Selection in Crisis Lending

Evidence from Chile's Government-Guaranteed Loans

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Motivation

- In recent crises, governments adopted large-scale **guaranteed loan programs** for SMEs
  - COVID-19: widespread adoption, 4–11% of GDP Hong & Lucas, '23
  - Global Financial Crisis: early adoption (US, Japan, UK, Italy)
- How guaranteed loan programs work
  - Commercial banks offer loans at attractive terms to SMEs
  - Governments insure banks against default risk → guarantee
- **This paper** evaluates the cost-effectiveness of guaranteed loans as a crisis response
  - Chile's program in 2020
  - Reduced-form evidence of dynamic effects on firm default
  - Estimate welfare using a dynamic structural model

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Findings

- Loans delayed defaults by 2 years, but did not prevent them over a 5-year horizon
  - Effects are driven by smaller and more leveraged firms
  - Policy induces banks to screen out the riskiest firms based on private information
- Delaying defaults is cost-effective
  - Welfare gains are 21% larger than taxpayers' cost, on aggregate
  - Why? It relaxes financial constraints for entrepreneurs with high growth potential
  - Entrepreneurs with low growth potential increase long-run default probability
- Recommendations for policy design
  - Common practice: larger guarantees for *smaller* firms, decrease cost-effectiveness
  - Proposal: larger guarantees for *younger* firms can improve cost-effectiveness
  - Why? age-based guarantees can reduce lending to firms with low growth potential

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- **Setting:** Guaranteed loan program in Chile, 2020
  - Similar design than in other countries
  - Administrative records + application level data
  - Track firms before and up to 5 years after the policy

- **Reduced-form evidence:**
  - Dynamic effects on default
  - Estimate bank-sided selection
  - IV strategy based on application data + sticky bank-firm relationships

- **Dynamic structural model of SME lending:**
  - Quantified to match IV estimates
  - Aggregate and firm-specific cost-effectiveness
  - Selection into the policy + moral hazard
  - Counterfactuals for policy recommendations

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Literature and Contribution

- **Crisis lending** US Paycheck Protection Program Autor, Cho, Crane, Goldar, Lutz, Montes, Peterman, Ratner, Villar & Yildirmaz '22a, '22b; Chodorow-Reich, Iverson, & Sunderam 2022; Granja, Makridis, Yannelis & Zwick '22; Dalton '23; Agarwal, Ambrose, Lopez & Xiao '24; Kim, Parker & Schoar '25; Partial guarantees Jiménez, Peydró, Repullo & Saurina, '18; Bachas, Kim & Yannelis, '21; Hackney '23; Jiménez, Laeven, Miera & Peydró, '24; Altavilla, Ellul, Pagano, Polo & Vlassopoulos, '25; In Chile Cerda, Gertler, Higgins, Montoya, Parrado & Undurraga '23; Huneeus, Kaboski, Larrain, Schmukler & Vera '25; Acosta-Henao, Fernández, Gomez-Gonzalez & Kalemli-Özcan '25

  → Early reductions on defaults are reverted over a 5-year horizon

- **Negative effects of subsidized lending** De Meza '02; Caballero, Hoshi & Kashyap '08; Gropp, Gruendl & Guettler '14; Brunnermeier & Krishnamurthy '20; Acharya, Borchert, Jager & Steffen '21; Crouzet & Tourre '21; Hoshi, Kawaguchi & Ueda '23; Segura & Villacorta '23; Acharya, Crosignani, Eisert & Eufinger '24; Ornelas, Pedraza, Ruiz-Ortega & Silva '24; Stillerman '24; Lucas '24; Li & Li '25; Martin, Mayordomo & Vanasco '25

  → Study selection and moral hazard jointly

- **Heterogeneous firms, default and financial frictions** Bernanke, Gertler & Gilchrist '99; Hennessy & Whited '05; Buera, Kaboski & Shin '11; Midrigan & Xu '14; Moll '14; Arellano, Bai & Kehoe '19; Senga, Thomas & Khan '17; Ottonello & Winberry '20; Corbae & D'Erasmo '21; Camara & Sangiacomo '22; Kochen '23; Leibovici & Wiczer '25

  → Cost-effective analysis of an optional policy loan

Outline

1. Setting and data
    a. Institutional details
    b. Microdata
    c. Descriptives
    d. Defaults
2. Reduced-form evidence
3. Quantitative model of SME lending
4. Conclusions

Institutional details

- COVID Crisis in Chile
  - March 2020: start of lockdowns, GDP fell by 14% in Q2
  - April 2020, guaranteed loan program is released: *FOGAPE COVID-19*

- Key design features
  - Low rate, same to all applicants: 3.5% 3pp over risk-free, 6pp below market loans
  - Long-term loan: 4 years
  - Capped loan size: <25% of pre-crisis annual sales
  - Partial guarantee: 60-85% of outstanding debt at time of default

- Eligibility: annual sales $<$ \$28M and no prior default

- Large-scale: 5% of GDP in new loans

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Microdata

- Linked administrative records
  - Tax records: sales, assets, returns, industry and county
  - Bank credit records: debt, default, firm-bank relationships, and risk-related metrics
  - Social Security records: employment, wage bill
  - Applications to the guaranteed loan program
- Main panel
  - 108,080 formal, eligible firms with pre-existing bank relationship (2019-2024)
- Auxiliary dataset
  - Bank-firm level applications

Sample Construction

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Selected descriptives

Group (share of firms, %)	Median firm by group Non-applicants (42)	Approved (50)	Rejected (8)
Scale of operations 2019			
Sales ('000 USD)	138	250	217
Assets ('000 USD)	124	149	159
Employees (units)	5	8	8
Age (years)	10	10	9
Risk-related metrics 2019			
Leverage (%)	9	22	20
Loan-loss provision (%)	1.02	1.24	1.51
Pr(default next year) (%)	1.59	1.92	2.02

- Non-applicants were smaller, and less risky than applicants *before the crisis*
- Approved firms sharply increased their debt due to the policy loan

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Debt growth 2019-20 (%)	**-7**	**80**	**-2**

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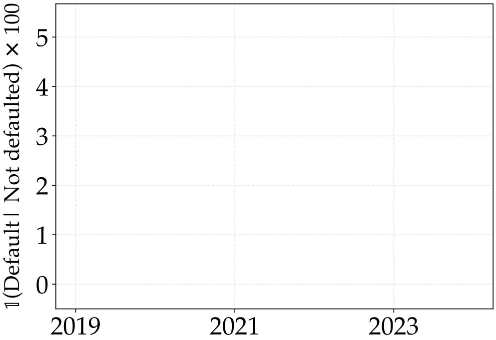
All descriptives

Default across groups



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- Cumulatively, approved default less than rejected → loan effects or bank-sided selection?

