Financial Stimulus and Microfinance Institutions in Emerging Markets

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- However, their participation in financial stimulus programs is still limited
  - High operational costs, less sophisticated institutions
- Whether promoting the participation of MFIs is desirable or not is an empirical question

$$\underbrace{\text{Target small firms with} \uparrow \text{needs of ext. financing}}_{>0} \text{ vs. } \underbrace{\uparrow \text{leverage of opaque firms}}_{<0} + \underbrace{\downarrow \text{screening incentives}}_{<0}$$

Question and context

This paper:

What are the effects of Loan Guarantee Programs (LGP) on financial stability?

What is the role of micro-finance institutions (MFIs) in shaping the aggregate effects of LGP?

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Context & Empirical approach:

Reactiva Perú, a program of loan guarantees to help firms dealing with Covid-19 restrictions

- Program represented 8% of GDP, key role of MFIs in bancarization, detailed MFIs credit data and balance sheet information

Tracing the effects of loan guarantees on small firm lending in a diff-in-diff setting

- Bank shock $\Rightarrow$ credit supply $\Rightarrow$ firms' delinquency rates

Mapping firm-level elasticities to allocation of loan guarantees across financial institutions

Empirical findings

Average effects:

- More treated banks expand credit supply relative to less treated ones after the program (1 SD $\Rightarrow \uparrow$ 7%), totally driven by LG, while normal loans decline (1 SD $\Rightarrow \downarrow$ 10%)
- Firms attached to highly treated banks increase total outstanding credit (1 SD $\Rightarrow \uparrow$ 10%), reduce normal debt (25%), and are less likely to exhibit repayment delays (3 ppts)

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Heterogeneous effects and the role of MFIs:

- Smaller firms are more responsive in terms of delinquency
  - Increasing credit by 10% reduces prob. of repayment delay in 5ppts (vs. 1ppts for larger firms)
- MFIs provide more guarantees to smaller firms: 52% of their LGP portfolio vs. 21% for big banks
- Limited participation: 52% of pre-Covid debt and 30% of guarantees

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BoE: decline in delinquency 4ppts without MFIs and 5ppts with MFIs

- key assumption: homogeneity within size-group

Theoretical results

Building blocks:

- Bank profits depend on firm characteristics and poaching probability
  - cash-in-hand, initial debt
- Banks trade-off client size and treatment effect
- Two types of banks: Big banks and MFIs
- Calibrated model: size-dependent average treatment effect + Banks distribution of clients

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Results and counterfactuals:

- Private allocation not necessarily optimal, depends on poaching & bank future profits from clients
- 30% gains from MFIs observed participation in terms of aggregate debt in default
- Negligible gains from further increasing MFIs' participation

Literature

Loan guarantees

- **Lelarge, Sraer, and Thesmar (2010)**, Brown and Earle (2017), Mullins and Toro (2018), Ru (2018), Cong et al. (2019), **Haas-Ornelas et al. (2020)**, Bachas, Kim, and Yannelis (2021), Barrot et al. (2021), González-Uribe and Wang (2021), Bonfim, Custódio, and Raposo (2022)
- Heterogeneous effects on delinquency rates and optimality of credit allocation

Financial stimulus in recessions

- Bartik et al. (2020), Faulkender, Jackman, and Miran (2020), Granja et al. (2020), Li and Strahan (2020), Autor et al. (2022), **Griffin, Kruger, and Mahajan (2022)**, **Huneeus et al. (2022)**, **Joaquim and Netto (2022)**
- Role of micro-finance institutions in shaping the allocation loan guarantees and aggregate effect on financial stability

Microfinance institutions in emerging markets

- Ahlin and Jiang (2008), Angelucci, Karlan, and Zinman (2015), Attanasio et al. (2015), Augsburg et al. (2015), Tarozzi, Desai, and Johnson (2015), Buera, Kaboski, and Shin (2020), **Breza and Kinnan (2021)**
- MFIs participation in a large scale program of guarantees in a global recession

Data & Empirical Framework

Program of guarantees: Reactiva Perú

- Government guarantees on private bank loans **[average = 97% , median = 98%]**
  - Stimulus equivalent to 29% of pre-covid total credit and 8% of GDP
- Allocated through first-price auctions where banks bid on interest rates
- Auctions for different types of loans
  - Loans to **micro-firms, small firms**, medium-size firms, large firms, corporations
- High operational costs limited MFIs from participating in the program
- The Central Bank launched auctions only for MFIs, increasing their participation

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- Data:
  - Credit registry: Outstanding debt at the bank-firm level in 2019-2021
  - Covid-19 relief funds: Loan guarantees at the bank-firm level in 2020-2021

