Credit Supply Shocks, Network Effects, and the Real Economy

Laura Alfaro[‡] Manuel García-Santana[*] Enrique Moral-Benito[✠]

[‡] Harvard Business School and NBER

[*] Universitat Pompeu Fabra and CEPR

[✠] Banco de España

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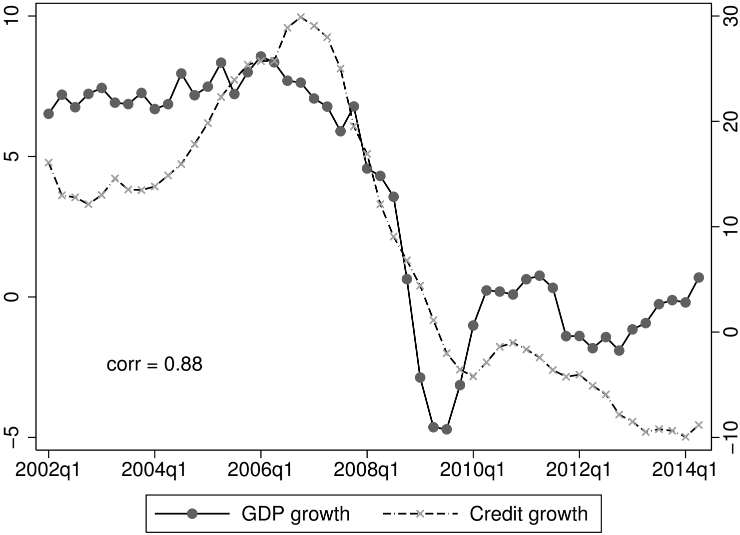
Credit and output growth in Spain



Challenges

- Investigating the link between credit shocks and the real economy poses different challenges:

(A) Data requirements.

(B) Identifying credit supply shocks.

(C) Quantifying aggregate real effects.

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(A) Data requirements.

(B) Identifying credit supply shocks.

(C) Quantifying aggregate real effects.

- In this paper:

(A) We exploit a novel database covering the quasi-census of Spanish firms and documenting their credit relations over 2002-2013.

(B) We disentangle the bank lending channel (supply of credit) from the firm borrowing channel (demand for credit).

(C) We document the existence of propagation effects at the firm level and use the Bigio and La'o (2016) model to quantify the aggregate effects of credit supply shocks.

In a nutshell

- We explore the real effects of credit supply shocks (bank lending channel) in Spain over the 2002-2013 period.
- The effects are significant and stronger during the global financial crisis 2008-2009, which reconciles different findings in the literature.
- We investigate how bank-lending shocks permeate the economy through input-output linkages.
- We find that the propagation effects are larger than the direct effects typically estimated in the literature.
- In aggregate terms, we find that around 20% of overall employment growth in Spain can be explained by credit supply shocks.

Related literature

- Bank lending channel literature:
  - Mostly empirical.
  - 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), Acemoglu, Akcigit, Kerr (2015), Barrot and Sauvagnat (2016), Boehm, Flaaen, and Nayar (2016).
  - Closest: Bigio and Lao (2016).

Roadmap

- **Data**.
- Identification and validation of credit supply shocks.
- Direct effects of credit supply on real outcomes.
- Propagation effects of credit supply shocks.
- Aggregate effects.

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][Coverage]

- 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.*

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Identification of bank-specific credit supply shocks

Khwaja and Mian (2008) meet Abowd, Kramarz, and Margolis (1999)

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

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

Identification of bank-specific credit supply shocks

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- 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

