(Unobserved) Heterogeneity in the bank lending channel: Accounting for bank-firm interactions and specialization

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The views expressed in this paper are our own and do not necessarily coincide with those of the Central Bank of Chile

Motivation

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  - Khwaja & Mian 2008, Paravisini 2008, Jimenez, Ongena, Peydro & Saurina 2012, Chodorow-Reich 2014, Paravisini, Rappoport, Schnabl & Wolfenzon 2015, Amiti & Weinstein 2018, and many others
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We ask:

- How important are bank-firm interactions for the transmission of credit shocks?

This project

- We develop a methodology that estimates the impact of bank and firm credit shocks allowing for bank-firm interactions $\Rightarrow$ heterogeneous effects
  - **Assumption:** Effect of credit shocks is allowed to vary across **groups/types** of firms
  - **Groups** of firms are **unobserved** and identified through machine learning techniques

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  - Researchers are uncertain about the specific dimensions of specialization, or
  - Bank specialization is determined by unobservable firm characteristics (lack of data)

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- We document significant heterogeneity in the bank lending channel
- Applications:
  1. Event study: heterogeneous transmission of credit shocks during GFC
  2. Estimate the impact of bank shocks on firm investment → *key to consider heterogeneity*
  3. How important is the bank-firm network structure for the transmission of credit shocks?

Related Literature

- **Estimating bank lending channel** (*assuming homogeneity*):
  - Khwaja & Mian 2008, Jimenez et al 2012, Chodorow-Reich 2014, Jimenez, Ongena, Peydro & Saurina 2012, 2014, Paravisini, Rappoport, Schnabl & Wolfenzon 2015, Cingano, Manaresi & Sette 2016, Amiti & Weinstein 2018, Bentolila, Jansen & Jimenez 2018, Greenstone et al 2019, Jimenez, Mian, Peydro & Saurina 2020, Degryse et. al 2019, Alfaro et al 2022, Samaniego de la Parra et al 2023, and many others.
- **(Observable) Heterogeneous transmission of bank shocks**:
  - Paravisini, Rappoport & Schnabl 2023 (export markets)
  - Ivashina, Laeven & Moral-Benito 2022 (loan type)
- **(Unobserved heterogeneity) Group Fixed-Effects Estimators**:
  - Hahn & Moon 2010, Bonhomme & Manresa 2015

Outline

1. Standard framework: homogenous transmission of credit shocks
   - Suggestive evidence of heterogeneity
2. A model with interactions: heterogenous transmission of credit shocks
   - Identification and estimation
   - Discussion: Interpretation of estimates
3. Empirical results (using Peruvian credit registry data)

Standard framework: *Homogeneous* transmission of credit shocks

- Let $y_{f,b}$ be the growth rate of loans between bank b and firm f
- Linear specification with two-sided heterogeneity

$$y_{f,b} = \alpha_f + \beta_b + \epsilon_{f,b}$$

  - Firm specific factors α_f (credit demand)
  - Bank specific factors β_b (credit supply)
  - $\epsilon_{f,b}$ is an idiosyncratic firm-bank factor
  - Note: $y_{f,b}$ is observed only if a connection exists ($D_{f,b} = 1$)

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- Key assumptions:
  1. Homogeneous effects:
     - Banks transmit credit shocks β_b equally to all firms
     - Firms transmit credit shocks α_f equally to all banks
  2. Exogenous network assumption: $E[\epsilon_{f,b} \mid D, \alpha, \beta] = 0$
     - No systematic interactions between banks and firms

Standard framework: *Homogeneous* transmission of credit shocks

- Let $y_{f,b}$ be the growth rate of loans between bank b and firm f
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Identification under homogeneous effects

- Multiple connections between banks and firms allow to estimate β_b and α_f as (time-varying) bank and firm "fixed" effects

- **Identifying β_b.** Differential borrowing of the same firm f from banks b and b_0

$$y_{f,b} - y_{f,b_0} = \beta_b - \beta_{b_0} + \epsilon_{f,b} - \epsilon_{f,b_0}$$