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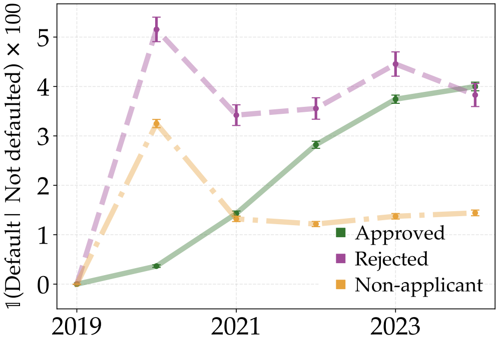

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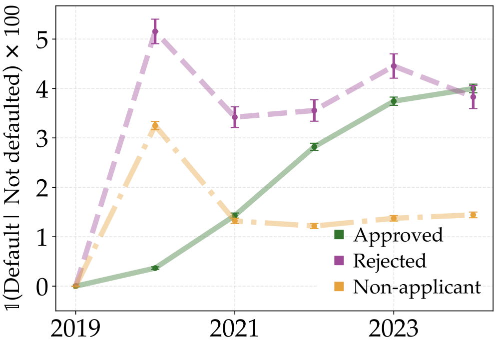

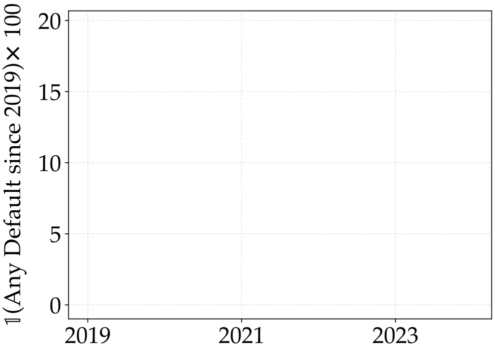

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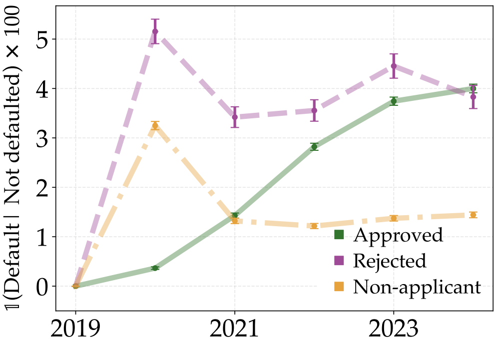

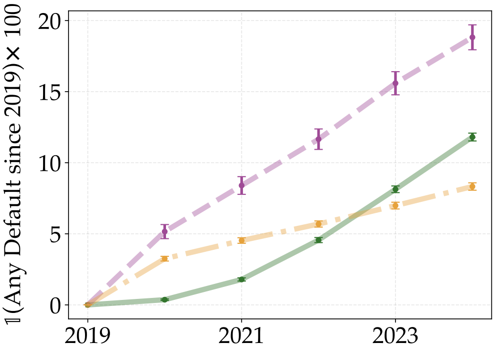

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Effects on default and bank selection

Goal: estimate the dynamic effect β_t of guaranteed loans on default, conditional on applicants

$$\mathbb{1}(\text{Any Default since 2019})_{ft} \times 100 = \beta_t \mathbb{1}(\text{Approved})_f + \gamma_t \text{Controls}_{f,2019} + \varepsilon_{ft}$$

- Key controls: assets, leverage, collateral, loan-loss provisions, default probability, quadratic terms, and bank, industry, and county FE Full list

Challenge: guarantees are partial

- Banks have incentives to approve firms less damaged by the crisis, so less likely to default
- OLS would overestimate the magnitude of the effect

Solution: IV to provide exogenous variation in loan approval

- $\beta_t^{IV} \rightarrow$ effect on default
- $\beta_t^{OLS} - \beta_t^{IV} \rightarrow$ bank-sided selection

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IV strategy

Intuition

- Take two firms that are identical pre-crisis, except for their banks
- Banks differ in approval leniency for policy loans *to this group of firms*
- The firm with a more lenient bank has a higher probability to get a policy loan
- This higher probability is unrelated to firm-level COVID shock

Key assumption: sticky firm–bank relationships

- Firms do not build relationships with banks in anticipation of or in response to COVID.
- 74% of relationships are 2+ years old; 37% are 7+ years old
- Stable firm–bank relationships in Chile Acosta-Henao, Pratap & Taboada, '23

Extra

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IV construction

Step 1: use application data to measure
bank leniency for specific firm groups

$$\mathbb{1}(\text{Approved})_{fb} = \delta_b \text{Controls}_{f,2019} + \eta_{fb}$$

Step 2: predict leniency $\widehat{\delta}_b \text{Controls}_{f,2019}$
for all combinations of firm-bank relationships

Step 3: use pre-crisis relationships as
exposure to bank leniency

$$\text{Instrument}_f := \frac{\sum_b \widehat{\delta}_b \text{Controls}_f \times \text{Relationship}_{fb}}{N_f}$$

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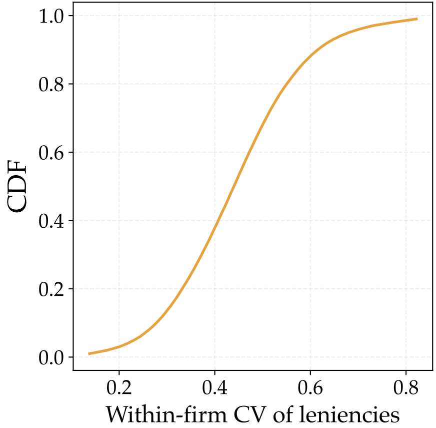
Within-firm leniency variation
("disagreement")



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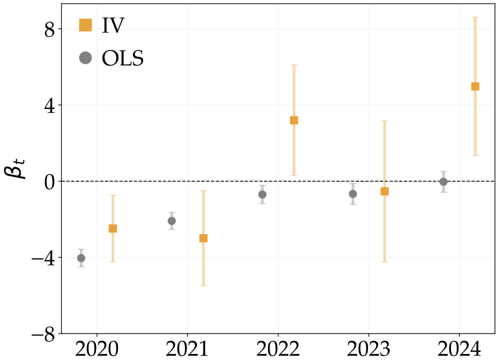
First stage	$\mathbb{1}$(Approved)
Instrument	0.572***
	(0.020)
F (1st stage)	826
Adj R2	0.073
Obs.	61,387
Controls '19	✓
County, Ind., Bank FE	✓

Challenges

Dynamic effects on firm default

Effects on default | not defaulting



- IV: negative effects on default in 2020–21, but positive effects thereafter
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Robustness