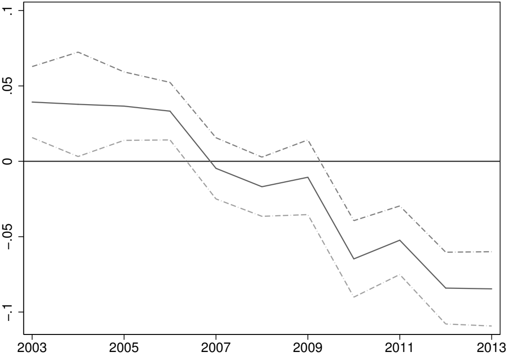
- We run this regression by relying only on multi-bank firms (75% of firms)

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)
- A bank is classified as weak if it was 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

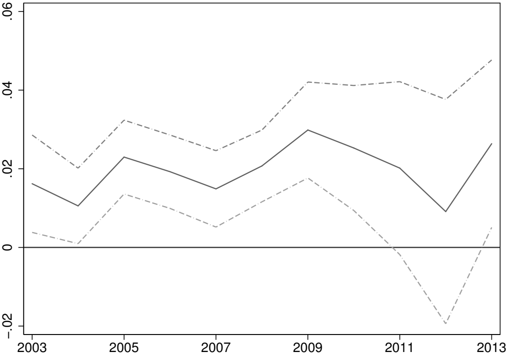
- In credit registry data, we can also observe loan applications evolving new bank-firm relationships
- This means that we observe when a firm applies for a loan to a bank with which was not connected before
- We can also measure whether the loan was granted or not
- Then, in a **given year** we can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

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The bank lending channel at the loan level

[Yearly]

$$
\begin{aligned}
\text{[Multibank firms]} \quad \Delta \ln c_{ijt} &= \beta \hat{\delta}_{it} + \eta_{jt} + v_{ijt} \\
\text{[All firms]} \quad \Delta \ln c_{ijt} &= \beta \hat{\delta}_{it} + \gamma \hat{\lambda}_{jt} + v_{ijt}
\end{aligned}
$$

The bank lending channel at the loan level

[Yearly]

$$\text{[Multibank firms]}\quad \Delta \ln c_{ijt} = \beta\hat{\delta}_{it} + \eta_{jt} + v_{ijt}$$
$$\text{[All firms]}\quad \Delta \ln c_{ijt} = \beta\hat{\delta}_{it} + \gamma\hat{\lambda}_{jt} + v_{ijt}$$

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

	2003-2013		
	(1)	(2)	(3)
Bank_shock	5.245***	5.406***	5.455***
(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 × 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

[Yearly]

$$
\begin{aligned}
\Delta \ln c_{jt} &= \beta^F \overline{\delta}_{jt} + \gamma^F \hat{\lambda}_{jt} + u_{jt} \\
\overline{\delta}_{jt} &= \sum_i \frac{c_{ij,t-1}}{\sum_i c_{ij,t-1}} \hat{\delta}_{it}
\end{aligned}
$$

The bank lending channel at the firm level

[Yearly]

$$\begin{aligned}\Delta \ln c_{jt} &= \beta^F \overline{\delta}_{jt} + \gamma^F \hat{\lambda}_{jt} + u_{jt} \\ \overline{\delta}_{jt} &= \sum_i \frac{c_{ij,t-1}}{\sum_i c_{ij,t-1}} \hat{\delta}_{it}\end{aligned}$$

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.

Real effects of credit supply shocks

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

- Y_{jt} refers to either
  - employment growth (in terms of $\log$ differences of number of employees)
  - output growth (in terms of $\log$ differences of Euros)
  - investment (capital stock in t minus capital stock in $t-1$ as a share of total capital stock in t).
- 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.

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.

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 $\times$ year	sector $\times$ year	sector $\times$ year	sector $\times$ year	sector $\times$ year	sector $\times$ 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.

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.

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 $\times$ year	sector $\times$ year	sector $\times$ year	sector $\times$ year	sector $\times$ year	sector $\times$ 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.

