Financial Stimulus and Microfinance Institutions in Emerging Markets*

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Abstract

We estimate the role of micro-finance institutions in shaping the aggregate effects of financial stimulus programs in emerging markets. We do so by studying a large program of loan guarantees implemented in Peru to help firms dealing with Covid-19 restrictions. We find that loan guarantees increase credit and reduce delinquency with substantial heterogeneous effects. The decline in delinquency is fifth times larger for the smallest borrowers and MFIs play a key role in distributing guarantees towards this group of firms. We build a model where MFIs and big banks have different portfolios of clients and face poaching threats, and calibrate it with our reduced-form estimates and micro-data. Different to social planner who maximizes aggregate treatment effect, banks trade-off between client size and treatment effect. Our model indicates that the observed MFIs' participation increases by 30 percent the effectiveness of the program, measured in terms of debt saved from default, relative to the constrained first-best. Further increasing MFI's participation to the optimal level leads to tiny additional gains.

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1 Introduction

Financial stimulus programs are usually implemented through the banking sector. Since big banks tend to attend bigger firms, many emerging countries have promoted the expansion of micro-finance institutions (MFIs) to reach out to small and young clients. However, as these institutions face high operational costs, which limits the pass-through of financial stimulus, or because they are less sophisticated, their participation in financial stimulus programs is still limited. In this paper, we estimate the role of MFIs in shaping the aggregate effects of financial policy in recessions.

Whether governments should promote the participation of MFIs in financial stimulus programs or not is a priori unclear. By targeting small firms with high needs of external financing, MFIs' could strength the aggregate effects of financial policy. However, increasing leverage of opaque borrowers might have negative effects on financial stability. Moreover, lowering the funding cost of financial intermediaries would lead to a reduction in screening incentives, which is particularly important for MFIs that rely on soft information, further deteriorating financial stability. Thus, whether MFIs participation weaken or strengthen the aggregate effects of financial stimulus programs in recessions is an empirical question.

We address this question in the context of *Reactiva Perú*, a program of loan guarantees implemented by the Peruvian government to help firms dealing with Covid-19 restrictions. We estimate the effects of loan guarantees on financial stability, defined by delinquency rates, and explore how microfinance institutions, shape the aggregate impact of the program. We use loan-level data covering the universe of lending relationships that firms have with each bank established in Peru in a quarterly frequency between 2019 and 2021. For each lending relationship we observe the balance of loans, the number of days of repayment delay, and the city where the loan was originated. On the firm side, we observe industry, age, and a measure of firm risk reported by lenders.

We estimate the effects of the program using a difference-in-differences strategy that exploits variation in banks takeover of loan guarantees, and focus on small firm lending in our analysis. We construct a continuum measure of treatment in the spirit of the reimbursement shock proposed by Granja et al. (2022) and identify the effect of loan guarantees on credit supply by comparing the balance of loans that firms have with more treated banks relative to less treated ones, before and after the program, controlling for firm-level demand shocks. Our identifying assumption is that absent the program, credit provided by more and less treated banks would have followed parallel trends. We provide evidence supporting our identification in three ways. First, we plot event study graphs showing that our measure of treatment had null effects on credit before the program, consistent with the parallel trends assumption. Second, even though our identification does not require for banks to be similar in levels, we include high dimensionality fixed effects to control for unobserved time-varying shocks taking place at different quartiles of the bank size distribution. By comparing similar banks, we deal with concerns related to a potential sorting of *better banks* with *better firms* that might be better prepared to face Covid-19 restrictions. We also conduct out estimation considering only MFIs in our sample. Finally, we report our estimated treatment effects during the months between the first Covid-19 case in Peru and the starting date of the program. Such effects are not statistically significant, consistent with our parallel trends assumption.

We present our empirical results in two main sections. In the first one, we report the average effect of the program on credit and delinquency rates. We start by estimating the response of credit supply using a within regression, following Khwaja and Mian (2008), where we control for time-varying firm demand shocks. Banks that are one standard deviation more treated expand credit supply by 7% after the program. We also find that these banks reduce the supply of non-Covid loans[1] by 10%, which we interpret as evidence of public guarantees partially crowding out the normal activity of banks. Then, we estimate the role of lending relationships in shaping firm access to the program. We do so by aggregating our data at the firm level and computing a measure of treatment that indicates how well connected firms are to more treated banks. This measure is equal to the weighted average bank treatment, where weights are based on the outstanding debt that firms had with each bank before Covid-19. We find that firms that are one standard deviation better connected to treated banks experience a 10% increase in total loans after the program, despite of a 25% reduction in non-Covid loans, suggesting an important role of lending relationships for the allocation of guaranteed loans. Finally, we estimate the effect of the program on delinquency rates using a difference-in-differences instrumental variable approach. We use our firm-level treatment to instrument total loans and estimate the elasticity of delinquency to credit. We find that a 10% increase of credit leads to a 3 percentage points decline in the probability of experiencing repayment delays. Our findings indicate that the need of external financing associated with Covid-19 restrictions played a more important role than firm risk-shifting incentives and weaker bank screening in shaping the average response of

[1]Throughout the text, we will refer to non-guaranteed loans as non-Covid loans.

delinquency rates.

The second part of the paper studies the heterogeneous effects of the program on delinquency rates and the role of MFIs in shaping the allocation and aggregate effects of loan guarantees. We split small firms into two groups based on their outstanding bank debt before Covid-19 as a proxy for firm size. We find that smaller borrowers exhibit a bigger elasticity of delinquency to credit, consistent with smaller firms facing higher needs of external financing in recessions. A 10% increase in credit reduces the probability of repayment delays by 5 percentage points for smaller firms and only by 3 percentage points for larger borrowers[2]. Despite this, smaller borrowers receive less credit from the program. We document that MFIs participation plays a key role in shaping the allocation of guarantees towards smaller, more sensitive firms. First, we estimate that the elasticity of delinquency to credit is size-dependent and not bank-dependent, i.e., smaller firms are more sesitive independently on whether they borrow from MFIs or banks. Second, we document that MFIs distribute guarantees equally across smaller and larger borrowers, while big banks allocate 80% of guarantees towards larger firms.

Motivated by our empirical evidence, we build a stylized model that accounts for these patterns and allows us to study the optimal participation of small firms. We build on Joaquim and Netto (2022) and incorporate bank specialization into this framework. Firms differ in terms of initial debt and cash-in-hand, which jointly determine their needs of external financing to survive the pandemic. There are two types of lender, MFIs and big banks, facing different distributions of clients. MFIs are specialized in small firms, with low levels of average debt and cash-in-hand, and big banks are specialized in larger firms. Specialization is exogenous in or framework and is calibrated using the observed distribution of firms across debt and revenue for both types of lenders. Both lenders maximize expected profits and face poaching threats if they do not attend their clients. We calibrate our model to match key features of the Peruvian banking sector, the Covid-19 guarantees' program, and our reduced-form evidence. Our model highlights the role of bank incentives and bank specialization in determining the optimal participation of MFIs in the program. First, lender incentives are not necessarily aligned with those of the social planner. The social planner maximizes the aggregate treatment effect of the program, which implies allocating guarantees toward firms with high treatment effect. On the other hand, due to poaching threats, financial institutions trade-off between attending firms with high treatment effect and preserving large clients with high probability of surviving without

[2]Notice that we identify smaller and larger borrowers within the group of small firms.

the program. The distribution of banks' portfolios and our estimated treatment effects across the firm size distribution determine the optimal participation of MFIs. Big banks tend to serve larger firms that can survive without the program, so their allocation is in principle further away from the social planner's. However, if guarantees are only distributed by MFIs, there will be a remaining share of small firms with high treatment effect that are attached to big banks and will not be attended if these banks do not participate in the program. The optimal participation of MFIs is the one that maximizes the amount of debt saved by the program, defined as the amount of debt that is not in default because of the program.

We use our model to explore the aggregate implications of MFIs participation in our setting. First, we compute the amount of debt saved by the program if only big banks distribute the guarantees and divide it by the amount of debt saved in the constrained first-best (where the social planner distributes the guarantees under the same constraints of the program). We find that if MFIs do not participate, the program would have saved 53 percent of the debt saved in the constrained first-best. We then quantify the role of MFIs in the program, where they obtained 30 percent of guarantees. The amount of debt saved by the program increases to 85 percent of the first-best scenario. Finally, we compute the optimal participation of MFIs and the associated gains. We show that the relationship between the debt saved by the program and MFIs participation is highly non-linear, and further increasing MFIs participation to the optimal level of 40 percent only increases the debt saved by the program in 3 additional percentage points.