- Smaller, more leveraged firms drive the results

By size and leverage
Other outcomes

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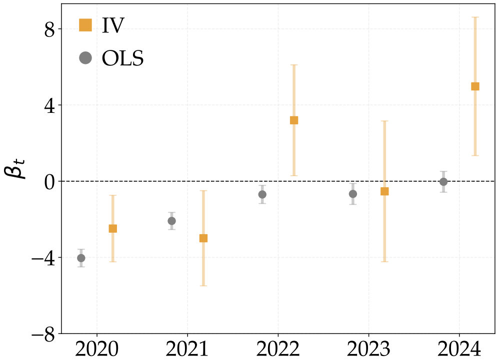

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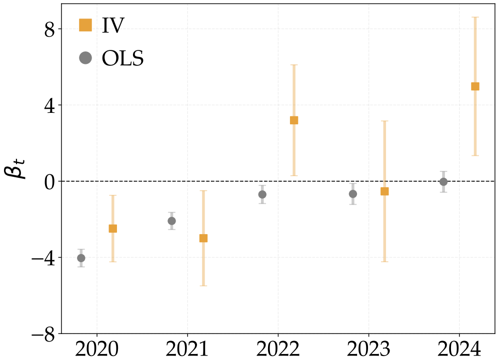
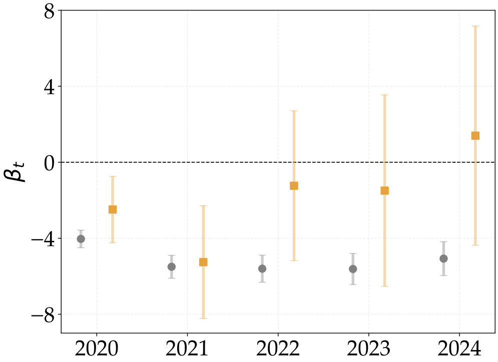


Effects on cumulative defaults



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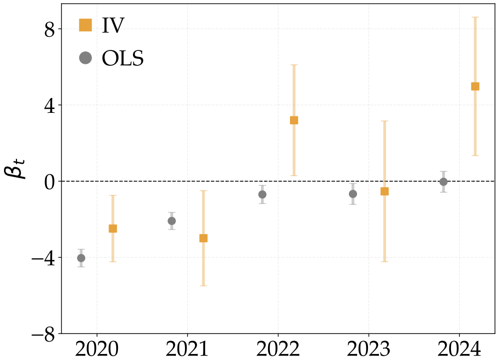

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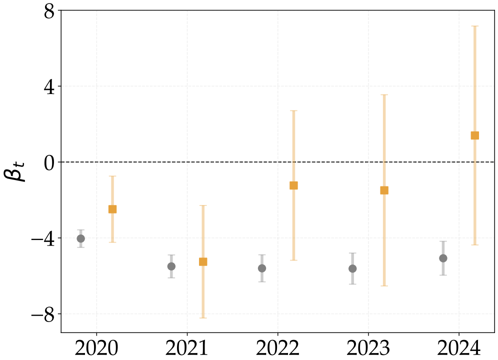

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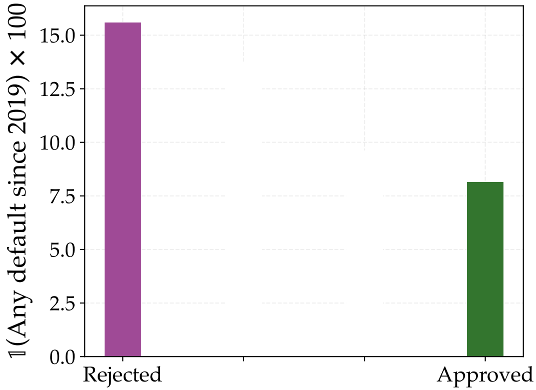

Differences in default rates, 2023: 7.5pp

- Baseline differences: 2pp
- Screening: 4pp All years
- Effect: 1.5pp

Positive screening

- Partial guarantees induce banks to screen based on private information
- Rules out "zombie lending"
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No application data

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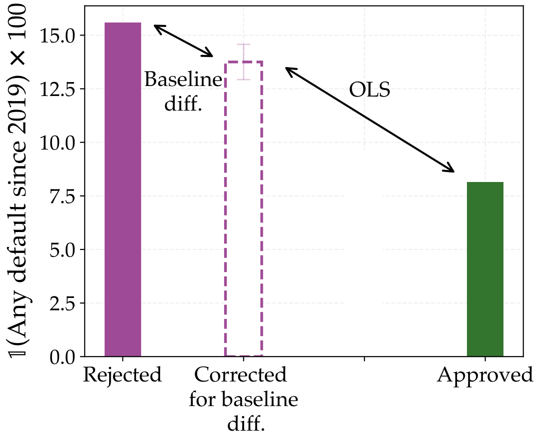

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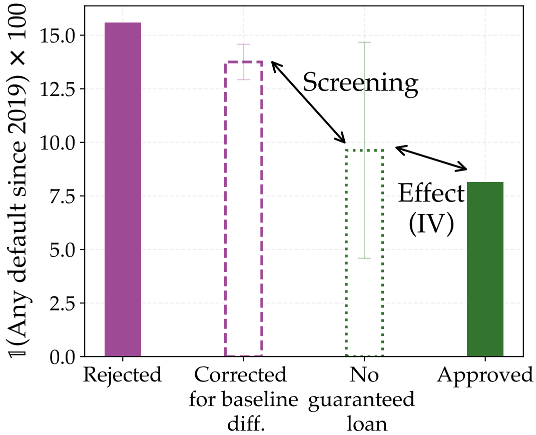

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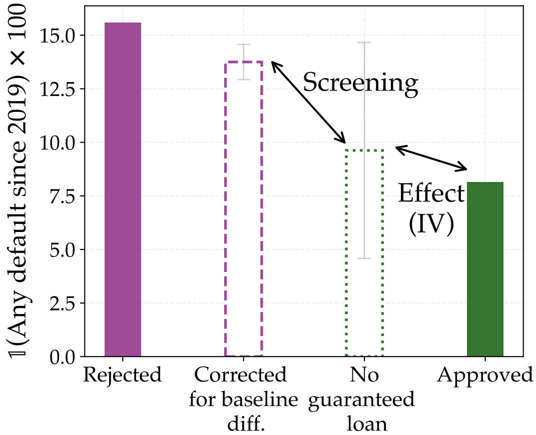