Real effects by firm size

Table: Real directs effects of credit shocks — by firm size

	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
Bank_shock	0.233***	0.539**	0.732	0.068***	0.204***	0.174	0.831***	0.706***	0.755
(s.e)	(0.071)	(0.221)	(0.499)	(0.021)	(0.052)	(0.344)	(0.072)	(0.098)	(0.737)
# obs	2,983,808	1,069,507	11,061	2,803,298	1,058,743	10,962	2,863,124	1,063,856	11,258
R2	0.031	0.061	0.045	0.052	0.075	0.070	0.026	0.037	0.023
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. 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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- Aggregate effects.

Propagation effects of credit supply shocks

- 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).

Propagation effects of credit supply shocks

- $DOWN_{jt,s}$ 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.

Propagation effects of credit supply shocks — 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.

Propagation effects of credit supply shocks — 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 × 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.

Propagation effects of credit supply shocks — 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 $\times$ 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.

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- **Aggregate effects [PRELIMINARY]**.

Aggregate direct effects — estimation

1. Credit-driven effects on firm growth:

$$\begin{aligned} Y_{jt} &= \phi^w \Delta \ln c_{jt} + \pi^w X_{jt} + u^w_{jt} \\ \Delta \ln c_{jt} &= \psi^w \overline{\delta}_{jt} + \Phi^w X_{jt} + v^w_{jt} \end{aligned}$$

2. The predicted values from the first stage regression give us the credit growth induced by supply factors:

$$\widetilde{\Delta \ln c}_{jt} = \hat{\psi}^w \overline{\delta}_{jt}$$

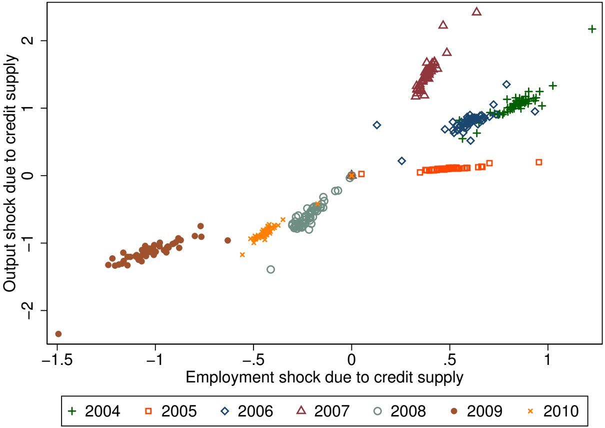
3. We estimate the counterfactuals that we would have observed in the absence of credit supply shocks:

$$\widetilde{Y}_{jt} = Y_{jt} - \hat{\phi}^w \widetilde{\Delta \ln c}_{jt}$$

4. We then aggregate across firms:

$$\widetilde{Y}_t = \sum_i \left(\frac{w_{i(t-1)}}{\sum_j w_{j(t-1)}} \right) \widetilde{Y}_{jt}$$

Aggregate direct effects by industry

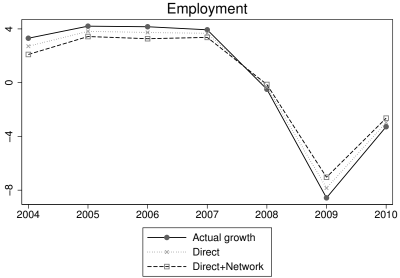


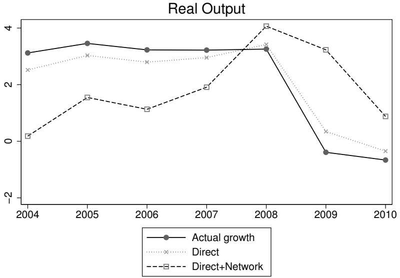
Notes. This figure plots the industry-specific shocks in terms of employment (x axis) and output (y axis) due to credit supply. These shocks are constructed from the aggregation of the firm-level shocks $\hat{\phi}^w \widetilde{\Delta \ln c_j}$.