Overall, our paper shows that MFIs play a crucial role in shaping the aggregate effects of financial stimulus programs in emerging markets. We document that government guarantees are effective in expanding credit supply and reducing delinquency rates with substantial heterogeneous effects across firms. The elasticity of delinquency rates to credit is fifth times bigger among smaller firms, and MFIs play a key role in allocating guarantees towards these firms. The aggregate implications of MFIs participation depend on our reduced form estimates and the distribution of banks' portfolios. Our calibrated model shows that MFIs strongly increase the effectiveness of the policy, but further increasing their participation will only lead to minor gains in terms of debt saved by the program.

Literature Our paper is related to three main strands of the literature. First, we contribute to the literature studying the effects of loan guarantees (Lelarge et al. (2010), Brown and Earle (2017), Mullins and Toro (2018), Ru (2018), Cong et al. (2019), Bachas et al. (2021), Barrot et al. (2020), Haas-Ornelas et al. (2021), González-Uribe and Wang (2021), Bonfim et al. (2022)). We contribute to this literature in two ways. First, we study the effects of loan guarantees on delinquency rates in recessions. We find that this program is effective in reducing repayment delays. Our findings contrast with those documented by Lelarge et al. (2010) in France. We interpret this discrepancy as evidence that the Covid-19 shock generated an unprecedented need of external financing that offset risk-shifting incentives associated with increasing firm leverage. Our second contribution is to focus on the role of micro-finance institutions in shaping the aggregate effect of loan guarantees. We document that small borrowers receive less credit when participating in the program, despite being more sensitive in terms of delinquency rates. These results are similar to those reported by Haas-Ornelas et al. (2021), who find that private banks tend to allocate public guarantees to bigger clients in Brazil. We show that MFIs play a key role in allocating guarantees towards smaller, more sensitive firms. Thus, by promoting the participation of MFIs, the Peruvian Central Bank improved the effectiveness of the program.

Second, our paper is related to the literature estimating the effect of micro-finance institutions in emerging markets. On the empirical side, this literature has estimated the effects of micro-credit using randomized controlled trials and documented tiny and insignificant effects on a variety of outcomes (Angelucci et al. (2015), Augsburg et al. (2015), Tarozzi et al. (2015), Attanasio et al. (2015)). On the theoretical side, the literature highlights the role of large shocks and general equilibrium effects (Breza and Kinnan (2021), Buera et al. (2020)). Our contribution is twofold. First, we estimate the role of micro-finance institutions in a large-scale program implemented during the Covid-19 recession. We find that MFIs play a critical role in distributing guarantees towards small, highly sensitive borrowers. Second, we rationalize these findings through the lens of a stylized model where banks face poaching threats and have different distributions of clients. MFIs specialized in small borrowers have better incentives in providing guarantees to highly sensitive firms.

Third, we contribute to the literature that estimates the effects of financial policy during the Covid-19 recession (Bartik et al. (2020), Faulkender et al. (2020), Granja et al. (2022), Li and Strahan (2020), Autor et al. (2022), Griffin et al. (2022), Huneeus et al. (2022), Joaquim and Netto (2022)). Our contribution to this literature is threefold. First, we use administrative loan-level data which allows us to cleanly estimate the effect of loan guarantees on credit supply. Second, we estimate the heterogeneous effects of the program and explore whether banks provided guaranteed loans to more sensitive firms or not. In this line, our paper is related to Joaquim and Netto (2022) who document that large firms and firms operating in industries that were less affected by Covid-19 restrictions obtained loans earlier in the context of the Paycheck Protection Program (PPP). Our paper is also close to Griffin et al. (2022), who explore the allocation of PPP loans and show that FinTech lenders were particularly exposed to misreporting and suspicious lending. To the best of our knowledge, our paper is the first one mapping the elasticity of delinquency rates to credit to the actual allocation of guarantees. Our findings provide clear evidence that targeting small firms could improve the effectiveness of the program in terms of delinquency rates and financial stability. Moreover, we document that governments could do so by encouraging the participation of small banks specialized in small businesses. Third, we contribute by studying the case of Peru. As in many other developing countries, high levels of informality and low access to bank credit are critical challenges for the design of financial policy.

We also contribute to the literature that studies political incentives in banking (La Porta et al. (2003), Sapienza (2004), Dinç (2005), Khwaja and Mian (2005), Claessens et al. (2008), Agarwal et al. (2016)), and, more importantly, bank specialization (Paravisino et al. (2023)). This literature has documented that political connections distort the allocation of public bank credit. We show that private banks incentives driven by bank specialization can also conflict with social goals. Our paper indicates that targeting more sensitive firms can improve the allocation of private bank lending. Finally, we contribute to the broad literature that studies the role of public policy in recessions (House and Shapiro (2008), Mian and Sufi (2012), Lucas (2016), Kelly et al. (2016), Zwick and Mahon (2017)). We contribute by studying the effects of loan guarantees highlighting the role of bank specialization.

The remaining of this paper is organized as follows. Section 2 describes our data and the institutional background, and section 3 presents our empirical framework. We report the average effect of loan guarantees on financial outcomes in section 4 and explore the heterogeneous effects of the program and the role of MFIs in section 5. Section 6 present our model and the main counterfactual analysis. Section 7 concludes.

2 Data and Institutional Background

2.1 Data

We use loan-level data from the *Reporte Crediticio de Deudores* provided by the Central Bank of Peru to estimate the effects of government guarantees on credit and delinquency rates. This is a quarterly panel going from 2019 to 2021 where we observe the balance of loans that firms hold with each bank established in Peru. Our dataset also includes the number of days of repayment delay and the city where loans are originated. On the firm side, we observe industry, credit risk reported by lenders, and the year when firms obtained their first loan.

2.2 Institutional Background

Reactiva Perú is the program of loan guarantees implemented by the Ministry of Finance and the Central Bank of Peru in May 2020 to help firms dealing with Covid-19 restrictions. The program consisted on guarantees allocated through first-price sealed-bid auctions where private banks bid on the average interest rate they will charge on these loans. The Ministry of Finance served as collateral and the Central Bank provided liquidity to banks. There were separate auctions for each of the five types of corporate loans: loans to micro firms, small firms, medium-size firms, large firms, and corporations. This classification is based on firms' sales and balance of credit. For example, loans to corporations are those granted to firms whose total sales in the past two years is above USD 60 million, while loans to micro firms are those provided to firms whose total debt in the banking sector is below USD 6 thousand. The guarantees ranged from 80 to 98% of the loan value, with higher guarantees being allocated towards micro and small firms loans. The average Covid-19 loan guarantee was 97% and the loan-size weighted average was 90%. In our analysis, we focus on micro and small firm lending, as MFIs have a negligible participation in other types of loans.

Private banks were in charge of screening borrowers and allocating Covid-19 loans. These loans were granted between May and December 2020, with an average duration of 36 months. The repayment period started 12 months after the loan was granted. Out of the 52 financial institutions established in Peru, 28 participated in the program, and provided USD 16 billion of Covid-19 loans, which represented 29% of the outstanding debt that firms had by December 2019 and 8% of Peruvian GDP.

2.3 Descriptive statistics

The Peruvian banking sector includes 52 financial institutions and is highly concentrated. The five largest banks accounted for 77% of corporate loans in December 2019. Banks provide five types of loans, as we described above. Table 1 provides summary statistics of the banking sector for each of these segments. There are 42 banks operating in the segment of micro-credit, with an average size of USD 77 millions, while the segment of corporations has 13 banks with an average size of USD 1 272 million. The segment of corporations is more concentrated, the five largest banks account for 94% of the market, while this share is only 58% for the segment of micro-credit.

Table 1: Peruvian Banking Sector

	Total Loans		Number of	Share Top 5
	Mean	Median	Banks	Banks
	(1)	(2)	(3)	(4)
Total	1 106	169	52	77
Loans to:				
Micro-credit	77	28	42	58
Small firms	190	50	45	56
Medium-size firms	263	13	48	86
Large firms	491	8	27	87
Corporations	1 272	166	13	94

This table reports bank-level summary statistics as of December 2019. We report the mean and median of the distribution of total loans across banks for each segment of corporate loans. Total loans are expressed in USD million.

Table 2 reports summary statistics for firms with positive outstanding debt in December 2019. The average firm has USD 6 thousand of credit and 12% of firms exhibited repayment delays. The average firm's age, defined as the number of years since its first loan, is 8 years. We observe around 3 million of firms borrowing in the banking sector by the end of 2019. The average firm in the segment of micro-credit has a smaller balance of loans and is younger than the average borrower in the segment of large firms.