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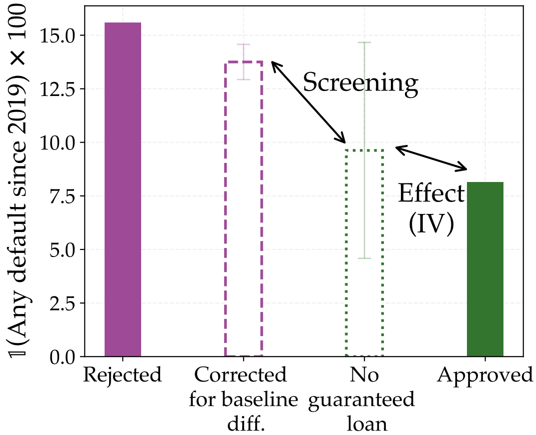

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Taking stock

- Guaranteed loans postponed defaults for 2 years
  - Small, highly-leveraged firms drive aggregate effects
- Banks screened out the riskiest firms based on private information
  - The policymaker can leverage bank's private information using a guarantee program
- Are these delays welfare increasing? $\rightarrow$ Quantitative model of SME lending

Outline

1. Setting and data
2. Reduced-form evidence
3. Quantitative model of SME lending
    a. Setup
    b. Quantification
    c. Results
4. Conclusions

Setup

- **Preferences:** infinite-horizon entrepreneurs with CRRA utility over consumption
- **Heterogeneity:** capital k, debt b, permanent TFP level A, TFP shock z
- **Technology:** invest k' today, get $zAk'^{\alpha} + (1-\delta)k'$ tomorrow, where $\alpha < 1$
- **Finance:** 1-period debt b from risk-neutral banks at break-even prices
- **Exit and Entry:** exit shock, and replacement by startup entrepreneur $\rightarrow$ growth dynamics
- **Default:** i. haircut on debt $H(b) \leq b$, ii. loss λ of sales, iii. temporary exclusion

Draw z, exit, and recovery shocks	Choose default unless already in default	If no exit, choose k' If no default, choose $b' \in \mathbb{R}$ After default, choose $b' \leq 0$	Start over

Bellman eqs.

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- **Crisis:** unanticipated, temporary shock to entrepreneurs' assets ε_k
  - Bad shock on average
  - Positive variance: some firms are hit by COVID, others benefit
  - Lower internal equity raises the demand of external finance
- **Policy:** 2-period loan at rate r^G and guarantee g, only available during crisis
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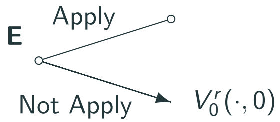

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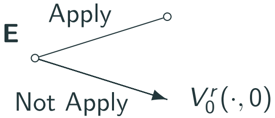

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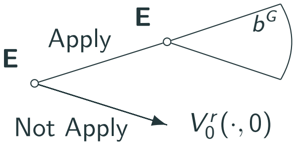

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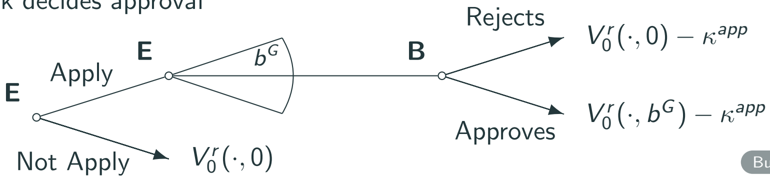

Budget constraints

Approval, Selection and Moral Hazard

- To approve an application, the bank considers
  1. The guarantee g and the interest rate r^G, set by the policymaker
  2. The long-run default probability of applicant i
  3. An idiosyncratic evaluation cost $\kappa_i^{bank} \rightarrow$ rejections

$$\underbrace{\frac{1 - Pr(\text{default})_i}{(1+r)^2}}_{\text{Full repayment}} + \underbrace{\frac{g\, Pr(\text{default})_i}{(1+r)^2}}_{\text{Taxpayer cost}} - \underbrace{\frac{1}{(1+r^G)^2}}_{\text{Cost of funds}} + \kappa_i^{bank} \geq 0$$

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- **Effect**: how does long-run default change when the policy is introduced?
  - If Δ long-run default $> 0 \rightarrow$ **moral hazard**

Quantification in three steps

Method	Parameter	Description	Value	Comment
Preset	σ	Risk aversion	1.5	Herranz et al. ('15)
	δ	Depreciation rate	0.10*	Kochen ('25)
	ρ_z	Persistence TFP shock	0.966*	Kochen ('25)
	h	Fractional haircut	85%	Observed
	r	Risk-free rate	2.7%*	Observed
	ψ	Exit shock	4%*	Observed
	χ	Re-entry probability	25%	Observed
	α	Capital shape	0.23	Independently estimated
	$\ln A$	Long-run TFP	[7.5, 11.1]	4 bins, Independently estimated
	σ_z	Volatility TFP shock	0.138	Independently estimated

* =annualized

Quantification in three steps

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Estimated (crisis)	μ_ε	Mean crisis shock	0.805	SMM to jointly match
	σ_ε	Volatility crisis shock	0.439	reduced form effect β^{IV}_{2021}
	μ_{app}	Mean application cost	9.48×10^{-4}	share of applicants and rejected,
	σ_{app}	Volatility application cost	3.92×10^{-3}	and 2021 default by group
	σ_{bank}	Bank evaluation noise	4.54×10^{-4}	

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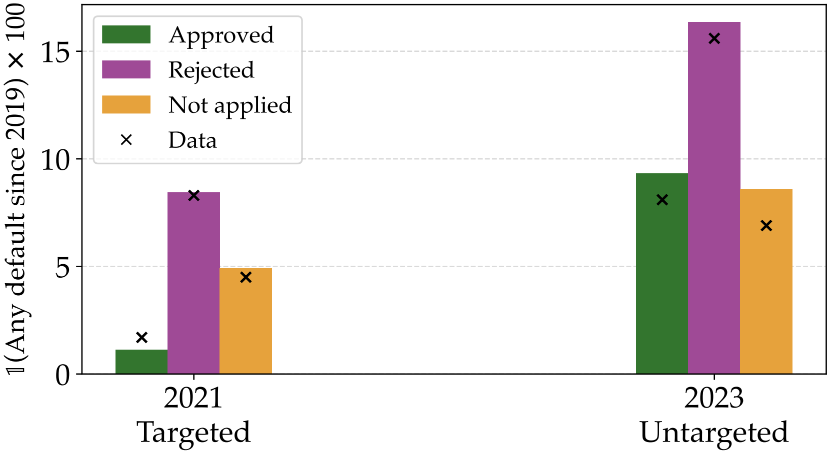
Validation



Approved
Rejected
Not applied
Data
$\mathbb{1}$(Any default since 2019) × 100
0
5
10
15
2021
Targeted
2023
Untargeted

Structural Results: Overview

1. **Aggregate:** the program is cost-effective
2. **Heterogeneity:** 62% of the policy budget goes to cost-effective firms
3. **Selection:** Less productive and harder-hit firms applied more; banks rejected the most affected
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1. Aggregate cost-effectiveness