Bank level exposure

- Exploit differences in banks' takeover of guarantees for each type of loan k

$$\text{Treatment}_{bk} = \frac{\text{Share of Covid-19 Loans}_{bk} - \text{Share of Total Loans}_{bk,0}}{\text{Share of Covid-19 Loans}_{bk} + \text{Share of Total Loans}_{bk,0}}$$

Reimbursement shock (Granja et al., 2022)

- Focus: small and micro credit

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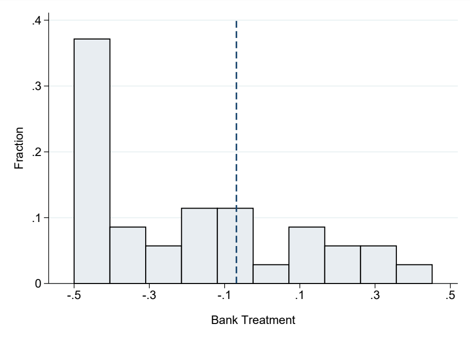

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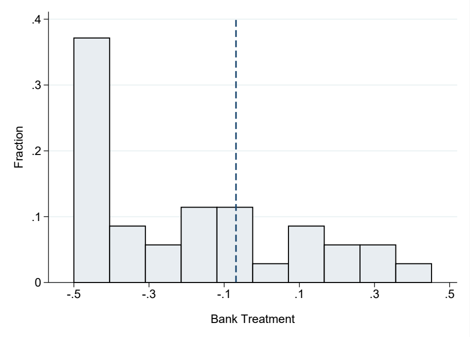
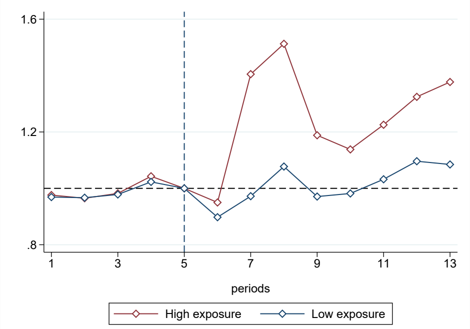


Ln Cred$_t$ / Ln Cred$_0$



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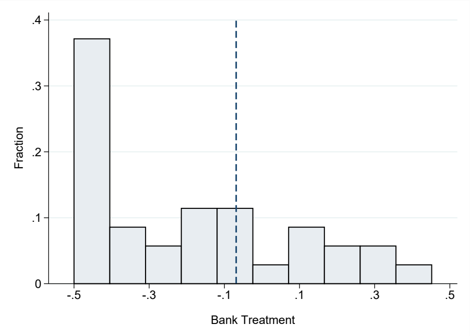
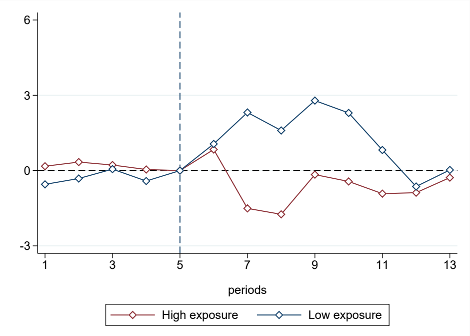


Delinq_t - Delinq_0



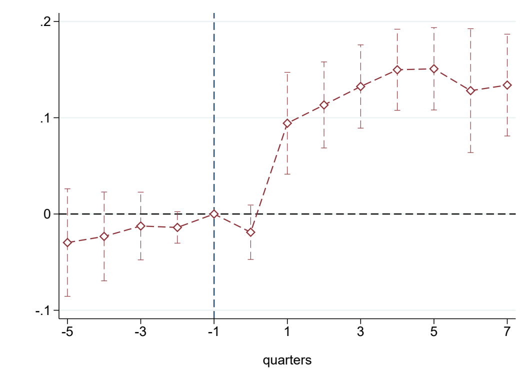
Empirical Results

Loan-level effects: Increasing total credit

$$\ln Y_{ibt} = \beta \times \text{Treatment}_b \times \text{Post}_t + \delta_{ib} + \delta_{q(b),t} + \delta_{it} + u_{ibt}$$

	(1) ln_total_loans	(2) ln_normal_loans
$\text{Treatment}_b \times \text{Post}_t$	0.073***	-0.098***
	(0.022)	(0.027)
Observations	19,387,365	18,927,164
Firm-bank FE	✓	✓
Firm-MFI-time FE	✓	✓
Ban size-MFI-time FE	✓	✓