We provide summary statistics describing the allocation of Covid-19 loans in Table 3. The program provided guarantees valued at USD 16 billion, which represents 29% of the balance of loans in December 2019. The program benefited 473 thousand firms, equivalent to 16% of firms with positive outstanding debt in the banking sector by December 2019. The relevance of the program varies across market segments. Guaranteed loans in the segment of micro-credit represent USD 1.2 billion, 37% of the balance of loans in this segment in 2019 and benefited 14% of firms. This value is USD 4.5 billion for large firms, 34% of the balance of loans and 82% of clients by the end of 2019.

Table 2: Characteristics of Borrowers

	Total Loans		Repayment Delay		Age		Num. of firms
	Mean	Median	Mean	Median	Mean	Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total	6	0.5	0.12	-	8	8	2 854
Loans to:							
Micro-credit	1	0.5	0.10	-	1	6	2 290
Small firms	11	7	0.14	-	10	10	545
Medium-size firms	116	30	0.23	-	10	11	36
Large firms	690	85	0.10	-	13	15	3
Corporations	5 850	630	0.03	-	14	15	0.5

This table reports summary statistics for borrowers in December 2019. We report the mean and median of the distribution of total loans and age across firms. Repayment delay is an indicator variable equal to one if the firm is in delinquency, and its average value is the share of firms in delinquency. Total loans are expressed in USD thousand. Age is equal to the number of years since firms receive their first loan. Number of firms is expressed in thousand.

Table 3: Guaranteed Loans by Type of Credit

	Guaranteed Loans		Benefited Clients	
	Value	Share of 2019	Number	Share of 2019
	(1)	(2)	(3)	(4)
Total	15.5	29	473.1	16
Loans to:				
Micro-credit	1.2	37	319.9	14
Small firms	3.6	42	121.8	22
Medium-size firms	5.9	46	28.8	81
Large firms	4.5	34	2.6	82
Corporations	0.4	3	0.2	36

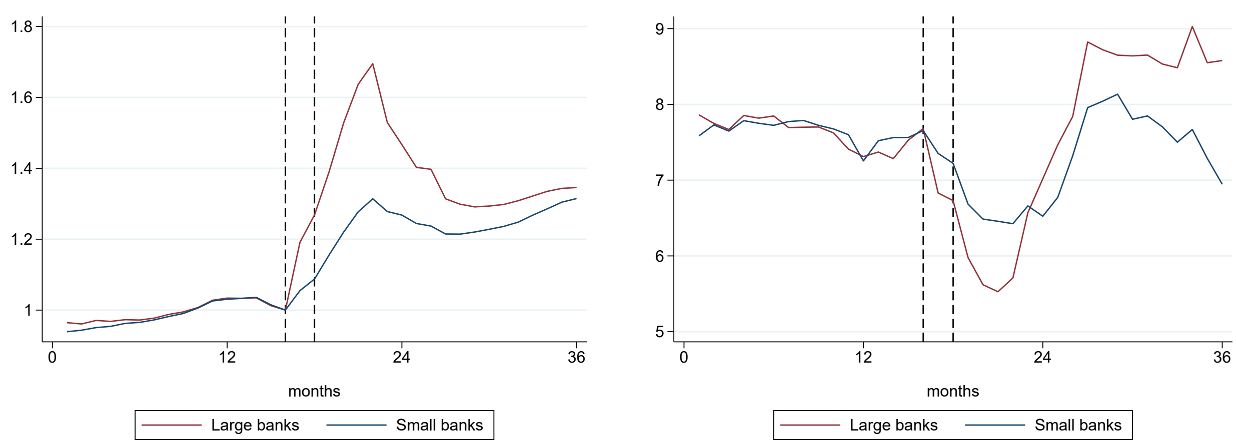
This table reports summary statistics of guaranteed loans in different segments of the market of corporate loans in December 2019. The value is expressed in USD billion and the number of clients is in thousand of firms. The shares are computed relative to the value in December 2019.

2.4 Participation of Micro-Finance Institutions

When the program began, large banks won most of the auctions in all segments of corporate loans. During the first two months of the program, mostly large banks received liquidity to distribute guaranteed loans, even in the segment of small firm loans, which is the focus of this paper.[3] Thus, the Central Bank promoted the participation of MFIs by launching separate specific auctions for these institutions.

Panel (a) in Figure 1 plots the evolution of credit relative to the pre-program period for big banks and MFIs[4] and Panel (b) shows the evolution of delinquency rates. The dotted lines denote the beginning of the program and the beginning of specific auctions for MFIs. We can observe a decline in delinquency after the program was implemented. This decline was faster for large banks but temporary (red line), and we can observe delinquency rates increasing above pre-Covid levels in the medium-run. On the other hand, despite the smaller increase in credit, MFIs' delinquency rates remained at similar levels as those registered in the pre-Covid period (blue line). This aggregate evidence suggests that MFIs were more efficient in distributing guarantees toward more sensitive clients. In the following sections, we explore the role of MFIs in shaping the aggregate impact of the program.

Figure 1: Credit Growth and Delinquency by Type of Bank



(a) Total Loans

(b) Delinquency Rates

[3]This was mainly due to high operational costs faced by MFIs, which led to non-competitive bids.

[4]Throughout the paper we refer to banks as big banks and MFIs as small banks. Specifically, MFIs include saving and loan institutions, financial enterprises, and enterprises for the development of small and micro firms. In Peru, banks and MFIs are regulated by the Bank Supervisor and report detailed financial information.

3 Empirical Framework

We exploit differences in banks takeover of loans guarantees to estimate the effect of the program on credit supply. We construct a continuum measure of treatment in the spirit of the reimbursement shock proposed by Granja et al. (2022). We compute this measure for each bank b in each segment k of the market of corporate loans as follows:

$$\text{Treatment}_{bk} = \frac{\text{Share of Covid-19 Loans}_{bk,2020} - \text{Share of Total Loans}_{bk,2019}}{\text{Share of Covid-19 Loans}_{bk,2020} + \text{Share of Total Loans}_{bk,2019}} \times 0.5 \qquad (1)$$

where the shares are based on the value of loans.

Figure 2 plots the distribution of bank treatment in the segment of micro-credit. We can observe a large heterogeneity in banks takeover of public guarantees. The dashed line indicates the median of bank treatment, weighted by pre-Covid market share. We use this value to split banks into two groups and plot aggregate credit and delinquency rates in each group of high and low-treated banks in Figure 3. We observe a bigger expansion of credit among highly treated banks relative to less treated ones and a bigger decline in delinquency rates in the short-term.

Figure 2: Distribution of Bank Treatment in Micro-credit

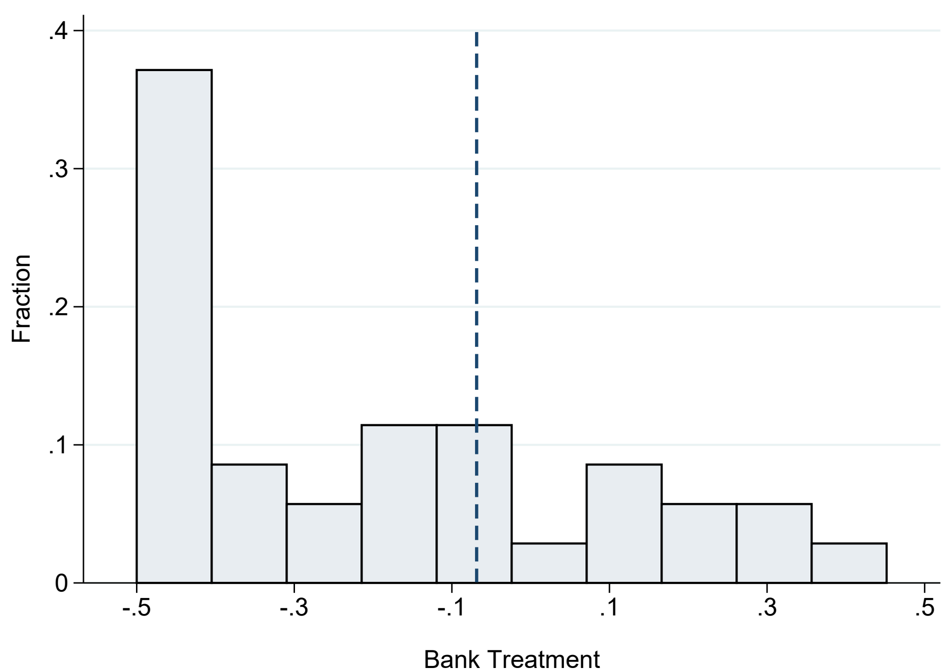
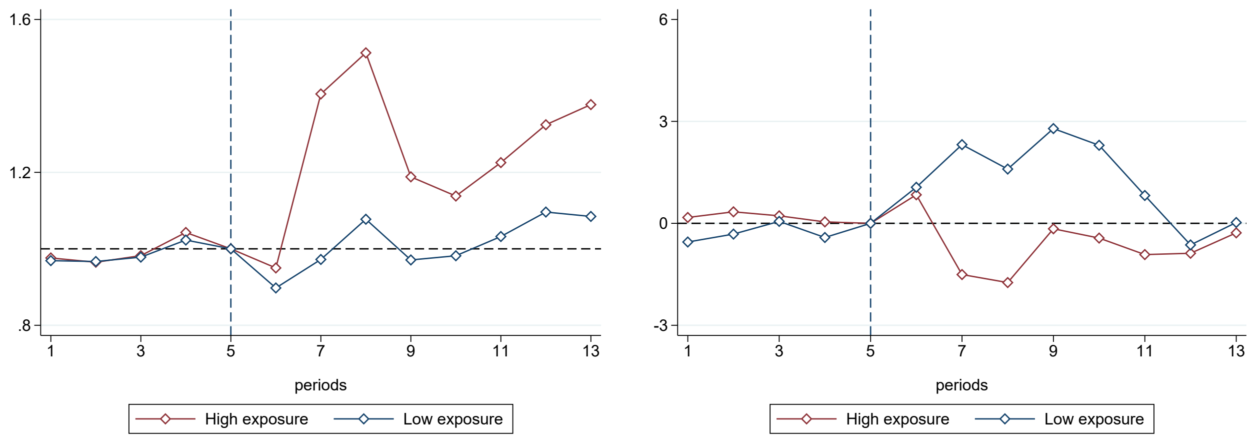