→ Homogeneous effects: firm shock α_f disappears

→ Exogenous network: Averaging across a set of firms $\mathbb{I}(b, b_0)$ connected to both banks

$$\mathbb{E}_{f\in\mathbb{I}(b,b_0)}\left[y_{f,b} - y_{f,b_0}\right] = \beta_b - \beta_{b_0}$$

or

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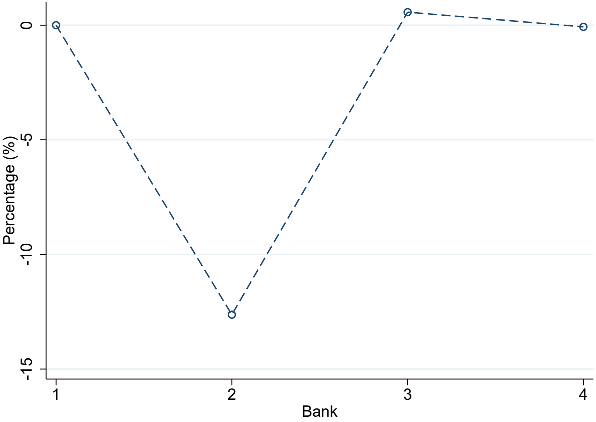
⇒ All systematic differences in the lending of two banks to the **same** set of firms is attributed to a bank shock (credit supply)

* Should hold for any common set of firms $\mathbb{I}(b, b_0)$

Suggestive evidence of heterogeneity

Average credit growth among firms connected to big four banks (relative to b_1)

$$\mathbb{E}_{f \in \mathbb{I}(b_1, b_2, b_3, b_4)} \left[y_{f,b} - y_{f,b_1} \right] = \beta_b - \beta_{b_1}$$



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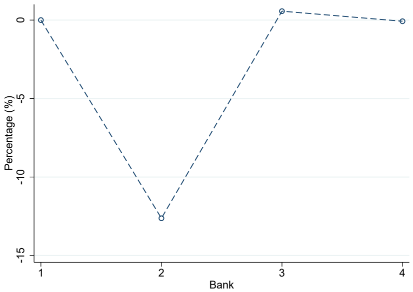
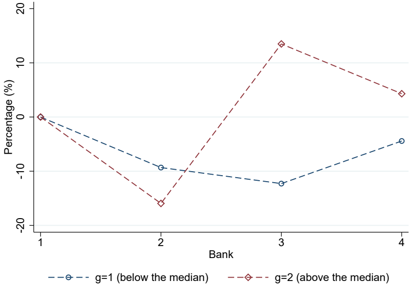
All connected firms



Two groups



other categories

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Model with interactions:

- Bank-firm interactions can be captured by:

$$y_{f,b} = \alpha_f + \beta_b + \psi_{f,b} + \epsilon_{f,b}$$

  - $\psi_{f,b}$: systematic interactions (can be correlated with α, β or D)
  - $\epsilon_{f,b}$: idiosyncratic interactions

$\Rightarrow$ We need some structure for identification $\rightarrow$ to separate $\psi_{f,b}, \epsilon_{f,b}$

Group heterogeneity

- Each firm f belongs to a discrete group $g(f) \in \{1, \ldots, G\}$

$$y_{f,b} = \alpha_f + \beta_{b,g(f)} + \epsilon_{f,b}$$

  - Bank shock affects differentially firms in different groups
  - Bank shock affects equally firms in the same group

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- Motivated by:
  - Banking model with lending specialization (see paper)
  - Examples: Groups of firms defined by
    - *Paravisini et al 2023*: Export market
    - *Ivashina et al 2022*: Type of loan (asset-based firms, cash flow-based firms)

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★ Exogenous network within groups: $E[\epsilon_{f,b} \mid D, \alpha, \beta_g] = 0$

  * Allows for endogenous networks/matching across groups

Discussion

Identification under heterogeneity

- If groups were known:
  - Identification mimics the homogenous case within group

$$\mathbb{E}_{f \in \mathbb{I}(b,b_0)}\left[y_{f,b} - y_{f,b_0} | g(f)\right] = \beta_{b,g(f)} - \beta_{b_0,g(f)}$$

  - Estimation: Standard approach applied within groups
    - Estimate $\beta_{b,g(f)}$, α_f as (time-varying) bank and firm "fixed" effects for each group

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⚠ **Issue:** groups ($g(f)$ and G) are unobserved by the econometrician

- Data may not be available (example: export destination not in the dataset)
- Heterogeneity may depend on unobservables
  - What if export market and loan type are both the source of the heterogeneity?
  - What if banks create special relationships with certain firms?
  - What if unobserved productivity drives the heterogeneity?

⋆ **Solution:** We use an unsupervised learning algorithm to estimate groups

Our algorithm

We build on:

1. Econometrics in Bonhomme & Manresa 2015 (grouped fixed effects)
   - Typically, clustering techniques are based on an observable dissimilarity measure
   - We cluster based on an heterogenous **response** to a **unobserved** bank credit shock
2. The bank lending framework (Khwaja & Mian 2008)

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For given number of groups G:

Step 0. Set $s = 0$. Guess initially some group assignment $g^{(s=0)}(f) \in \{1,\dots,G\}$.