The model: Bigio and La'o (2016)

- Production: n industries operate in the economy. [Link]
- Financial frictions: How much a firm can borrow is limited to a fraction of its revenue — ϕ_i. [Link]
- Households: A representative household maximizes utility depending on consumption and labor. [Link]
- Equilibrium: (i) firms and the representative household solve their maximization problem; (ii) the markets clear. [Link]
- We solve the model for the year 2003 and subsequently match our estimated direct effects year-by-year in the horizontal economy. [Link]
- We use full model with IO linkages to recover the propagation effects. [Link]

Aggregate effects (I)





Aggregate effects (II)

Table: Aggregate effects on employment and output

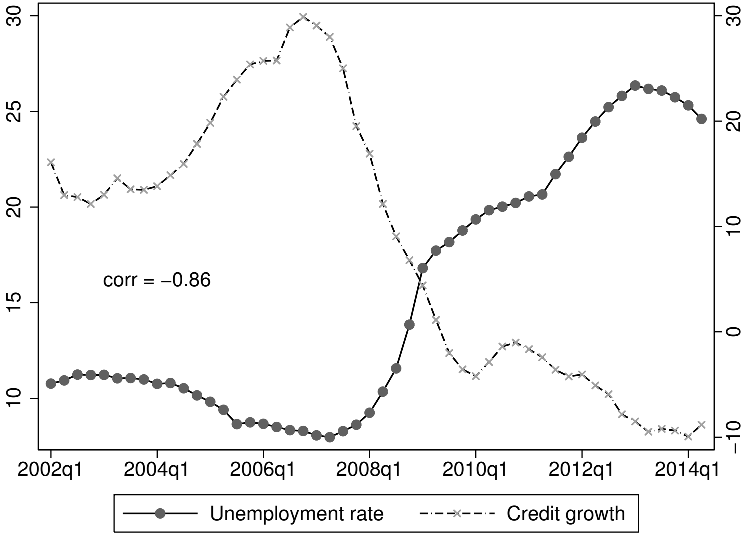
Year	Direct Effect (model)	Network Effect (model)	Total Effect (model)	Actual growth (data)
Panel A: Employment growth				
2004	0.60	0.61	1.21	3.31
2005	0.39	0.39	0.77	4.20
2006	0.43	0.46	0.89	4.16
2007	0.26	0.30	0.56	3.93
2008	-0.17	-0.19	-0.35	-0.49
2009	-0.73	-0.80	-1.53	-8.57
2010	-0.31	-0.33	-0.64	-3.28
2004-2007	0.42	0.44	0.86	3.90
2008-2010	-0.40	-0.44	-0.84	-4.11
Panel B: Real output growth				
2004	0.60	2.34	2.94	3.12
2005	0.43	1.48	1.91	3.46
2006	0.43	1.67	2.10	3.23
2007	0.26	1.05	1.31	3.22
2008	-0.16	-0.65	-0.81	3.26
2009	-0.74	-2.89	-3.62	-0.39
2010	-0.31	-1.23	-1.54	-0.66
2004-2007	0.43	1.63	2.06	3.26
2008-2010	-0.40	-1.59	-1.99	0.73

Notes. This Table shows the growth of employment and output predicted by the model across different years. The first column (*Direct Effect*) refers to the predicted change in output by the horizontal economy version of the model in which IO linkages are absent. The second column (*Network*) effect shows the change in output predicted by the full model minus the change in output predicted by the horizontal economy model. The third column shows the change in output predicted by the full model. The fourth column shows the actual change in employment and output as measured in the data.

Concluding remarks

- Credit supply matters for real economic activity, especially during financial crises and for SMEs.
- This paper brings into the picture the existence of propagation effects, which are found to be larger than the direct effects typically estimated in the literature.
- According to our quantification, credit supply shocks might explain around 20% of employment growth in Spain.

Credit growth and unemployment in Spain



SABI-CBI dataset

Table: Firm size distribution in terms of turnover (million euros).