Figure 3: Credit, Delinquency and Bank Treatment



(a) Total Loans

(b) Delinquency Rates

Bank-firm level specification. We identify the effect of loan guarantees by comparing the outstanding debt that firms hold with more treated banks relative to less treated ones, before and after the program, using a difference-in-differences approach. Our identifying assumption is that absent the program, credit provided by more and less treated banks would have followed parallel trends, i.e., treatment should have null effects absent the policy. Specifically, we quantify the effect of the program on total loans and non-Covid-19 loans by estimating the following equation:

$$Y_{ibt} = \theta \times \text{Treatment}_{bk(i)} \times \text{Post}_t + \delta_{ib} + \delta_{it} + \delta_{q(b),t} + u_{ibt} \tag{2}$$

where Y_{ibt} denotes the balance of total loans and non-Covid-19 loans (in logs) that firm i has with bank b in period t, and Treatment_{bk} is the standardized treatment of bank b in the segment k. Notice that we define the segment of the market of corporate loans at the firm level based on 2019 data. We include firm-bank fixed effects δ_{ib} to control for match-specific time-invariant characteristics like bank specialization in a given industry. δ_{it} denote firm-by-period fixed effects and remove any time-varying shock at the firm level. We also include time-varying fixed effects for each quartile of the bank size distribution $\delta_{q(b),t}$ to account for any shock affecting banks in the same size bin. A potential concern is that bigger banks might be more likely to serve bigger firms that are better prepared to deal with Covid-19 restrictions using internal resources. Moreover, bigger banks might be able to bid a lower interest rate and take more guarantees. We deal with this concern by including $\delta_{q(b),i,t}$, which allows us to compare credit obtained from more versus less treated banks within the same size bin. Finally, standard errors are clustered at the bank level.

Firm level specification. We aggregate our dataset at the firm level to estimate the role of lending relationships in shaping firms access to Covid-19 loans and to estimate the response of delinquency rates. We do so by constructing a measure of treatment at the firm level as follows:

$$\text{Treatment}_i = \sum_b \frac{L_{bi}}{L_i} \times \text{Treatment}_{bk} \tag{3}$$

where L_{bi} denotes the outstanding debt that firm i holds with bank b in December 2019 and Treatment_{bk} is defined in equation (1). Then we estimate the following equation for multiple firm-level outcomes:

$$Y_{ikt} = \beta \times \text{Treatment}_i \times \text{Post}_t + \delta_i + \delta_{x(i)kt} + u_{ikt} \tag{4}$$

where Y_{ikt} denotes the balance of total loans and non-Covid-19 loans (in logs), and delinquency rate[5] of firm i participating in segment k in period t. We include firm-specific fixed effects δ_i to control for any time-invariant heterogeneity across firms. $\delta_{x(i)t}$ denotes time-varying fixed effects for the vector $x(i)$ of firm characteristics such as city, industry, risk category, age-bin, size-bin measured by pre-Covid debt, and segment of the corporate loans market. By including such high-dimensionality fixed effects we account for multiple demand shocks taking place at such levels. Finally, we cluster standard errors at the industry level.

Our parameter of interest β measures the average effect of being better connected to treated banks. To identify this parameter it is critical to control for firm-specific characteristics that might determine banks incentives to provide credit. As pointed out by Joaquim and Netto (2022) in the context of the Paycheck Protection Program in the US, banks preferred to attend firms with higher levels of outstanding debt to avoid larger losses if these clients default. Moreover, banks might have less incentives to provide credit to firms operating in industries and cities that were strongly hit by Covid-19 restrictions as they have less chances to survive. Thus, a naive specification that does not account for firm size or industry would lead to biased estimation results if, for example, smaller firms were systematically worse connected to treated banks.

[5] We define delinquency rates at the firm level as an indicator variable equal to one if firms experience more than 30 days of repayment delay on any loan at a given point in time.

4 Average Effects

4.1 Bank-firm level effects

We start by estimating the effect of the program on credit supply. We estimate equation (2) using the log of total loans as the dependent variable. Our results are reported in columns 1 in Table 4. We find that one standard deviation higher treatment leads to a 7% increase in credit supply in our benchmark specification. Our results are robust to different specifications that partially exclude fixed effects as reported in the Appendix.

Panel (a) in figure 4 plots event study graphs for the response of credit supply. We show the estimated quarterly treatment effect before and after the program, including the same fixed effects used in our benchmark specification. We normalize the quarter before the program implementation to zero. Treatment had null effects before the policy, which is consistent with our identifying assumption. Moreover, treatment has null effects in the first quarter of the policy when only a tiny amount of Covid-19 loans were granted. The balance of loans experience a significant and persistent increase since the third quarter of 2020. Figure A1 in the Appendix plots event-study graphs for the other specifications, showing no evidence of pre-trends. Our results indicate that the program was effective in increasing credit supply.

Table 4: Effect of the Program on Credit Supply

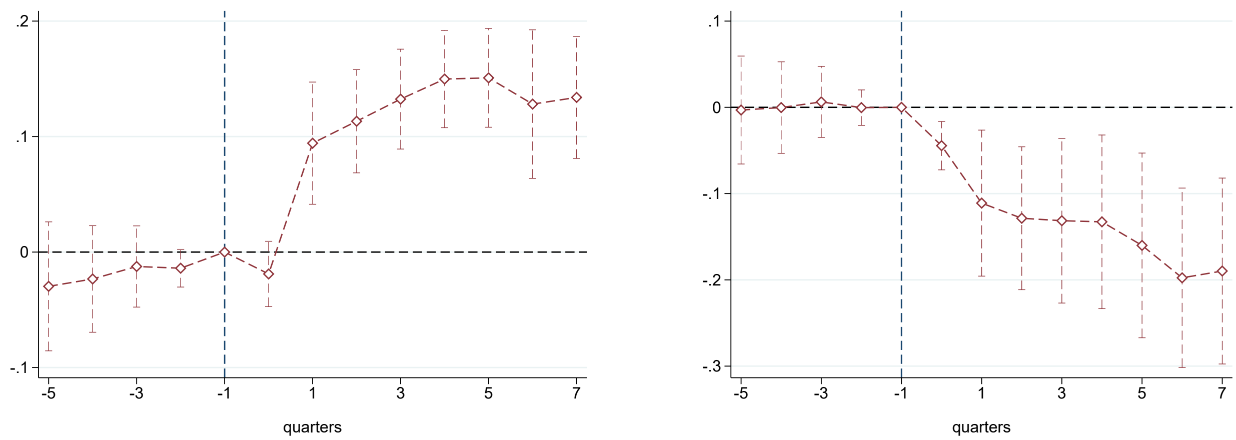
	Total Loans (1)	Non-Covid-19 Loans (2)
$\text{Treatment}_{bk} \times \text{Post}_t$	0.073***	-0.098***
	(0.022)	(0.027)
Observations	19,387,365	18,927,164
Firm-bank FE	✓	✓
Firm-time FE	✓	✓
Ban size-time FE	✓	✓

This table shows the effect of the program on the balance of total loans and non-Covid-19 loans at the bank-firm level. Treatment is standardized. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the bank level.