Step 1. For given $g^{(s)}(f)$, estimate **time-varying firm and bank-Group "fixed" effects**

$$\left(\hat{\beta}^{(s)}_{b,g(f),t}, \hat{\alpha}^{(s)}_{f,t}\right) = \arg \min_{\alpha_{f,t}, \beta_{b,g^{(s)}(f),t}} \sum_{f=1}^{N_F} \sum_{b=1}^{N_B} \left(y_{f,b,t} - \alpha_{f,t} - \beta_{b,g^{(s)}(f),t}\right)^2 \tag{1}$$

Step 2. For given $\hat{\beta}^{(s)}_{b,g(f),t}$, $\hat{\alpha}^{(s)}_{f,t}$ select optimal group assignment: For all $f = 1,\dots,N_F$

$$g^{(s)}(f) = \arg \min_{g \in \{1,\dots,G\}} \sum_{b=1}^{N_B} \left(y_{f,b,t} - \hat{\alpha}^{(s)}_{f,t} - \hat{\beta}^{(s)}_{b,g,t}\right)^2 \tag{2}$$

Step 3. Set $s = s + 1$, iterate until convergence.

Properties of our estimator

- **Theorem (Consistency):** *Assume a fixed number of groups G and a grouping function $g_t(f)$ for which assumptions within groups (homogeneity and exogenous network) hold. Then, under suitable regularity conditions the estimator $(\widehat{\alpha}, \widehat{\beta})$ provide consistent estimates of $(\alpha_{f,t}, \beta_{b,g_t(f),t})$ as N_F and N_B become large, and for all $\delta > 0$:*

$$\widehat{\beta}_{b,g_t(f),t} = \underbrace{\widehat{\beta^u}_{b,g_t(f),t}}_{\text{known groups}} + o_p\left(N_B^{-\delta}\right) \qquad \text{for all } b, g, t$$

Inside the black box

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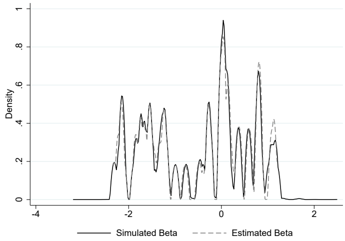
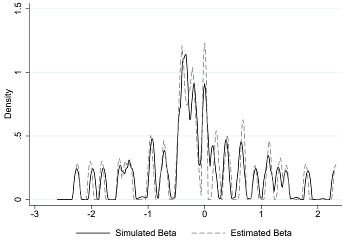
Inside the black box

- **Simulation.** Nice properties!

Consistency: N_F very large



Calibrated to dataset: $N_F = 5000, N_B = 10$



Simulation Example

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   - Discussion: Interpretation of heterogeneous estimates
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Discussion. Interpretation of heterogenous estimator: Demand or Supply?

- Our algorithm will detect any interaction occurring at the bank-firm-group level

$$y_{f,b,t} = \alpha_{f,t} + \beta_{b,g(f),t} + \epsilon_{f,b,t}$$

- But, what is the interpretation of $\beta_{b,g(f),t}$?

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     - Assumption: X_b uncorrelated with bank-specific credit demand
     - Would the **homogenous estimator** provide an **average** “credit supply" effect? → NOT in general!
  b. In real effects regression: Control for demand with group-fixed effects
     - Demand shocks are common to firms in group → common effect on real outcomes
     - Assumption: **Ex-ante** differential exposure to banks **within groups**

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   - Evidence of significant heterogeneity

   i. Heterogeneity in the international transmission of liquidity shocks during GFC

   ii. Real effects of credit supply shocks: How do banks affect firm investment?

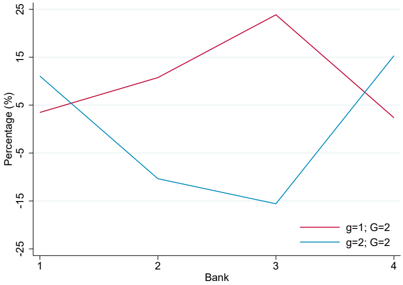
   iii. Bank-firm matching channel: Do bank-firm relationships enhance credit growth?

Data

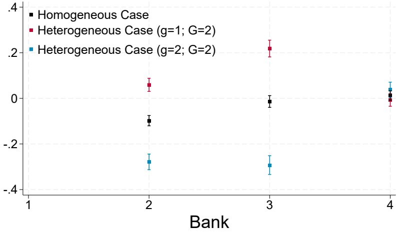
- **Peruvian Credit Registry (RCD)**:
  - Period: 2005-2017
  - Sample: Corporate loans
    - Firms with annual sales above 5 million of dollars
    - 55 percent of all commercial loans
  - We observe the total borrowing for each firm at a given bank
- **Peruvian Stock Exchange (SMV)**:
  - Period: 2007-2017
  - Sample: All the firms that report information to the Peruvian Stock Exchange
  - We observe all their financial statements

Results I: Evidence of heterogeneity

Average credit growth $E[y_{f,b,t}|b,t]$
$G = 2$ (identified by our algorithm)



Bank shocks estimates by bank $\hat{\beta}_{b,g(f),t}$



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   iii. Bank-firm matching channel: Do bank-firm relationships enhance credit growth?