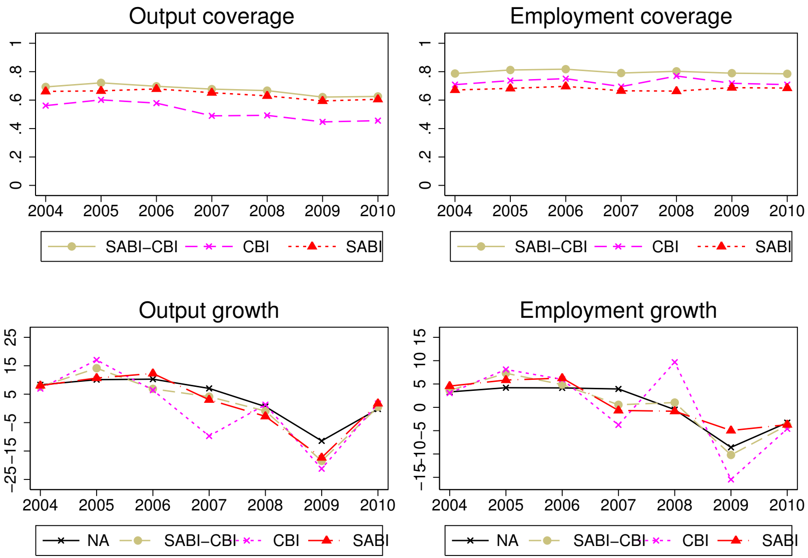
	0-0.06	0.06-0.6	0.6-1.5	1.5-6.0	6.0-30	+30
SABI-CBI	91%	79%	90%	92%	86%	82%
CBI	90%	73%	81%	81%	60%	59%
SABI	19%	63%	84%	90%	85%	79%

Table: Firm size distribution in terms of number of employees.

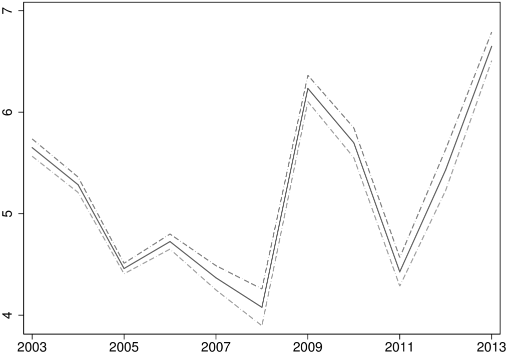
	0 to 9	10 to 19	20 to 49	50 to 200	+200
SABI-CBI	81%	108%	106%	95%	93%
CBI	77%	98%	93%	73%	76%
SABI	38%	99%	99%	89%	86%

Notes. Each cell corresponds to the number of firms in total economy from each database relative to the number of firms in the AEAT statistics (tax authority census) for turnover and in the DIRCE statistics (census from the National Statistics Institute) for employment. All figures refer to the average over the 2004-2010 period.