- **Welfare gains:** cash transfer ω_i to entrepreneur i such that

$$V_{0,i}^{\text{no policy}}(\,.\,,\omega_i) = V_{0,i}^{\text{policy}}(\,.\,,0)$$

- **Taxpayer cost:**

$$\tau_i = \frac{g\, Pr(\text{default})_i}{(1+r)^2}\, b^G$$

- **Aggregate:** the policy generates welfare gains 21% larger than the cost to taxpayers

$$\sum_i \omega_i = \mathbf{1.21} \sum_i \tau_i$$

- Not all policy loans are cost-effective:

$$CE_i = \omega_i / \tau_i \; < 1$$

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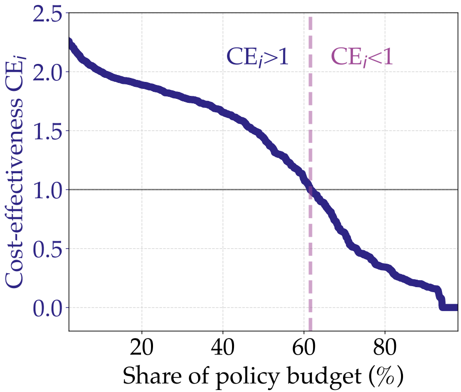

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  - 73% of firms are cost-effective

2. Heterogeneity in cost-effectiveness

Diff. in means in pp.	
Assets	-55
Leverage	22
Age	-34
Crisis shock	-37
A	12

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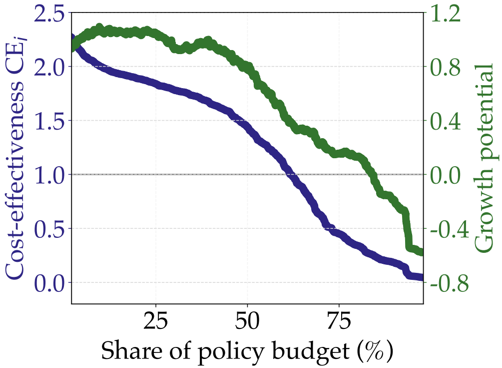
- **Cost-effective firms:** smaller, more leveraged, younger, harder-hit by crisis, and more productive
- **Shared feature:** growth potential

$$\ln k_i^* - \ln \varepsilon_{k,i} k_{0,i}$$

  - Long-run scale: k_i^*
    $\rightarrow$ Higher ceiling for high-productivity firms
  - After-crisis assets: $\varepsilon_{k,i} k_{0,i}$
    $\rightarrow$ Lower floor for harder-hit or smaller firms

2. Heterogeneity in cost-effectiveness



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Welfare gains: guaranteed loan relaxes financial constraints for firms with high growth potential

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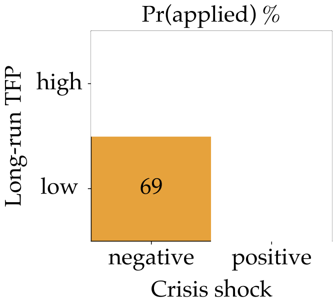

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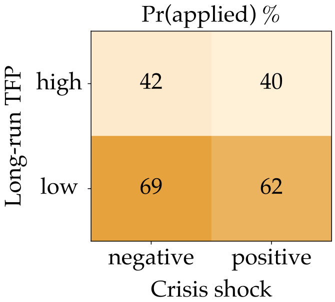

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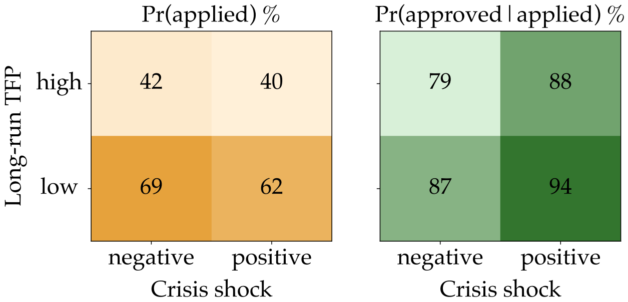

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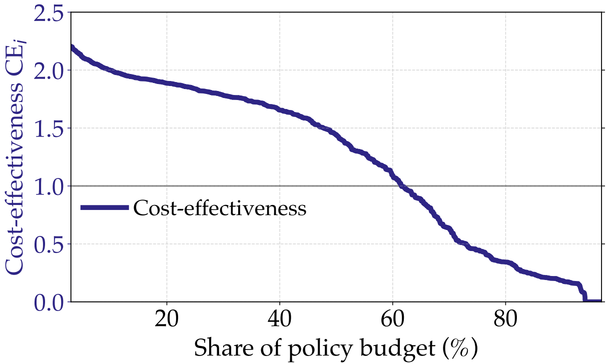

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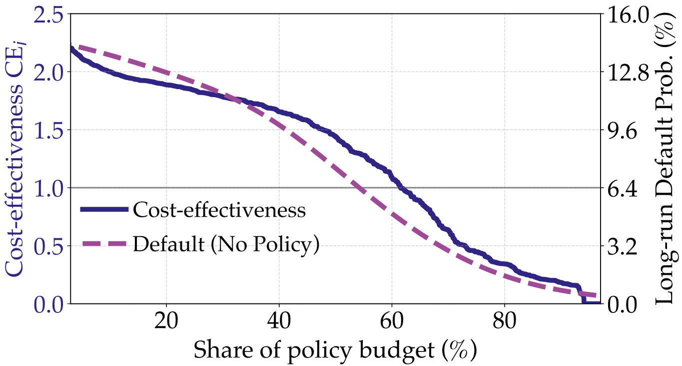

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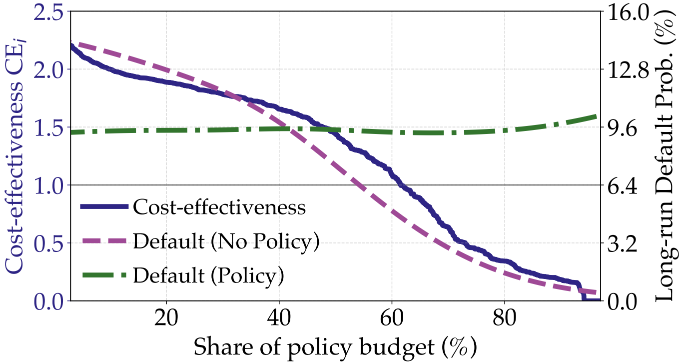

Structural Results: Overview

1. **Aggregate:** the program is cost-effective
2. **Heterogeneity:** 62% of the policy budget goes to cost-effective firms
3. **Selection:** Less productive and harder-hit firms applied more; banks rejected the most affected
4. **Moral hazard:** policy increases default of ineffective firms
5. **Policy design:** age-based guarantees can outperform size-based guarantees