I. Event study: Transmission of an observable credit shock during GFC

- Regression a la Paravisini et al 2015 (similar approach as in Khwaja & Mian 2008)
  - Observable bank shock X_b measuring exposure to 2008 crisis
    - X_b = dummy for high/low foreign liabilities
  - Estimate:

$$y_{f,b} = \ln L_{f,b,\text{Post}} - \ln L_{f,b,\text{Pre}} = \alpha_f + \theta X_b + \epsilon_{f,b}$$

    - "Pre/Post": before/after financial crisis (2008-2009)

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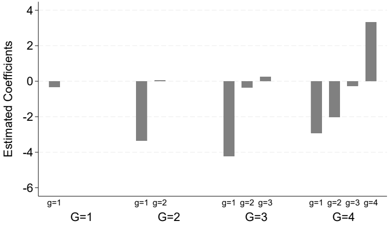
$\hat{\theta}_{b',g}$ for exposed bank b'



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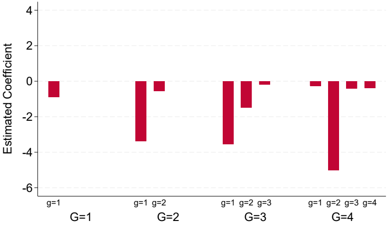

Average Bank Effect

Groups: Observable characteristics

$G=2$	Mean $(g=1)$	Mean $(g=2)$	Mean $(g=3)$	Mean $(g=4)$
Collateral	12.18	9.82	-	-
Debt Size	16.69	12.02	-	-
Exports	26.81	23.97	-	-
# Firms	156	2,207	-	-
$G=3$				
Collateral	7.34	11.65	8.24	-
Debt Size	12.64	14.58	9.01	-
Exports	31.71	29.66	13.78	-
# Firms	226	1,258	879	-
$G=4$				
Collateral	12.89	9.84	9.64	10.46
Debt Size	21.72	11.21	11.88	11.37
Exports	56.88	15.23	24.43	11.21
# Firms	140	260	1,638	325

Groups: Observable characteristics

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II. Real effects of credit supply shocks

- Credit supply shock at firm level:

$$\text{Supply}_{f,t} = \sum_b \omega_{f,b,t-1} \hat{\beta}_{b,g(f),t} \quad \text{with} \;\; \omega_{f,b,t-1} = \frac{L_{f,b,t-1}}{\sum_b L_{f,b,t-1}}$$

- Estimate:

$$\text{Investment}_{f,t} = c + \phi_f^F + \phi_{g(f),t}^G + \beta_1 \hat{\alpha}_{f,t} + \beta_2 \text{Supply}_{f,t} + \epsilon_{f,t}$$

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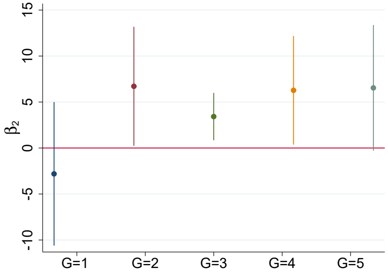

- Homogeneous effects: not significant (and very imprecise) estimated effect
- Heterogeneous effects: significant estimated effect
  - $\Rightarrow$ 1% change in credit supply increases investment by 4-6%

III. The role of bank-firm network

Do banks and firms create relationships that amplify or smooth out credit shocks?

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- Counterfactual network: random assignment of bank-firm connections
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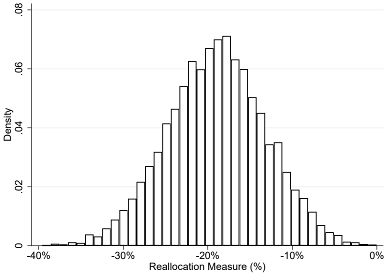
$$\% \text{ Change in } \mathbb{E}_{f \in \mathbb{I}_F, b \in \mathbb{I}_B, \mathbb{1}\{D_{f,b,t}=1\}} \left[y_{f,b,t} \right] \text{ (for } t = 2017)$$



$\Rightarrow$ Endogenous matching expands credit growth by 20% relative to random network

Bank-firm matching channel

Concluding Remarks

- We propose a method to estimate the heterogenous transmission of bank shocks
  - We find evidence of significant heterogeneity
  - Consistent with bank specialization
- Considering heterogeneity is *key* to learn the real effects on firm
- Bank-firm network structure matters for bank lending channel!
  - We quantify a *bank-firm matching channel*
  - → Banks and firms form relationships in a way that enhances credit growth

Appendix

Discussion: Does the **homogeneous** estimator identify an **AVERAGE effect**?