SABI-CBI dataset

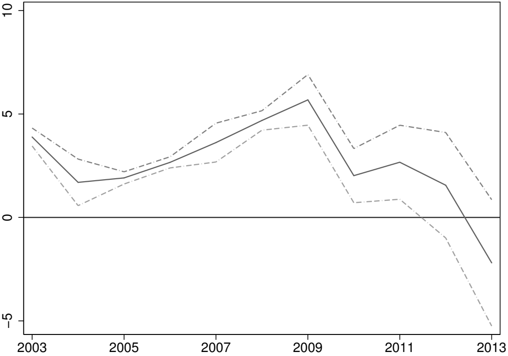


BLC at the loan level — yearly regressions



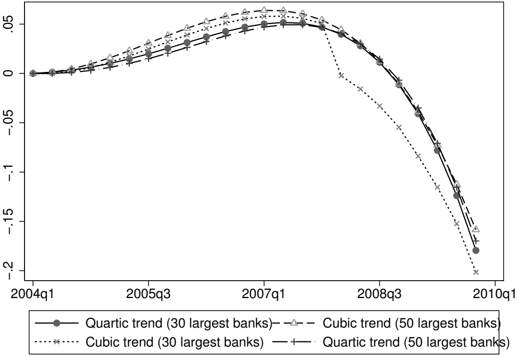
Notes. This figure plots the β estimates from year-by-year regressions given by equation $\Delta \ln c_{ij} = \alpha + \beta\hat{\delta}_i + \eta_j + v_{ij}$. The estimation sample comprises, on average, 1,667,718 loans and 887,992 firms in each year. Standard errors used to construct the confidence bands are multi-clustered at the bank and firm level.

BLC at the firm level — yearly regressions



Notes. This figure plots the β^F estimates from year-by-year regressions given by $\Delta \ln c_j = \alpha^F + \beta^F \overline{\delta}_j + \gamma^F \hat{\lambda}_j + u_j$, which identify the bank lending channel at the firm level. The estimation sample comprises, on average, 841,911 firms in each year. Standard errors used to construct the confidence bands are clustered at the main bank level, i.e., the largest lender for a firm.

Aggregate credit supply over time



Notes. This figure plots the aggregate credit supply indicator resulting from averaging the bank-specific credit supply trends estimated the following equation $\Delta \ln c_{ijt} = \mu_{jt} + \zeta_i + K_i' \times T + \xi_{ijq}$ where $\Delta \ln c_{ijt}$ refers to credit growth between bank i and firm j in quarter t.

The model (I): Technology and market structure

- There are n industries operating in the economy
  - Given the level of disaggregation in Spanish IO tables ($n = 64$)
- A perfectly competitive firm operates in each industry $i = 1, ..., n$...
- ...using the following Cobb-Douglas production function:

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

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
- $\eta_i \in (0, 1)$ governs the fraction of revenue devoted to cover input expenditures
- $\alpha_i \in (0, 1)\ \forall i$ determines the share of labor in total input expenditures
- w_{ij} determines the share of intermediate good j in total expenditure in intermediate goods of industry i, with $\sum_{j=1}^{n} w_{ij} = 1$

The model (II): Financial Constraints

- We assume the existence of working capital
  - Wages and the cost of intermediate goods must be paid in advance
  - Firms want to borrow to afford this cost before production takes place
- Firms can borrow just up to a fraction χ of their revenue

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

The model (III): Preferences

- A representative household whose preferences are represented by the following utility function:

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

  where

  - $C = \prod_{i=1}^{n} c_j^{v_j}$ with $v_j \in (0,1)$ and $\sum_{j=1}^{n} v_j = 1$
  - l is the amount of labor supplied by the household
  - $\gamma \geq 0$ captures the income effect on labor supply
  - $\epsilon > 0$ captures the inverse of the Frisch elasticity

The model (IV): Firms' maximization problem

- Firm operating in industry i solves the following maximization problem:

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

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

The model (IV): Firms' maximization problem

- This problem is solved in two stages

  1. given level of firm's expenditure E_i, the firms decides how to allocate this expenditure across the different production factors
  2. the firm decides the level of expenditure E_i. This expenditure must satisfy:

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

- under DRS, the firm would always like to borrow an amount equal to

$$\eta_i p_i y_i = \eta_i R_i$$

- Then, when $\eta_i > \chi_i$ the firm will borrow less than optimally

The model (IV): Households

- The representative household maximizes the following problem:

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

$$\text{subject to:} \quad C = \prod_{i=1}^{n} c_j^{v_j}$$

$$\sum_j^n p_j c_j \leq wl + \sum_i^n \pi_i$$

The model (IV): Households

- This problem can also be solved in two stages
  1. 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.
  2. Given that 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:

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

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

where $\bar{p} = \prod_{j=1}^{n} \left(\frac{p_j}{v_j}\right)^{v_j}$ is the price index.