An important question for policymakers is whether loan guarantees crowd out the normal activity of banks or not (Stiglitz (1993), La Porta, Lopez-de-Silanes, and Shleifer (2002), Ru (2018)). We use our detailed administrative data to evaluate the impact of the program on non-Covid-19 loans. We estimate equation (2) using the log of non-Covid-19 loans as our dependent variable. We report our results in columns 2 of Table 4. We estimate that one standard deviation higher treatment leads to a decline of 10% in the supply of non-Covid-19 loans.

We plot the event study graphs for the response of non-Covid loans in Panel (b) of figure 4. We include the same fixed effects used in our benchmark specification. We find no evidence of pre-trends. The balance of non-Covid-19 loans exhibit a steady decline after the program. Figure A2 in the Appendix plots event-study graphs for the other specifications. Our results indicate that the program reduced the supply of non-guaranteed loans, consistent with the crowding out hypothesis. However, this reduction in non-guaranteed loans is more than compensated by the expansion of Covid-19 loans as we showed above.

Figure 4: Effect of the Program on Credit



(a) Total Loans (b) Non-Covid-19 Loans

This figure plots the quarterly effects of the program on total credit and non-Covid loans at the bank-firm level. The dependent variable is in logs. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter fixed effects. We normalize the treatment effect at the quarter right before the implementation of the program to be equal to zero. The confidence interval is at the 95% level.

4.2 Firm-level effects

To study how this program affected firms' access to credit and delinquency rates, we aggregate our data at the firm level and calculate treatment as described in equation (3). Our firm-level treatment indicates how well connected are small firms with more treated banks. Notice that while the program led to an expansion of credit provided by highly treated banks, it does not mean that better connected firms will receive more credit. If lending relationships were fully flexible, firms that are not well connected will easily switch towards highly treated banks and obtain more credit. Otherwise, if lending relationships were sticky, better connected firms will experience an expansion in credit relative to worse connected ones. This is a first layer of *general equilibrium effects* taking place at the firm level and we explore its relevance by estimating equation (4) using total loans as our dependent variable. Our results are reported in column 1 of Table 5. We find that one standard deviation better connected firms experience a 10% increase in total loans after the program. We report quarterly treatment effects in panel (a) of Figure 5. We observe null effects in the pre-Covid-19 period. We find that better connected firms have more credit, and this effect is significant up to two years after the program implementation. This result indicates that lending relationships play a key role in shaping the ability of firms to obtain Covid-19 loans.

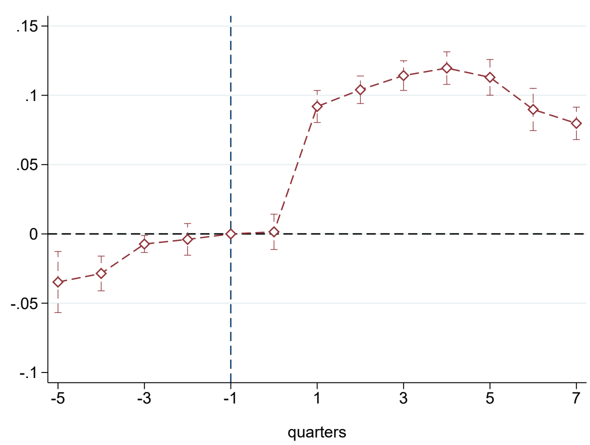
While this result shows that better connected firms obtain more credit, it does not tell us whether non-Covid-19 loans can partially help worse connected firms or not. We address this question by estimating equation (4) using the balance of non-Covid-19 loans as our dependent variable. We report our results in column 2 of Table 5. One standard deviation better connected firms have a 25% lower balance of non-Covid-19 loans relative to worse connected firms after the program. As we discussed in the previous subsection, this result is consistent with public guarantees crowding out the normal activities of private banks. Even though worse connected firms receive more non-Covid-19 loans, it is not enough to offset their lack of ability to obtain public guarantees. Panel (b) of Figure 5 reports quarterly treatment effects, showing no evidence of pre-trends.

Table 5: Lending Relationships, Credit, and Delinquency Rates

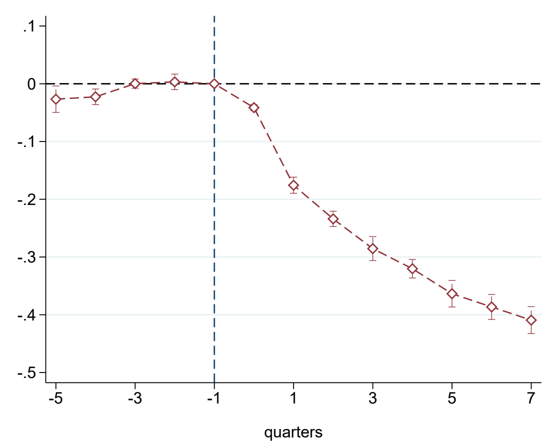
	Total (1)	Non-Covid-19 (2)	Delinquency (3)
Treatment$_i$ $\times$ Post$_t$	0.098***	-0.245***	-0.031***
	(0.007)	(0.007)	(0.003)
Fixed Effects			
Firm	✓	✓	✓
City-period	✓	✓	✓
Industry-period	✓	✓	✓
Risk group-period	✓	✓	✓
Age group-period	✓	✓	✓
Debt size bin-period	✓	✓	✓
Observations	12,478,501	12,324,192	12,478,501

This table shows the effects of being better connected to treated banks on the balance of total loans, non-Covid-19 loans, and delinquency rates at the firm level. Treatment is standardized. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level.

Figure 5: Lending Relationships and Credit



(a) Total Loans

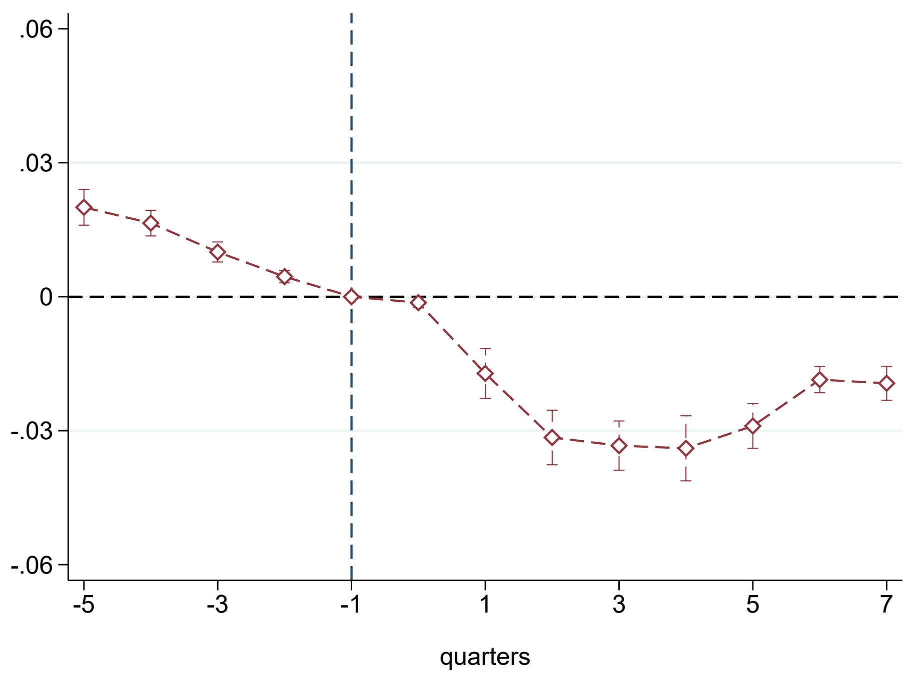


(b) Non-Covid-19 Loans

This figure plots the quarterly effects of being better connected to treated banks on total credit and non-Covid-19 loans at the firm level. The dependent variables are in logs. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter fixed effects. We normalize the treatment effect at the quarter right before the implementation of the program to be equal to zero. The confidence interval is at the 95% level.