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Proposition. *Let $\widehat{\theta}^{Homo}$ be the homogeneous estimator (as in Khwaja & Mian 2008). Then,*

$$E[\widehat{\theta}^{Homo} | X_b, D] = \sum_b \sum_g \omega_{b,g(f)} \frac{N_{b,g}}{N} E[\theta_{b,g} | X_b, D],$$

where $\omega_{b,g(f)}$ add up to 1, but may be negative!

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⚠ Negative weights may imply $\Rightarrow E[\hat{\theta}^{\text{Homo}}] > 0$ even when ALL $\theta_{b,g} < 0$!

Simulated Example with Bank Specialization

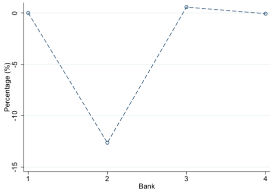
Suggestive evidence of heterogeneity

Average credit growth among firms connected to big four banks (relative to b_1)

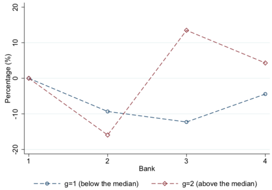
$$\mathbb{E}_{f\in\mathbb{I}(b_1,b_2,b_3,b_4)}\left[y_{f,b,t}-y_{f,b_1,t}\right]=\beta_{b,t}-\beta_{b_1,t}$$

Figure 1: Mean differential loan growth rate for $t = 2017$ (relative to bank 1), by firm classification

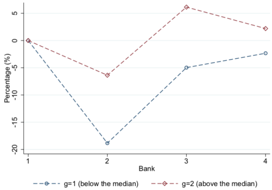
(a) All firms ($G = 1$)



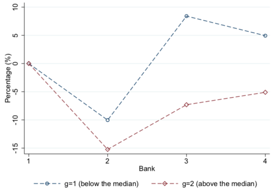
(b) Splitting by firm average credit



(c) Splitting by collateral size



(d) Splitting by firm age



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Simulation Example

- Calibrated to our dataset: $N_F = 5000$, $N_B = 10$
- We use firm observables from our dataset: $x_{f,1}$ (firm collateral), $x_{f,2}$ (firm age)
- We model group heterogeneity based on those observables with G=4 and:

$$g(f) = g' \Leftrightarrow \lambda_1 x_{f,1} + \lambda_2 x_{f,2} \in Q(g')$$

- We simulate:
  1. Credit growth model with group interactions:

$$y_{f,b} = \alpha_f + \beta_{g(f),b} + \epsilon_{f,b}$$

  2. Endogenous matching on group interactions:

$$D_{f,b} = 1\left\{a_0 + a_1 \alpha_f + a_2 \beta_{g(f),b} + \nu_{f,b} > 0\right\}$$

back

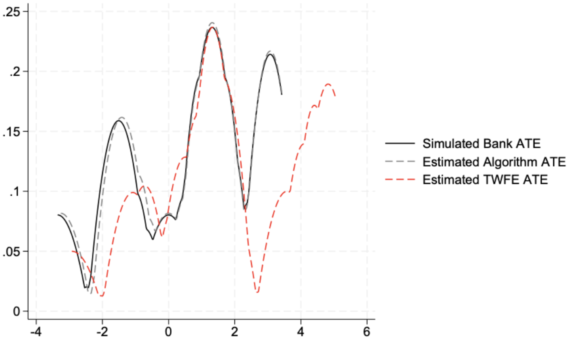
Simulation example

Estimation results:

- Probability of misclassification: 11% for $N_B = 10$
- Average Bank Effect $\rightarrow \overline{\beta}_b = E[\beta_{g(f),b}|b]$:

Figure 2: ATEs properties at the Bank Level: Monte Carlo simulation

(a) Comparison with a TWFE model



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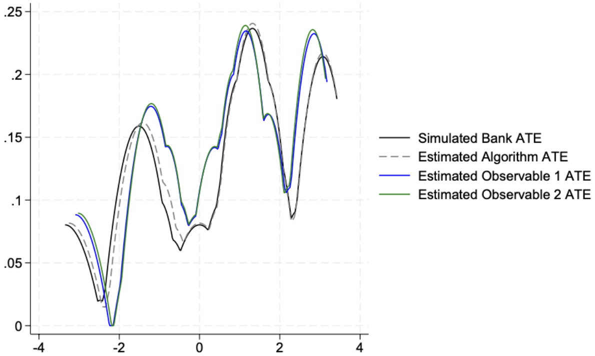
(b) Comparison with a model that uses observable characteristics