Standard errors clustered at the bank-level
*** p<0.01, ** p<0.05, * p<0.1



Loan-level effects: Decline in normal loans

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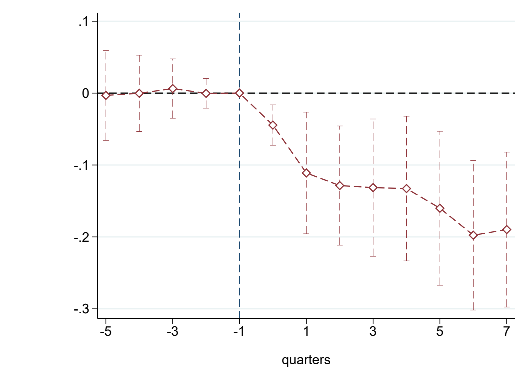

The program increased total credit, partially crowding out the normal activity of banks

Firm-level effects: Total credit increases for better connected firms

$$\ln Y_{it} = \theta \times \text{Exposure}_i \times \text{Post}_t + \delta_i + \delta_{x(i),t} + u_{it}$$

	(1) ln_total_loans	(2) ln_normal_loans	(3) ln_delinq
$\text{Exposure}_i \times \text{Post}_t$	0.098***	-0.245***	-0.031***
	(0.007)	(0.007)	(0.003)
Observations	12,478,501	12,324,192	12,478,501
Firm FE	✓	✓	✓
Firm size-Year FE	✓	✓	✓
Age-Year FE	✓	✓	✓
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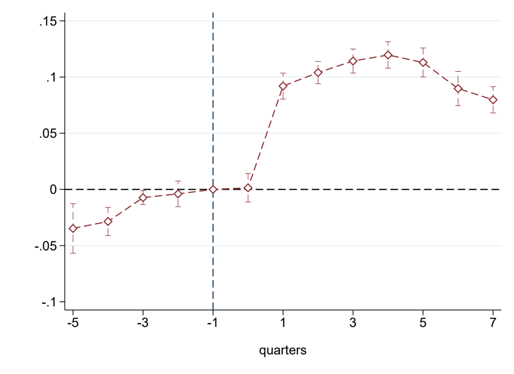

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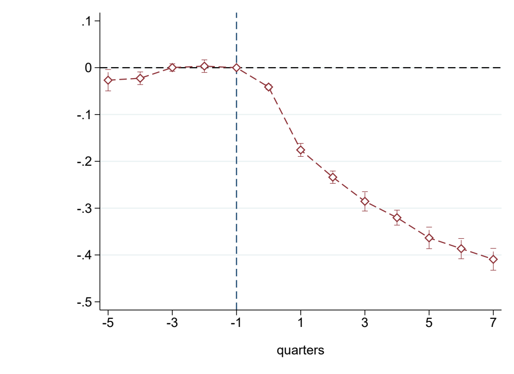

Firm-level effects: Better connected firms are less likely to delay in repayment

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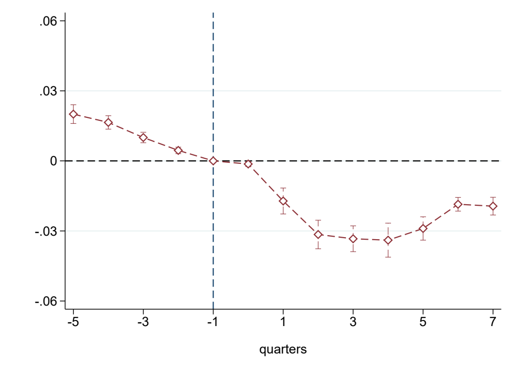

The program expanded credit supply and reduced repayment delays

- Need of external financing >> risk-shifting / weak screening

Heterogeneity and Allocation

Heterogeneity: Role of need of external financing.
Are smaller firms more sensitive?

$$\text{Delinquency}_{it} = \beta_2 \times \ln \text{Loans}_{it} + \delta_i + \delta_{x(i),t} + u_{1,it}$$

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	All firms	Bottom Quintiles	Top Quintil
ln total loans	-0.317***	-0.521***	-0.143***
	(0.030)	(0.024)	(0.010)
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Allocation: Who reach out small, more sensitive firms?

MFI distributed their guarantees equally across quintile groups

Financial institution	Type of client	Share of pre-Covid debt	Share of guarantees
MFI	Bottom Quintiles	.29	.52
	Top Quintile	.71	.48
non-MFI	Bottom Quintiles	.09	.21
	Top Quintile	.91	.79

MFIs represent 52% of pre-Covid loans but obtained 30% of LG

Financial institution	Share of pre-Covid debt	Share of guarantees
MFI	.52	.30
non-MFI	.48	.70