The model (IV): 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
2. Households solve their optimization problem
3. Markets clear:

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

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

The model (V): Aggregate effects of financial frictions:

- Real income in this economy can be represented by the following aggregate production function:

$$\text{real GDP} = \underbrace{\Phi\left(\phi\right)}_{\text{efficiency}} \underbrace{L^{\bar{\eta}}}_{\text{labor}} \tag{1}$$

  where

  - $\Phi(\phi)$ depends on sectoral financial frictions
  - L is the endogenous amount of labor in the economy
  - $\bar{\eta}$ is a constant that reflects the decreasing returns in firms' technology

The model (V): Aggregate effects of financial frictions

- This representation of real income allows to decompose the effects of financial frictions shocks into the:
  - *efficiency:*
    - A decrease in ϕ increases the wedge between firms' marginal revenue and marginal cost
    - Dispersion in $\phi \Rightarrow$ dispersion in these wedges $\Rightarrow$ misallocation of labor across sectors
    - IO linkages generally amplify the dispersion in these wedges
  - *labor supply:*
    - Falls in ϕ decrease aggregate labor demand
    - This implies an innefficiently low equilibrium wage
    - Which implies an innefficiently low amount of labor in equilibrium

The model (VI): Calibration - strategy

1. We calibrate the model to the year 2003 (using data on IO, consumption, etc.)
2. A standard identification problem is this type of models:

$$\frac{E_i}{R_i} = \phi_i \eta_i$$

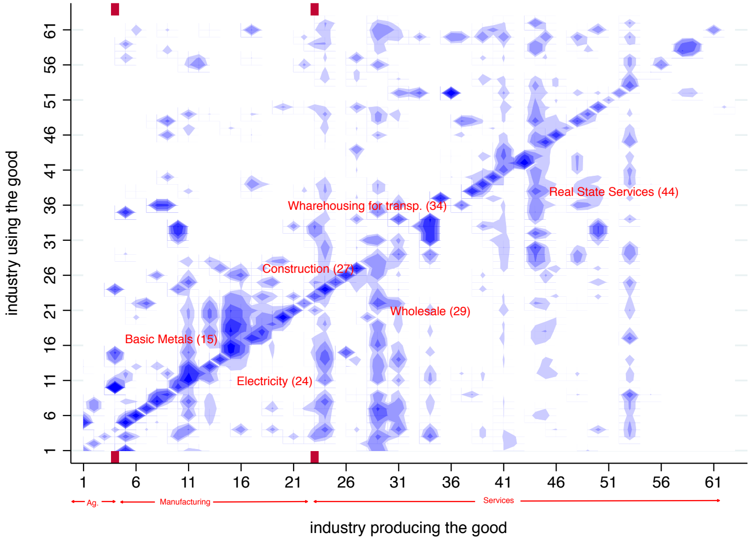
   - For the moment: we fix $\eta_i = 1 \;\; \forall i$ so we can easily recover ϕ_i for each industry

3. We assume that all parameters except the ϕ's remain constant over time.
4. We then use our estimated "direct" credit supply effects to identify the vectors of ϕ's for the years 2004-2010.

The model (VI): Calibration - strategy - In practise

- Remember that, for each industry-year, we have the predicted fall in employment due to the credit supply shocks (absent of GE effects)
- Then, we make an *horizontal* economy version of the model (with NO IO linkages) to match those estimated falls in employment
- Example: our estimated direct effect on employment of the financial shock suffered by the industry *"Water Transport Services"* was +1.6% between 2003 and 2004
- Given the ϕ for this sector in 2003, we find the one for 2004 such that the model generates such an increase in employment
- We proceed similarly for 2005, 2006, etc
- Then we plug these shocks into the full model with IO linkages

The model (VI): Calibration - Spanish IO table



Notes. This figure shows the IO structure of the Spanish economy for the year 2010. In particular,