We now explore the response of delinquency rates defined as an indicator variable equal to one if the firm experience repayment delays in a given quarter. We then estimate equation (4) using this measure as a dependent variable. Our results are reported in column 3 of Table 5. We find that firms connected with highly treated banks perform better after the program. One standard deviation higher treatment reduces in 3 ppts the probability of experiencing repayment delays. Figure 6 plots the quarterly effect of the program on delinquency rates. Better connected firms experience a persistent and significant decline in repayment delays after the program and there is no evidence of pre-trends.

Figure 6: Lending Relationships and Delinquency Rates



This figure plots the quarterly effects of being better connected to treated banks on delinquency rates, defined as an indicator variable of experiencing repayment delays. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter fixed effects. We normalize the treatment effect at the quarter right before the implementation of the program to be equal to zero. The confidence interval is at the 95% level.

Overall, our results show that lending relationship play a crucial role in shaping access to credit and delinquency rates. Better connected firms receive more credit and are less likely to face repayment delays after the program. Worse connected firms obtain more non-Covid-19 loans, although this effect is not enough to offset their lack of ability to obtain guaranteed loans. Te decline of delinquency is consistent with the unprecedented need of external financing firms faced due to Covid-19 restrictions, which offsets the negative impact on financial stability of firm risk-shifting incentives and less bank screening. In the next section, we explore the heterogeneous effects of the program and study the role of MFIs in distributing guarantees towards more sensitive clients.

5 Heterogeneity and allocation of Covid-19 loans

In this section we estimate the heterogeneous effects of the program and study the role of MFIs in allocating loan guarantees towards more sensitive firms. We estimate the elasticity of delinquency rates to credit using an IV diff-in-diff approach as follows:

$$\begin{aligned} \text{Delinquency}_{ikt} &= \beta_2 \times \ln L_{ikt} + \delta_i + \delta_{x(i)kt} + u_{ikt} \\ \ln L_{ikt} &= \rho_2 \times \text{Treatment}_i \times \text{Post}_t + \delta_i + \delta_{x(i)kt} + u_{ikt} \end{aligned} \tag{5}$$

Where we instrument total loans with our firm-level measure of treatment in the first stage. Our coefficient of interest β_2 measures the elasticity of delinquency to credit. We report our results in Table 6. Column 1 shows our estimation results for the average small firm in our sample. A 10 percent increase in credit reduces the probability of experiencing repayment delays by 3 percentage points. This is around a third of the average delinquency rate in the pre-Covid period. Our results suggest that loan guarantees were effective in reducing delinquency during the Covid-19 recession.

We then split firms into two groups based on their outstanding debt in 2019. We define firms in the top quintil of the debt distribution as larger firms and the rest of firms as smaller borrowers. Then, we estimate equation (5) for each group of firms. Larger firms account for 75 percent of total debt in the pre-Covid period, while smaller clients account for the remaining 25 percent. Our estimation results are reported in columns (2) and (3) of Table 6. The elasticity of delinquency rates to credit among smaller firms is fifth times that of larger borrowers, suggesting that smaller companies face higher needs of external financing during the Covid-19 recession.

Table 6: Elasticity of Delinquency Rates to Total Credit

	All firms (1)	Bottom Quintiles (2)	Top Quintil (3)
ln total loans	-0.317***	-0.521***	-0.143***
	(0.030)	(0.024)	(0.010)
Observations	12,478,501	9,548,762	2,929,739
Fixed Effects			
Firm	✓	✓	✓
City-period	✓	✓	✓
Industry-period	✓	✓	✓
Risk group-period	✓	✓	✓
Age group-period	✓	✓	✓
Debt size bin-period	✓	✓	✓

This table shows the effects of credit on delinquency rates. Column (1) considers all small firms, while columns (2) and (3) consider the smallest and larger firms within small companies. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level.

5.1 Micro-finance institutions and allocation of guarantees

We now study the allocation of guarantees across smaller and larger firms by type of financial institution. We define micro-finance institutions as all lending institutions that are regulated by the Peruvian Bank Supervisor but are not classified as banks. Thus, our definition of MFIs encompasses saving and loan institutions, financial enterprises, and enterprises for the development of small and micro firms. First, we document that the elasticity of delinquency rates to credit is size-dependent and does not vary across financial institutions. We split firms into two groups: those that only borrow from MFIs, and the rest of firms with access to traditional banks. We then estimate equation (5) for each group of firms. Our results are reported in Table 7. Small firms are more sensitive than large borrowers independently on whether they borrow from MFIs or banks. Moreover, the elasticity of each group of firms is not statistically different across financial institutions.

Table 7: Elasticity of Delinquency to Credit by Firm Size and MFI Dependence

	Attached to MFIs only		Access to traditional banks	
	Bottom Quintiles	Top Quintil	Bottom Quintiles	Top Quintil
	(1)	(2)	(3)	(4)
ln total loans	-0.442***	-0.219***	-0.629***	-0.123***
	(0.045)	(0.012)	(0.033)	(0.009)
Observations	12,478,501	9,548,762	2,929,739	
Fixed Effects				
Firm	✓	✓	✓	✓
City-period	✓	✓	✓	✓
Industry-period	✓	✓	✓	✓
Risk group-period	✓	✓	✓	✓
Age group-period	✓	✓	✓	✓
Debt size bin-period	✓	✓	✓	✓

This table shows the effects of credit on delinquency rates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level.

Finally, we explore the allocation of guarantees across firms for both financial institutions. Table 8 reports the share of smaller and larger firms in the portfolio of MFIs and big banks' pre-Covid debt and guaranteed loans. The first two rows report these shares for MFIs. We can observe that, despite larger firms representing a bigger share of MFIs portfolio of pre-Covid loans, they distribute guarantees equally across smaller and larger clients. On the other hand, big banks portfolios of pre-Covid debt and loan guarantees are both concentrated towards larger borrowers. Thus, MFIs play a critical role in reaching out small, more sensitive borrowers. Their participation is still limited, they represent 34% of pre-Covid loans but obtained only 11% of guarantees. In the next section, we explore the gains from MFIs participation in the program.

Table 8: Share of pre-Covid debt and Guaranteed loans by Firm Size and Financial Institution

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

This table reports the participation of smaller and larger firms in MFIs and banks portfolios of pre-Covid debt and loan guarantees.

6 Model

We build a simple model with two types of financial intermediaries that differ in terms of the characteristics of their clients. Our framework is based on Joaquim and Netto (2022). We assume firms are indexed by their initial debt and cash-in-hand. Banks' portfolios are concentrated over larger firms, while microfinance institutions are specialized in small clients. Size-dependent elasticity of delinquency to credit and the heterogeneous distributions of MFIs and banks clients determine the optimal participation of financial institutions in the program.

6.1 Firms

Firms are heterogeneous in initial debt obligations b_j and cash-in-hand ρ_j. Net cash holdings are given by $c_j = \rho_j - b_j$. We model the pandemic as a shock that generates a reduction of ν_j in cashflows. We assume that firms borrow φb_j when participating in the program. Firm j can survive the pandemic under the following condition:

$$\rho_j - b_j + \varphi b_j > \nu_j \tag{6}$$

We assume firms who can survive want to survive. Cashflow shocks are drawn from the following distribution:

$$\tilde{\Phi}(\nu;\eta) = \begin{cases} 0, & \text{if } \nu < 0 \\ \left(\frac{\nu}{c_0}\right)^{\eta}, & \text{if } \nu \leq c_0 \\ 1, & \text{if } \nu > c_0 \end{cases} \tag{7}$$

where $\eta > 0$. Thus, we can define the effect of the program on the probability of surviving the recession T_j as follows:

$$T_j = \Pr\left(\nu \leq \rho_j - b_j + \varphi b_j\right) - \Pr\left(\nu \leq \rho_j - b_j\right) \equiv \Phi_j(\varphi) - \Phi_j(0) \tag{8}$$

where $\Phi_j(z) = \tilde{\Phi}(\rho_j - b_j + z b_j)$.