Model

Building blocks

- Bank k profits depend on firm j's characteristics and poaching probability (ψ_C)
  - net cash $(\rho_j - b_j)$, firm future profits $(\psi_F b_j)$, prob. of survival $(\Phi_j(\varphi), \Phi_j(0))$, participation $(\ell_j^k; \varphi)$

$$
\begin{aligned}
\Pi_j^k = & \ell_j^k \left\{\Phi_j(\varphi)\left(1+\psi_F\right) + \big(1-\Phi_j(\varphi)\big)\delta\right\} b_j \\
& + \left(1-\ell_j^k\right)\left\{\Phi_j(0)\left[\left(1-\psi_C\right)\left(1+\psi_F\right)+\psi_C\right] + \big(1-\Phi_j(0)\big)\delta\right\} b_j = \ell_j^k \Omega_j^k b_j + \Theta_j^k b_j
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\text{where} \quad \Omega_j^k = T_j\left[(1-\delta)+\psi_F\right] + \Phi_j(0)\psi_C\psi_F
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$$\text{where} \quad \Omega_j^k = T_j\left[(1-\delta)+\psi_F\right] + \Phi_j(0)\psi_C\psi_F$$

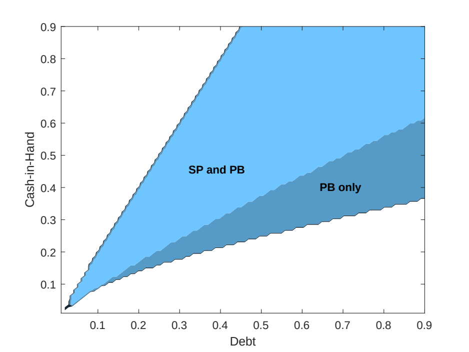
- Banks trade-off: client size (b_j) vs. treatment effect $(T_j \equiv \Phi_j(\varphi) - \Phi_j(0))$

$$\max_{\ell_j^k \in \{0,1\}} \int \ell_j^k \Omega_j^k b_j dG^k(\rho_j, b_j) \qquad \text{s.t.:} \quad \int \ell_j^k \varphi b_j dG^k(\rho_j, b_j) = \gamma_k M$$

- Firm survives iff $\rho_j - b_j + \ell_j \varphi b_j > \nu_j$ with $\nu \sim \tilde{\Phi}(.)$
- Size-dependent T_j + distribution of clients G^k determines optimal participation of MFIs

Main results

Private allocation is not socially optimal



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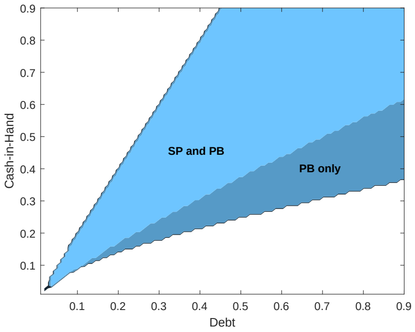
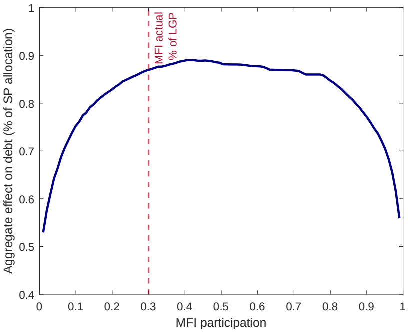


MFIs strengthen aggregate effects



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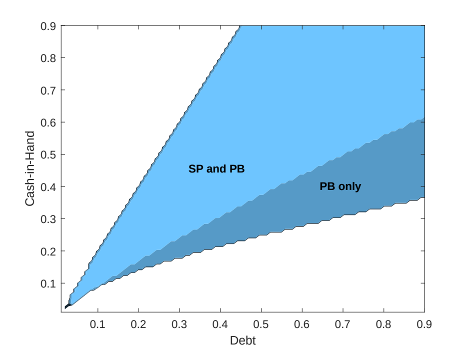

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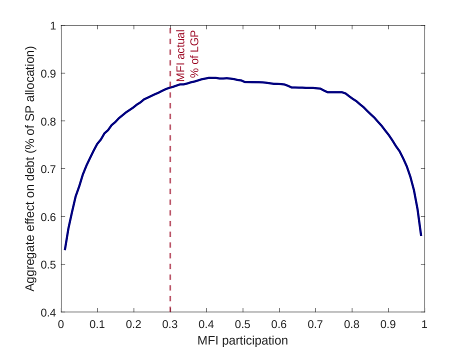

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  - Non-participation leads to 50% of debt saved by the program relative to constrained first best
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- MFIs can lead to substantial aggregate gains by improving the allocation of LG
  - Model where banks trade-off treatment effect and client size, calibrated with micro-data
  - 30% gains from MFIs observed participation in terms of aggregate debt in default
    - Non-participation leads to 50% of debt saved by the program relative to constrained first best
  - Negligible additional gains from increasing MFI's participation to the optimal level