0.10)	(0.02)	(0.02)	(0.06)	(0.07)
DOWN	0.47*	0.59*	0.41***	0.55***	0.66***	0.81***
	(0.24)	(0.34)	(0.11)	(0.17)	(0.17)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

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

Channel 2: The role of general equilibrium effects

- Firms' credit supply shocks may also propagate downstream through changes in relative prices — standard GE mechanism in IO models.

Figure: Change in industrial price indexes and credit supply shocks



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

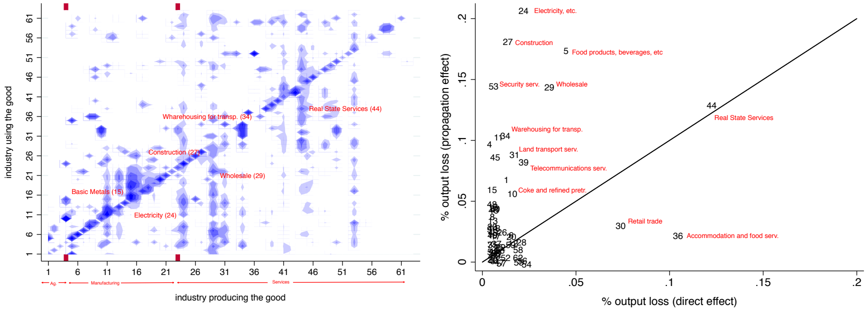
Channel 2: The role of general equilibrium effects - quantification

- We further explore the general equilibrium channel by quantifying the Bigio, La'o (2017) model
- A standard GE model of IO propagation extended to the presence of financial constraints
- We consider a two-step strategy
  1. We calibrate the model to the Spanish economy for the year 2003.
  2. We discipline the over time changes in the financial friction parameters using our estimated real effects of credit shocks at the industry level.
     - Identify changes financial frictions in each industry by making a horizontal economy version of the model to generate the changes in employment implied by our reduced form estimates of the direct real effects described below.

Channel 2: The role of general equilibrium effects - quantification

- We carry out two exercises:
  1. Shock all industries at the same time over the entire period
     - e.g. for 2009-2010
     - The model predicts a fall in employment of -0.60 pp. (-0.29 direct + -0.31 indirect)
     - Actual growth was -3.28%
  2. Shock one industry at a time during the financial crisis period (2008-09)

IO structure and output losses from industry shocks



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. 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.

Concluding remarks

- Credit supply shocks matter for real economic activity, especially during financial crises.
- This paper brings into the picture the existence of indirect effects.
- The propagation through buyer-seller interactions substantially amplifies the aggregate impact of credit shocks on real activity.
- Both trade credit extended by suppliers and price adjustments in general equilibrium explain our findings.
- This finding points to an underestimation in the estimates available in the literature.