5. Policy design

- Small firms have tighter financial frictions Gertler & Gilchrist, '94
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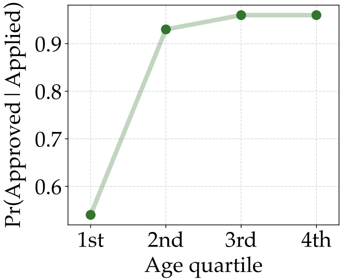

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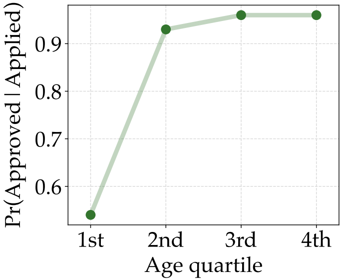

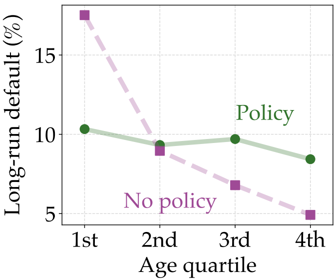

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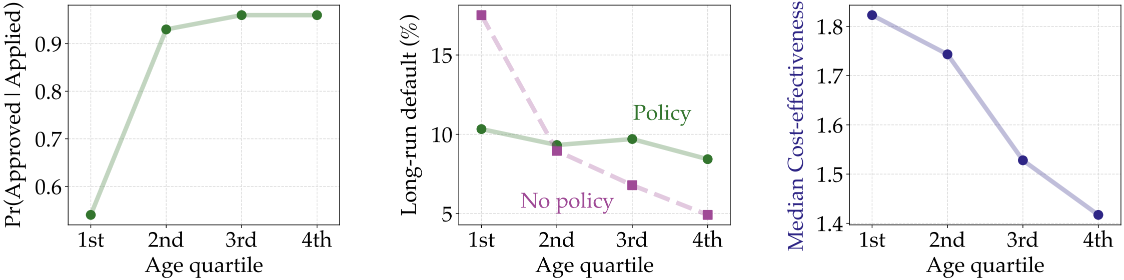
  - Guaranteed loans *reduces* long-run default risk among the youngest firms
  - Younger firms are very *cost-effective*



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A. ↑ guarantee for the **smallest** quartile
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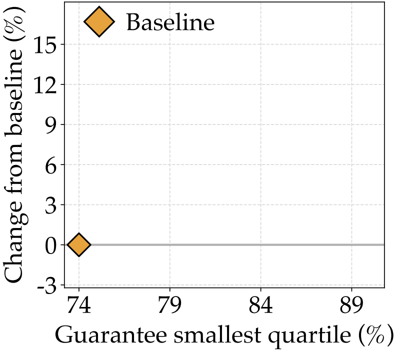

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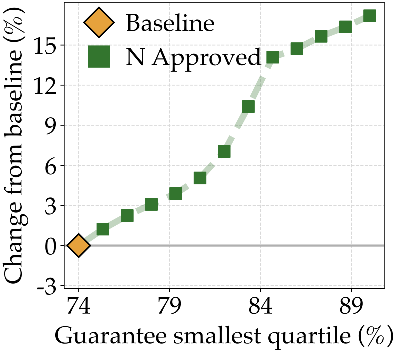

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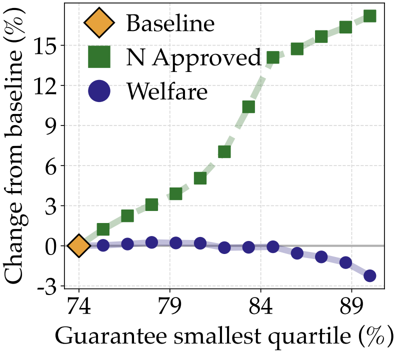

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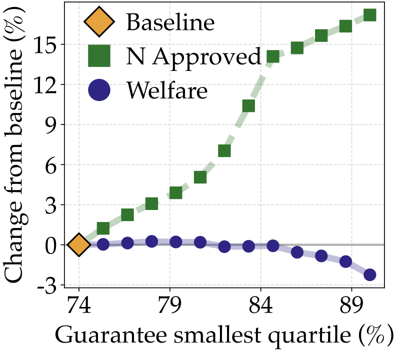

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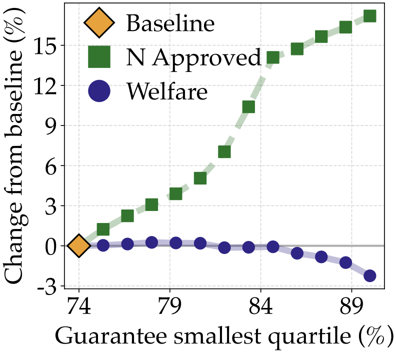

B. ↑ guarantee for the **youngest** quartile
↓ for the rest, keeping budget neutral

- ▷ ↑ loans approved, ↑ welfare

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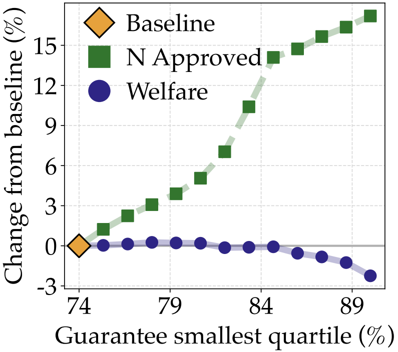

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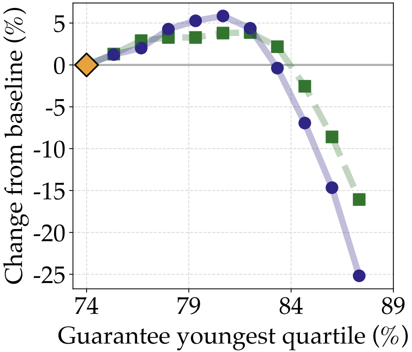


Conclusions

- Guaranteed loans can be a cost-effective tool to support firms during crises
  - Partial guarantees preserve bank screening, leading banks to reject the riskiest firms
- The program performs best when supports firms with high growth potential
  - It also supports safe or low-productivity firms, which undermines effectiveness
  - During crises, the benefits outweigh the costs
- While growth potential is difficult to observe, firm age provides a useful proxy
  - Age-based guarantees can outperform size-based guarantees

Appendix

Sample Construction

1. IDs with positive sales in 2019: 925,072
2. With social security records in 2019: 367,577
3. With bank relationships in 2019: 197,123
4. With positive assets in 2019: 133,003
5. No financial, education, health or public administration sectors: 122,807
6. Guaranteed Loans Cleaning: 120,330
7. Below $ 28M annual sales: 119,054
8. Not closed by April 2020: 112,459
9. Eligible by payment due date: **108,080**