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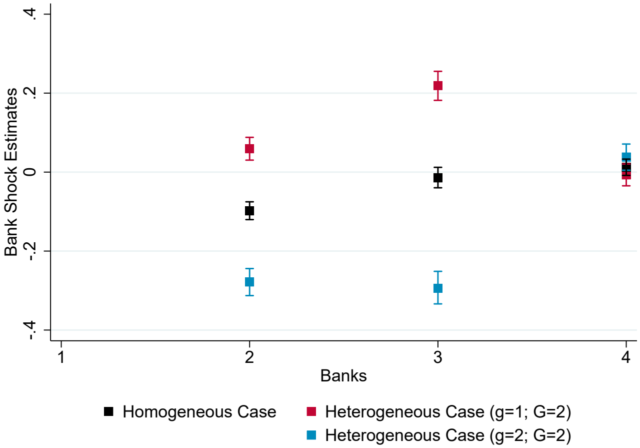
Results I: Evidence of heterogeneity

- Bank shocks estimates by bank $\hat{\beta}_{b,g(f),t}$ (for $t = 2017$)



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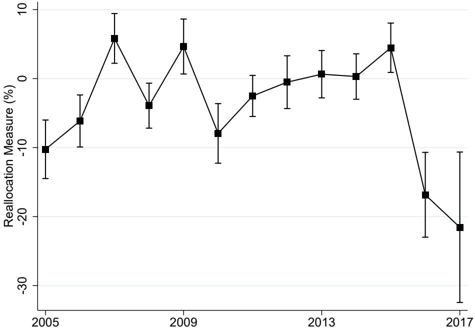
The *bank-firm matching* channel

- Counterfactual: random assignment of bank-firm connections

Average credit growth in random network relative to observed network



⇒ Endogenous bank-firm matching enhances credit growth for most years!

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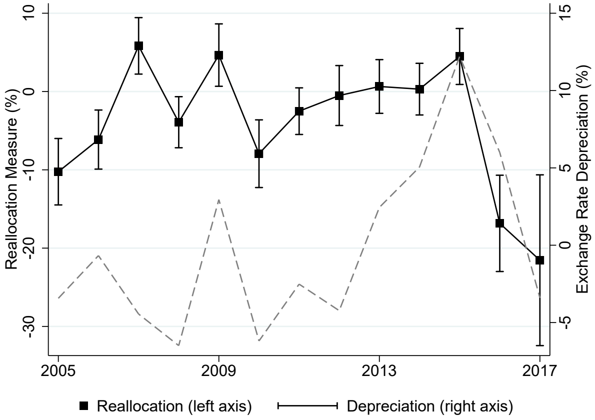
The *bank-firm matching* channel and currency depreciation



⇒ Possible interpretation:

- currency appreciation leads to a positive shock to banks' balance sheets
- endogenous matching leads to the propagation of such credit shock in way that enhances aggregate credit

back

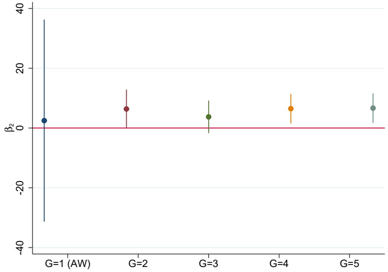
Results III: Real effects of credit supply shocks

- Credit supply shock at firm level (as in Amiti & Weinstein 2018):

$$\text{Supply}_{f,t} = \sum_b \theta_{f,b,t-1} \hat{\beta}_{b,g(f),t} \quad \text{with} \;\; \theta_{f,b,t-1} = \frac{L_{f,b,t-1}}{\sum_b L_{f,b,t-1}}$$

- Estimate:

$$\text{Investment}_{f,t} = c + \phi_f^F + \phi_{g(f),t}^G + \beta_1 \hat{\alpha}_{f,t} + \beta_2 \text{Supply}_{f,t} + \epsilon_{f,t}$$



(unclustered standard errors)

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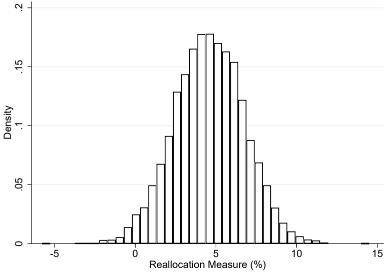
Results IV: Transmission of an observable credit supply shock