6.2 Banks

There are two types of financial intermediaries, big banks and microfinance institutions, facing two different distributions of clients. Big banks tend to serve larger firms with higher initial debt and cash-in-hand according to the distribution $G^B(b,\rho)$, while MFIs are specialized in small firms and face the distribution $G^{\mathrm{MFI}}(b,\rho)$. MFIs distribute a given fraction γ_{MFI} of total guarantees. When firms survive, loans are repaid and, additionally, banks obtain $\psi_F b_j$, which represents future profits from preserving the lending relationship. If firms survive without guaranteed loans, the relationship ends with probability ψ_C and, while outstanding debt is still repaid, banks do not get any future profits from this relationship. If firms do not survive, banks get a fraction δ of outstanding debt. Thus, bank k gets the following expected profits from client j:

$$\begin{aligned}\Pi_j^k =& \ell_j^k \left\{\Phi_j(\varphi)\left(1+\psi_F\right)+\left(1-\Phi_j(\varphi)\right)\delta\right\} b_j \\ &+\left(1-\ell_j^k\right)\left\{\Phi_j(0)\left[\left(1-\psi_C\right)\left(1+\psi_F\right)+\psi_C\right]+\left(1-\Phi_j(0)\right)\delta\right\} b_j=\ell_j^k \Omega_j^k b_j+\Theta_j^k b_j \\ &\qquad \text{where} \quad \Omega_j^k=T_j\left[(1-\delta)+\psi_F\right]+\Phi_j(0)\psi_C\psi_F\end{aligned} \tag{9}$$

Where ℓ_j^k is an indicator variable that equals one if lender k provides guarantees to firm j. Lenders choose which firms to attend in order to maximize their expected profits as follows:

$$\max_{\ell_j^k \in\{0,1\}} \int \ell_j^k \Omega_j^k b_j dG^k(\rho_j, b_j) \qquad \text{s.t.:} \quad \int \ell_j^k \varphi b_j dG^k(\rho_j, b_j)=\gamma_k M \tag{10}$$

Thus, financial intermediaries will not necessarily attend most sensitive firms with high T_j. Instead, they will trade-off such sensitivity with the probability of firms surviving without the program. When poaching threats are more relevant, banks will prefer to attend firms that can survive without the program, leading to an inefficient allocation of guarantees.

6.3 Constrained First-Best

Social planner chooses which firms to attend in order to maximize the total debt saved by the program. We assume that when firms default, they do it on all their loans. Then, the social planner's problem is:

$$\max_{\ell_j^{SP} \in[0,1]} \int \ell_j^{SP} T_j b_j dG(\rho_j, b_j) \qquad \text{s.t.:} \quad \int \ell_j^{SP} \varphi b_j dG(\rho_j, b_j)=M \tag{11}$$

where $G(\rho_j,b_j)=G^B(\rho_j,b_j)/(1-s^{\mathrm{MFI}})+G^{\mathrm{MFI}}(\rho_j,b_j)/s^{\mathrm{MFI}}$ is the distribution of all firms in the economy over cashflows and outstanding debt. Thus, the social planner attends firms with the highest treatment effect T_j. Misallocation in the private bank equilibrium arises when $\Omega_j \neq T_j$. As we discussed above, the degree of misallocation depends on firms' probability of surviving without the program $\Phi_j(0)$, poaching probability ψ_C, and bank future profits to firm current debt ratio ψ_F. The probability of surviving without the program depends on b and ρ. Thus, different degrees of bank and MFIs participation in the program lead to different levels of misallocation of funds. As we will discuss below, the optimal participation of MFIs depends on the distributions G^k that we calibrate using our micro-data, and treatment effects T_j that we estimated in the empirical section.

6.4 Calibration

We assume that the two marginal distributions governing firm-level debt and cash-in-hand are beta, $b \sim F_b^k = \text{Beta}(\alpha_b^k, \mu_b^k)$ and $\rho \sim F_\rho^k = \text{Beta}(\alpha_\rho^k, \mu_\rho^k)$, with densities f_b^k and f_ρ^k, for $k \in \{B, S\}$. We construct the bivariate distribution $G^k(b, \rho)$ using Frank's Copula to allow for correlation in these characteristics to be governed by a single parameter ζ^k. We calibrate α_ρ^k, α_b^k, μ_ρ^k, and μ_b^k as follows. First, we normalize aggregate cash-in-hand to one. Second, we match the aggregate debt to GDP ratio, using aggregate cash-in-hand as GDP. Third, we match the average and aggregate leverage of big banks and MFIs clients. Fourth, we match banks' clients share of debt and revenue. Finally, we calibrate ζ to match the relevant correlation between b and ρ observed in the data, where we use total sales in a given year as a proxy for cash-in-hand.

We use an additional parameter s_{MFI} to scale G^k to match the share of clients attended by banks and MFIs before Covid-19, while the participation of MFIs in the program is determined by γ_{MFI}, and M matches the size of the program relative to outstanding debt and GDP. We assume a recovery rate δ of 10 percent consistent with estimates from the bank regulator and a bank profit parameter ψ_F of 1.3 percent that matches the ratio of bank profits to GDP. We calibrate the value of guaranteed loans φ to match the expansion of credit for the average firm participating in the program. Finally, c_0 and η are calibrated to match our estimated treatment effects, and ψ_C is estimated from the data and matches the share of unattended firms that switch banks.

Table 9: Model Calibration

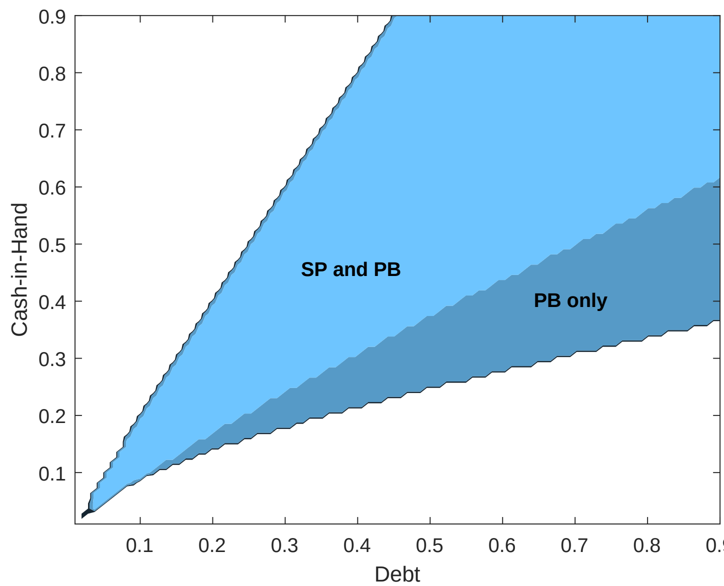
	Description	Value	Targeted Moments
α_b^{MFI}, μ_b^{MFI}	Debt distribution across MFI clients	1 and 16	Bank clients share of debt and cash-holdings,
α_b^{B}, μ_b^{B}	Debt distributi on across bank clients	2 and 18	aggregate leverage of bank and MFI clients,
$\alpha_\rho^{\mathrm{MFI}}$, μ_ρ^{MFI}	Revenue distribution across MFI clients	2.5 and 6.5	average leverage of bank and MFI clients,
α_ρ^{B}, μ_ρ^{B}	Revenue distribution across bank clients	5.7 and 10	country leverage, and tot. revenue equals 1
ζ	Copula parameter	-1	Empirical correlation between b and ρ
s_{MFI}	MFI share of clients before Covid	.6	Observed participation
c_0, η	Covid-19 shock distribution	10 and 0.5	Average treatment effects at both quintiles
φ	Guaranteed loans to pre-Covid debt	0.18	Credit growth of participants
ψ_C	Poaching probability	0.1	Prob. of switching main bank: non-participants vs. participants
ψ_F	Lender share of firm future profits	0.013	Financial sector net profits to GDP ratio
δ	Recovery rate	0.1	Estimates from bank supervisor
M	Size of the program	0.03	Guaranteed loans to GDP ratio
γ_{MFI}	MFI share of guarantees	.3	Observed participation

Notes. This table describes and shows the parameter values in the model.

6.5 Numerical Results

We use our calibrated model to compare the allocation of guarantees in two different scenarios. First, we consider the constrained first-best, where a social planner chooses which firms to attend in order to solve the problem in equation (11). Figure 7 plots the region of firms attended by the social planner and big banks. The light blue area plots the region attended in both equilibria. We can see the trade-off the social planner faces. For a given level of cash-in-hand, very low levered firms do not require the program to survive, so they are not attended. Similarly, highly levered firms will not be attended as their probability of surviving the pandemic is very low even if they participate in the program. The dark blue area plots the region of firms attend in the market equilibrium only, where banks solve the problem in equation (10). We can notice that, in our calibrated model, big banks are more likely to attend larger clients relative to the social planner. This is because of the second term of Ω defined in equation (10). The probability of small firms surviving the pandemic without the program is relatively low, so banks prefer not to attend them despite the high treatment effect T_j.

Figure 7: Social Planner and Market Equilibrium



The shaded areas show the firms (indexed by debt b and cash-in-hand ρ) attended in the social planner equilibrium and the market equilibrium in our calibrated model. The dark blue area highlights firms attended only in the market equilibrium, and the light blue area represents the region of firms attended in both equilibria.