→ 30% of GDP

→ 50% of Employment

Back

Descriptives

Back to descriptives Back to regression

	Mean	Std. Dev.	10th Pct.	Median	90th Pct.
Applications					
Applied to GGL (indicator)	0.58	0.49	0.00	1.00	1.00
Approved for GGL (indicator)	0.50	0.50	0.00	1.00	1.00
GGL size/sales (%) *only approved*	14.33	10.03	5.00	12.18	24.88
Guarantee share (%) *only approved*	74.14	18.98	42.50	85.00	85.00
Pre-crisis characteristics (2019)					
Sales (Th. USD)	818.14	1981.39	30.75	195.90	1797.04
Employees (units)	26.97	66.13	1.00	7.00	58.00
Wage bill (Th. USD)	131.19	319.90	3.57	29.47	293.12
Assets (Th. USD)	1231.90	3834.43	16.45	139.78	2402.70
Debt to assets (%)	34.43	56.34	1.16	15.75	80.10
Returns on 2019 assets (%)	35.62	83.31	-23.40	22.77	112.29
Number of banks (units)	1.60	0.97	1.00	1.00	3.00
Bank average assets (M USD)	0.04	0.01	0.03	0.04	0.05
Age (years)	11.47	7.35	3.00	10.00	23.00
Past default events (units)	0.01	0.09	0.00	0.00	0.00
Past delay events (units)	0.04	0.23	0.00	0.00	0.00
Share of debt backed by collateral (%)	15.10	25.67	0.00	0.00	55.98
Share of debt provisioned by the bank (%)	2.02	3.39	0.22	1.16	2.88
Model-implied probability of default (%)	2.14	1.52	0.56	1.79	4.18

Sample size: 108080 firms, over 100 industries, 341 counties, and 19 different banks

Application data reveals banks selecting safer firms

Back

	Effect of Guaranteed Loan on $\mathbb{1}$(Any Default since 2019) $\times$ 100				
	2020	2021	2022	2023	2024
Panel A: Applicants Only ($N = 61,387$)					
$\hat{\beta}^{\text{IV}}$	-2.487^{***}	-5.257^{***}	-1.236	-1.491	1.4
	(0.891)	(1.514)	(2.012)	(2.571)	(2.944)
$\hat{\beta}^{\text{OLS}}$	-4.036^{***}	-5.501^{***}	-5.602^{***}	-5.619^{***}	-5.072^{***}
	(0.236)	(0.308)	(0.364)	(0.419)	(0.456)
$\hat{\beta}^{\text{OLS}} - \hat{\beta}^{\text{IV}}$	-1.549	-0.244	-4.366	-4.128	-6.472
Panel B: All Firms ($N = 104,016$)					
$\hat{\beta}^{\text{IV}}$	-4.249^{***}	-5.096^{***}	-1.459	-1.978	-0.04
	(1.322)	(1.777)	(2.161)	(2.594)	(2.903)
$\hat{\beta}^{\text{OLS}}$	-3.203^{***}	-3.724^{***}	-2.948^{***}	-1.655^{***}	-0.255
	(0.097)	(0.127)	(0.155)	(0.182)	(0.204)
$\hat{\beta}^{\text{OLS}} - \hat{\beta}^{\text{IV}}$	1.046	1.372	-1.489	0.323	-0.215

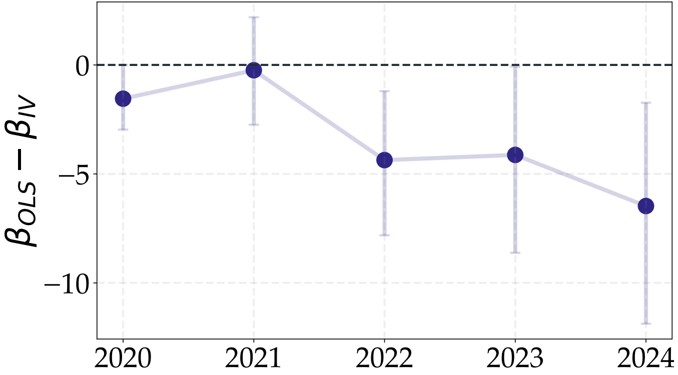
Robustness

Back

	Effect of Guaranteed Loan on $\mathbb{1}$(Any Default since 2019) $\times$ 100				
	2020	2021	2022	2023	2024
Baseline	−2.487***	−5.257***	−1.236	−1.491	1.4
	(0.891)	(1.514)	(2.012)	(2.571)	(2.944)
Obs.	61387	61387	61387	61387	61387
Cond. not defaulted	−2.487***	−2.902**	3.913***	−0.353	3.058*
	(0.891)	(1.273)	(1.455)	(1.832)	(1.779)
Obs.	61387	60867	59871	58139	55932
Always Sell	−2.302***	−5.69***	−4.231**	−3.109	0.817
	(0.839)	(1.357)	(1.801)	(2.467)	(3.011)
Obs.	53001	53001	53001	53001	53001
No market loan	−1.07	−3.19**	−0.328	1.968	5.085
	(1.074)	(1.548)	(2.156)	(2.784)	(3.260)
Obs.	38883	38883	38883	38883	38883

Selection: all years

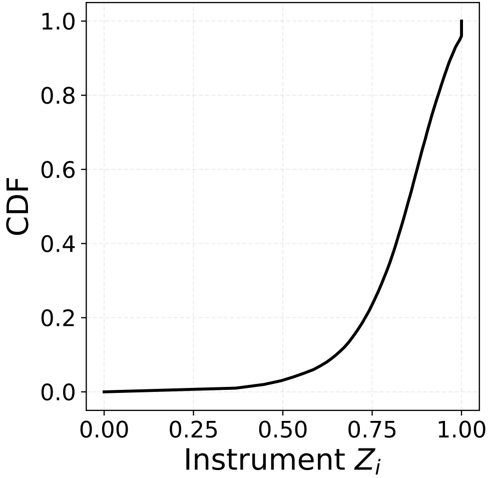
Back



Difference in OLS and IV estimates on cumulative defaults

Standard errors by bootstrap (1000 samples)

Instrument details: variation



Production function estimation

Back

- We construct a panel for 2016-2019 with firms in the range of p5–p95 pre-crisis characteristics of our main sample
  - Reduces survival bias
- We estimate

$$\ln(sales_{ft}) = \ln A_f + \ln z_{ft} + \alpha \ln(k_{ft-1}) + controls_{ft} + \varepsilon_{ft}$$