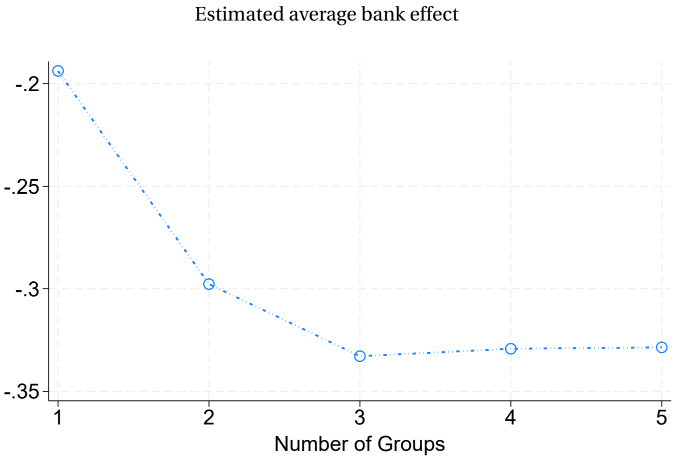
- Transmission of the observed credit supply shock under random allocation

Reallocation using observable bank shock ($G = 3$)



⇒ Bank-firm observed network amplifies the negative credit shock so that credit growth is 5% lower than under a random matching

Event study: Average Bank Effect



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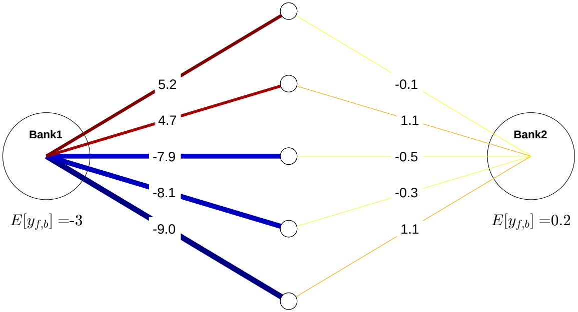
Identification intuition: “Inside the Black Box"

Example with $N_F = 5$

$$y_{f,b} = \alpha_f + \beta_{b,g(f)} + \epsilon_{f,b}$$



- Lower average credit from bank 1 (rel. bank 2) → but significant differences across some firms

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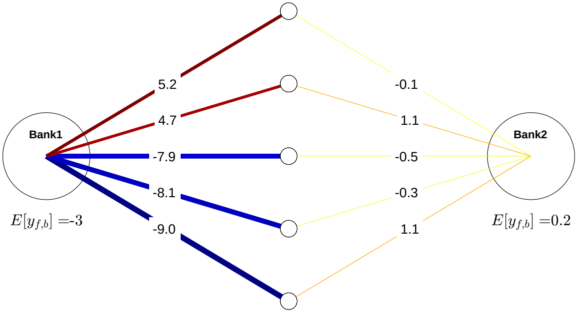

- Lower average credit from bank 1 (rel. bank 2) → but significant differences across some firms
- Such differences could be explained by either $\beta_{b,g(f)}$ or $\epsilon_{f,b}$

back

Identification example

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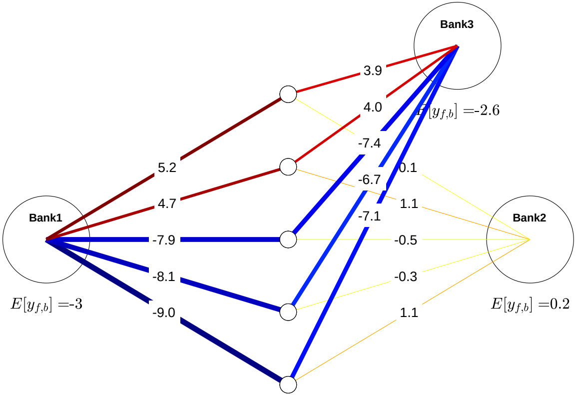

- Grouping is learned by observing cluster of firms treated systematically different by banks!

⇒ Grouping estimation improves with N_B! .. but very fast!

