Financial Stimulus and Microfinance Institutions in Emerging Markets*

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Abstract

We quantify the role of microfinance institutions (MFIs) in shaping the allocation and aggregate impact of financial stimulus policies in emerging markets. To do so, we study a huge program of loan guarantees implemented in Peru during the last recession and estimate the response of small businesses. We find that the program expanded credit supply and improved small firm performance with substantial heterogeneous effects. A 10 percent increase in credit supply led to a 5 percentage points decline in delinquency rates among smaller firms, and only 1 percentage point among bigger borrowers. While MFIs distributed 50 percent of their guarantees to smaller borrowers, traditional banks distributed only 20 percent of their guarantees to these firms. We build a stylized model where MFIs and traditional banks face poaching threats and attend heterogeneous firms. Our calibrated model indicates that, by orienting the allocation of guarantees towards smaller borrowers, MFIs reduced the aggregate share of non-performing loans in 30 percent relative to a counterfactual scenario where only traditional banks distribute guarantees.

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1 Introduction

Small firms face strong difficulties in obtaining formal credit, especially in emerging markets. A salient explanation is that, since hard information is typically scarce, financial institutions must invest in relationship lending to acquire soft information from small entrepreneurs. Unlike traditional banks that rely mainly on hard information, microfinance institutions (MFIs) are small, usually local lenders, specialized in building lending relationships through in-person interactions with borrowers and customized products such as microcredit. Thus, to increase small firm credit access, most developing economies have promoted the expansion of MFIs over the past decades. However, the real effects of MFIs remain unclear, and whether they can promote economic development in the long run or foster economic recovery in recessions remain open questions.

In this paper, we study the role of MFIs in shaping the allocation of financial stimulus and, through this channel, the aggregate impact of financial policy in recessions. Notice that whether MFIs can improve the allocation of financial stimulus or not is a priori unclear. On the one hand, very small borrowers might be more sensitive to financial conditions during economic downturns. Thus, since MFIs are specialized in very small businesses, they could have strong incentives to distribute financial stimulus to this group of firms, increasing the aggregate impact of financial policy.[1] However, very small firms are usually opaque, and higher debt ratios could encourage them to invest in risky projects. Then, by targeting these firms, MFIs can actually increase the vulnerability of the financial sector, dampening the aggregate impact of financial policy. Thus, whether MFIs can improve the allocation of financial stimulus and, through this channel, amplify the aggregate impact of financial policy 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 the restrictions of Covid-19. This setting is particularly useful for learning about the role of MFIs for multiple reasons. First, Peru has one of the best global business conditions for microfinance according to the Inter-American Development Bank[2]. Indeed, the Peruvian microfinance is a mature industry that accounts for over 50 percent of small firm lending. Second, bank regulations require

[1] Notice that this might not be the case if there were no frictions in credit markets. For example, if all the relevant information of firms was observable, the more sensitive firms would receive financial stimulus independently of whether it is distributed by specialized MFIs or non-specialized traditional banks.

[2] See, for example `https://graphics.eiu.com/assets/images/public/Microscope_on_Microfinance_2014/EIU-Microscope-Dec-2015.pdf`

MFIs to provide detailed data on their operations. Thus, we can access loan-level information on outstanding debt of Peruvian firms with traditional banks and microfinance institutions. Finally, the program of loan guarantees was a large shock, equivalent to 8 percent of Peruvian GDP, capable of generating important general equilibrium effects. Overall, our setting allows us to cleanly estimate the impact of loan guarantees on small firm performance, quantifying the role of MFIs in shaping the allocation and aggregate impact of financial stimulus programs in recessions.

We use monthly loan-level data covering the universe of lending relationships that small firms maintain with each traditional bank and MFI established in Peru from 2019 to 2021. For each lending relationship, we observe the loan balance, the number of days of repayment delay, and the city where the loan was originated. On the firm side, we observe industry, age, and an assessment of firm risk reported by lenders. We combine this loan-level data with annual tax reports, including sales, total wages and capital for the universe of small firms in the Peruvian formal sector. Our unique dataset provides a full picture of small firms' balance sheets, helping us to understand how traditional banks and MFIs distribute loan guarantees across heterogeneous firms.