- We include as controls unmodeled heterogeneity: industry, county, ln(age) and ln(age)^2.
- We bin $\ln \widehat{A}_f$ into 4 firms types
- From $\widehat{Var}(\varepsilon_{ft})$ and given an autocorrelation ρ_z, we back out the variance of innovations

Budget constraints at $t = 0, 1, 2$

Back

At $t = 2$, the guaranteed loan b^g has to be repaid if no prior default

$$c = zAk^{\alpha} + (1-\delta)k - b - b^{G} + q(z, b', k')b' - k'$$

At $t = 1$, the guaranteed loan is not yet due.

$$c = zAk^{\alpha} + (1-\delta)k - b + q(z, b', k')b' - k'$$

At $t = 0$, crisis hits and the funds are received after approval

$$c = zA(\varepsilon_k k)^{\alpha} + (1-\delta)\varepsilon_k k - b + q(z, b', k')b' + q^{G} b^{G} - k'$$

Challenges to identification

Back to intuition Back to construction

- **Bank sorting:** low-resilience firms might be concentrated in more lenient banks
  1. Use only top 6 banks, with national coverage, to avoid regional or sectoral banks
  2. Control for pre-crisis default risk using loan provisions, collateral, and default prob.
  3. Industry-year, and county-year FE to control for industry and county level shocks
  4. FE at bank-level control for mean residual differences of COVID impact across banks
- **Bank shopping:** firms damaged by the crisis might search for lenient banks
  - Use only pre-crisis bank relationships
  - Relationships are long-standing
- **Joint effects:** If guaranteed loans trigger extra lending $\rightarrow$ joint effect
  - Robustness: drop firms that received other loans, similar effects

Bellman equations at $t > 2$ (exit shocks omitted)

Back

Value before default choice d:

$$\widehat{V}(s) = \max_{d \in \{0,1\}} d\widehat{V}^d(s') + (1-d)\widehat{V}^r(s') \text{ where } s = (z, b, k, A)$$

Value in repayment:

$$\widehat{V}^r(s) = \max_{k' \geq 0, b' \in [\underline{b}, \overline{b}]} u(c) + \beta \mathbb{E}\left[\widehat{V}(s') \mid s\right]$$

$$\text{s.t.} \quad c = zAk^\alpha + (1-\delta)k - b + qb' - k'$$

$$q = \mathbb{E}\left[1 - d(s') \mid z\right](1+r)^{-1}$$

Value in default

$$\widehat{V}^d(s) = \max_{k' \geq 0, b' \leq 0} u(c) + \beta \mathbb{E}\left[\chi \widehat{V}(s') + (1-\chi)\widehat{V}^d(s')\right]$$

$$\text{s.t.} \quad c = (1-\lambda)zAk^\alpha + (1-\delta)k - H(b) + q_{rf} b' - k'$$

Heterogeneous effects of guaranteed loans

Back

Outcome	All	Assets < p50		Assets > p50	
1(Any Default since 2019) ×100		Lev. < p50	Lev. > p50	Lev. < p50	Lev. > p50
2020	−2.487***	−2.043	-4.292*	−2.648*	−1.212
	(0.891)	(2.915)	(2.372)	(1.450)	(1.319)
2021	−5.257***	−3.754	-15.538***	−2.553	−1.136
	(1.514)	(4.162)	(4.309)	(2.209)	(2.643)
2022	−1.236	−2.083	-9.337*	−1.407	0.889
	(2.012)	(5.847)	(5.437)	(3.079)	(4.208)
2023	−1.491	−2.530	−11.450	−2.617	−0.240
	(2.571)	(7.121)	(7.100)	(3.858)	(5.491)
2024	1.400	4.533	−8.151	3.290	−5.923
	(2.944)	(8.154)	(8.071)	(4.453)	(6.528)
Obs.	61387	15334	15302	15345	15330
F (1st stage)	826	114	161	231	183
Controls '19	✓	✓	✓	✓	✓
County, Industry & Bank FE	✓	✓	✓	✓	✓

- Smaller, highly-leveraged firms drive short-run effects

Other outcomes

Back

	2020	2021	2022	2023	2024
	1(any exit since 2020)				
Approved (OLS)	-	−2.872***	−4.63***	−5.884***	−6.844***
	-	(0.272)	(0.365)	(0.435)	(0.487)
Approved (IV)	-	−2.251	−1.933	−0.372	−3.206
	-	(1.394)	(2.019)	(2.516)	(2.964)
$\mathbb{E}$[Outcome | Approved]	0.000	2.244	5.042	8.631	12.652
Obs.	61387	61387	61387	61387	61387
	Ln(Sales)				
Approved (OLS)	0.06***	0.065***	0.07***	0.084***	0.109***
	(0.009)	(0.011)	(0.012)	(0.014)	(0.018)
Approved (IV)	−0.059	−0.089	−0.156*	−0.185*	−0.232*
	(0.059)	(0.073)	(0.082)	(0.097)	(0.120)
Obs.	53001	53001	53001	53001	53001
Controls '19	✓	✓	✓	✓	✓
County & Industry FE	✓	✓	✓	✓	✓

- No significant effects on exit or sales

Direct evidence

Back

	2020	2021	2022 $\mathbb{1}$(Invested)	2023	2024
$\mathbb{1}$(Approved)	-0.016	-0.050	-0.035	-0.050	-0.035
	(0.036)	(0.038)	(0.038)	(0.038)	(0.040)
$\mathbb{1}$(Approved)	-0.062	-0.093**	-0.066	-0.083**	-0.072*
	(0.040)	(0.042)	(0.042)	(0.042)	(0.043)
$\mathbb{1}$(Approved) $\times$ $\mathbb{1}$(hi pre-crisis growth)	0.050***	0.036***	0.033***	0.016***	0.011**
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
$\mathbb{1}$(Approved)	-0.038	-0.071*	-0.055	-0.062	-0.045
	(0.037)	(0.039)	(0.038)	(0.038)	(0.040)
$\mathbb{1}$(Approved) $\times$ $\mathbb{1}$(hi pre-crisis returns)	0.052***	0.049***	0.048***	0.027***	0.023***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\mathbb{1}$(Approved)	-0.010	-0.049	-0.035	-0.055	-0.032
	(0.037)	(0.039)	(0.038)	(0.038)	(0.040)
$\mathbb{1}$(Approved) $\times$ $\mathbb{1}$(age $> p50$)	-0.012	-0.002	-0.001	0.009	-0.005
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$\mathbb{1}$(Approved)	-0.059	-0.072*	-0.034	-0.034	-0.015
	(0.037)	(0.039)	(0.039)	(0.039)	(0.040)
$\mathbb{1}$(Approved) $\times$ $\mathbb{1}$(good covid)	0.088***	0.044***	-0.003	-0.032***	-0.039***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)