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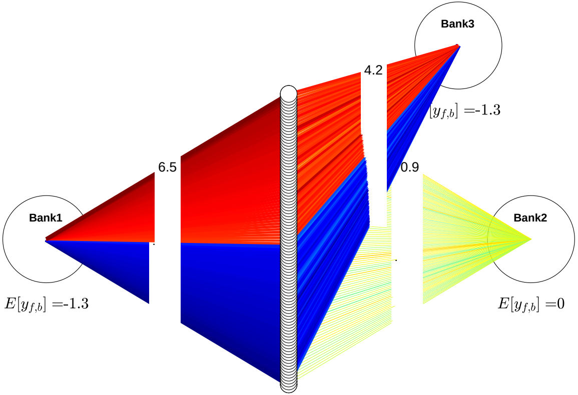
Identification example

Example with $N_F = 100$ and Low σ_ϵ

$$y_{f,b} = \alpha_f + \beta_{b,g(f)} + \epsilon_{f,b}$$



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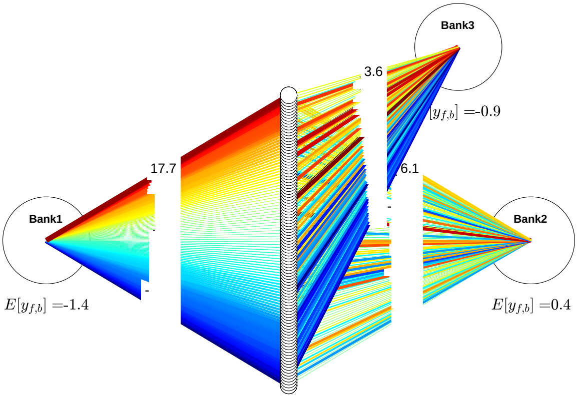

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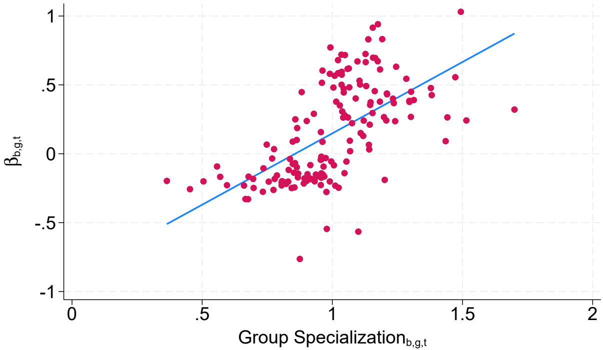
Bank Specialization and estimated bank-firm interactions

- We define bank specialization in our estimated groups:

$$\text{Group Specialization}_{b,g,t} = \frac{\frac{L_{b,g,t}}{\sum_{g'} L_{b,g',t}}}{\frac{\sum_b L_{b,g,t}}{\sum_b \sum_{g'} L_{b,g',t}}}$$

- Bank specialization correlate with our estimated interactions!



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Groups' observable characteristics

- Case with $G = 2$ and grouping $g_t(f)$ estimated every year

Group ($G = 2$)	Firm Debt Size (million of soles)	Risk Score (from 0 to 4)	Collateral Size (million of soles)	Export Value (million USD)
Group (g=1)	23.49	0.24	16.71	28.73
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- Observable characteristics can predict group change:

	(1) $\text{Prob}(g_{t+1} = 2 \mid g_t = 1)$	(2) $\text{Prob}(g_{t+1} = 1 \mid g_t = 2)$
$\triangle \ln$ (Firm Debt Size)	-0.0434**	0.0295***
	(-2.50)	(5.24)
$\triangle$Risk Score	-0.0317*	0.00532
	(-1.75)	(0.46)
$\triangle \ln$ (Total Collateral Size)	0.00120	-0.000898
	(0.27)	(-0.50)
$\triangle \ln$ (Exports)	0.00580	-0.00176
	(1.38)	(-0.67)
Firm	Yes	Yes
Sector-Year	Yes	Yes
Exporter-Year	Yes	Yes
Age-Year	Yes	Yes
R-squared	0.53	0.55
N	4,688	8,265

Example with bank specialization

- Consider a Negative credit event and following banks:
  1. Unexposed $X_{b_0} = 0$,
  2. Mediumly-exposed $X_{b_M} = 0.8$,
  3. Highly-exposed $X_{b_H} = 1$.
- Imagine: Highly-exposed bank is specialized in firms in $g = 1$ and shields them from the shock... relative to the mediumly-exposed bank which is not specialized.
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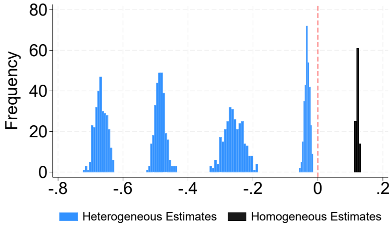
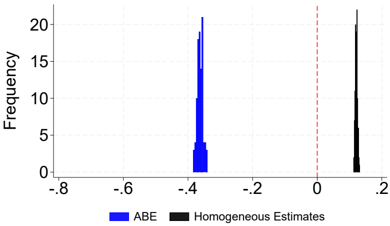


$\hat{\theta}_{b'',g}$ for exposed bank b''



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