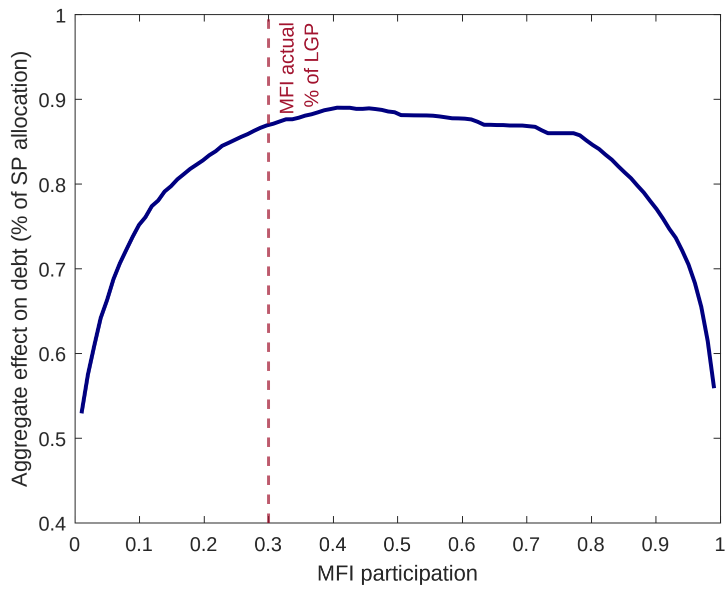
Optimal Participation of Micro-Finance Institutions. We now explore the optimal participation of MFIs. To do so, we define the share of debt saved by the program relative to the constrained first-best:

$$\text{Market allocation relative to SP}(\gamma_{\text{MFI}}) = \frac{\int \ell_j^{\text{B}} T_j b_j dG^{\text{B}}(\rho_j, b_j) + \int \ell_j^{\text{MFI}} T_j b_j dG^{\text{MFI}}(\rho_j, b_j)}{\int \ell_j^{\text{SP}} T_j b_j dG(\rho_j, b_j)} \quad (12)$$

Figure 8 plots this ratio for different levels of MFIs participation γ_{MFI}. As we can observe, when MFIs participation is very low, we are further away from the constrained first-best equilibrium. The effects of MFIs participation are highly non-linear. The loss ratio declines rapidly as we increase the participation of small banks and reaches a plateau at the optimal participation of 40 percent. Our model indicates that if all guarantees were distributed by big banks, the program would have saved 53% of debt from default, relative to the constrained first best. The observed MFIs' participation increases this ratio to 85%. Further increasing MFI's participation to the optimal level leads to tiny additional gains.

Overall, our model highlights the role of lender incentives and lender specialization in shaping the allocation and aggregate impact of loan guarantees. First, lender incentives are not necessarily aligned with those of the social planner. While the social planner maximizes the aggregate treatment effect of the program, which implies allocating loans toward firms with the highest treatment effect, financial institutions maximize expected profits, trading-off high treatment effect versus size and probability of surviving without the program. Lender specialization determines the role of firms with high $\Phi_j(0)$ in banks portfolios. The optimal participation of MFIs will maximize equation (12).

Figure 8: Loss function by small bank participation



This figure plots the aggregate effect on debt defined in equation (12) for different levels of MFI's participation.

7 Conclusions

Financial stimulus programs are usually implemented through the banking sector. Since big banks tend to attend bigger companies, many emerging countries have promoted the expansion of micro-finance institutions (MFIs) to reach out to small and young firms. However, their participation in financial stimulus programs is still limited. In this paper, we estimate the role of MFIs in shaping the allocation and aggregate impact of loan guarantees in recessions.

We study a large financial stimulus program implemented by the Peruvian government, which provided guaranteed loans to help firms dealing with Covid-19 restrictions. We find that loan guarantees increase credit and reduce delinquency with substantial heterogeneous effects across firms. We document that the decline in delinquency rates is fifth times bigger for the smallest borrowers, and that MFIs play a key role in distributing guarantees towards this group of firms. We build a model where MFIs and big banks face poaching incentives and have different portfolios of clients as observed in the data. Our model indicates that if all guarantees were distributed by big banks, the program would have saved 53% of debt from default, relative to the constrained first best. The observed MFIs' participation increases this ratio to 85%. Further increasing MFI's participation to the optimal level leads to tiny additional gains.

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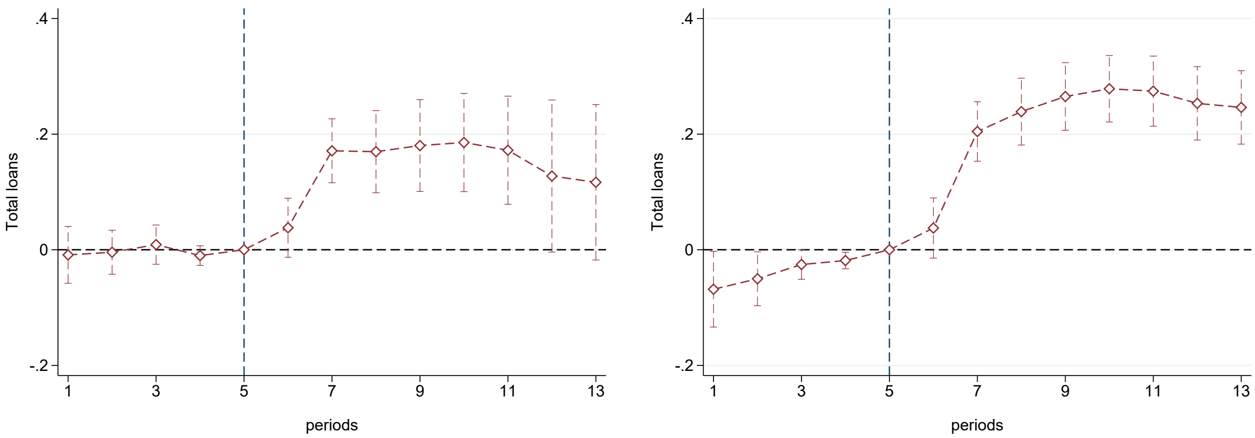
Appendix A: Additional Specifications

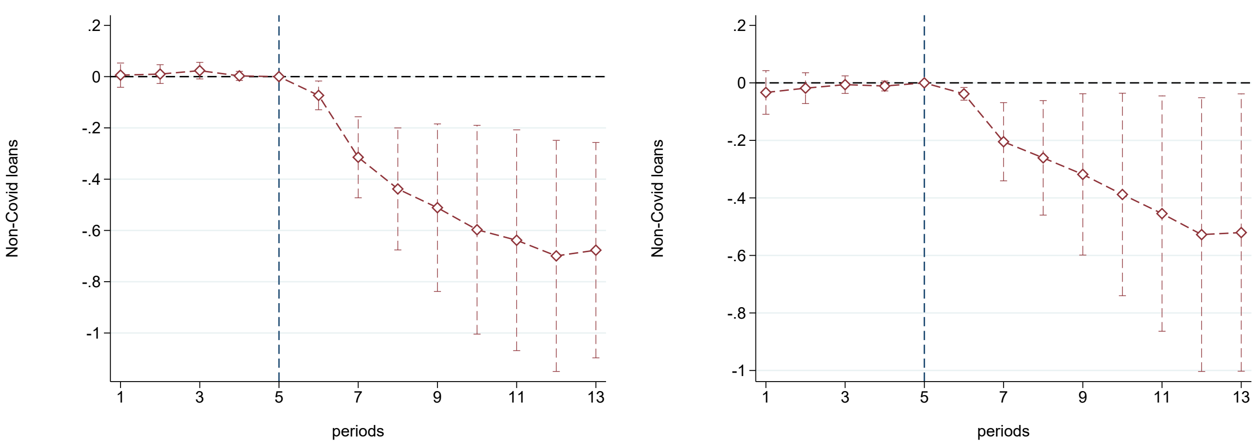
Figure A1: Effect of the Program on Total Loans



(a) Bank, Firm, and Quarter FE (b) Firm-Quarter and Firm-Bank FE

This figure plots the quarterly effects of the program on total credit at the bank-firm level. The dependent variable is in logs. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter fixed effects. The confidence interval is at the 95% level.

Figure A2: Effect of the Program on Non-Covid-19 Loans



(a) Bank, Firm, and Quarter FE (b) Firm-Quarter and Firm-Bank FE

This figure plots the quarterly effects of the program on non-Covid-19 loans at the bank-firm level. The dependent variable is in logs. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter fixed effects. The confidence interval is at the 95% level.