We estimate the effects of the program using a difference-in-differences strategy that exploits variation in financial institutions' takeover of guarantees, and focus on small firm loans 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 lenders 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 should have followed parallel trends. We provide evidence supporting our identification in two ways. First, we plot event study graphs showing that our measure of treatment had null effects on credit before the program, consistent with our parallel trend 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 *bigger banks* with *bigger firms* that might be better prepared to deal with recessions.

Since we exploit variation in lenders' takeover of guarantees, one possible concern is that treatment could be endogenous. For example, financial institutions might look for more loan guarantees because their clients are more affected by the recession, which can bias our results. We evaluate the plausibility of this concern by exploiting a delay in the program implementation that gives us three months with Covid-19 restrictions but without the program. If firms attached to highly treated banks are more affected by the recession, we should observe a strong correlation between our treatment measure and the balance of loans or credit ratings within this subperiod. Our results show that this correlation is statistically zero. We interpret this result as evidence of the unpredictability of the shock regarding depth and persistence, mainly in the market of small firm loans, where information is usually scarce. Such unpredictability generates randomness in banks' takeover of guarantees that our identification exploits.

We present our empirical results in two main sections. In the first one, we report the average effect of the program on credit and firm performance. We start by estimating the bank-lending channel following Khwaja and Mian (2008) where we control for time-varying firm-level demand shocks. Financial institutions that are one standard deviation more treated expand credit supply by 11 percent after the program, and reduce the supply of normal loans not collateralized by the government in 22 percent, which we interpret as evidence of public guarantees partially crowding out the normal activity of financial institutions. It is worth noticing that these results only indicate that the program expanded credit supply of highly treated lenders relative to less treated ones. Since we are interested in estimating the impact of the program on small firm performance, we need to aggregate our data at the firm-level and construct a corresponding measure of treatment. We do so by computing the weighted average bank treatment, where wights are defined by the share of banks on firms' total credit, following Jimenez et al. (2020). This measure indicates how well connected firms are to more treated banks.

We find that one standard deviation higher treatment is associated with a 10 percent increase in firm total credit after the program, and a 24 percent reduction in normal loans. These results indicate that pre-existing lending relationships with highly treated banks are key for firms to obtain loan guarantees. We then estimate the effect of the program on delinquency rates using a difference-in-differences instrumental variable approach. We use our firm-level treatment as an instrument to estimate the elasticity of delinquency to credit. We find that a 10 percent increase in credit leads to a 3 percentage points decline in the probability of experiencing repayment delays. Our findings indicate that the need of external financing in the last recession played a more important role in shaping the response of small firm performance than other channels such as firm risk-shifting incentives and weaker screening of financial intermediaries.

In the second part of our empirical analysis, we document the heterogeneous response of small entrepreneurs and explore whether MFIs improve the allocation of financial stimulus by targeting more sensitive firms or not. We start this section by documenting some empirical facts about lender specialization. We split small firms in deciles based on the pre-recession debt distribution, which is our proxy for firm size.[3] Traditional banks concentrate 98 percent of their small firm loans at the top decile, while MFIs only allocate 59 percent of their portfolio towards these firms. Moreover, the top decile represents 18 percent of traditional banks' clients and only 8 percent of MFIs' borrowers. We provide evidence that such specialization is not driven by industry nor city specific characteristics.

Then, we estimate the heterogeneous effects of credit on small firm performance. We do so by splitting firms into two groups, those at the top quintil of the pre-recession debt distribution and those at the bottom four quintiles. We call the former gorup as bigger firms and the latter as smaller ones. While a 10 percent increase in credit leads to a 5 percentage points decline in delinquency among smaller firms, the decline is only 1 percentage point for bigger firms. Our results are not driven by industry nor location specific characteristics. Moreover, we find that the heterogeneous response of small firm performance is size-dependent and not lender-dependent, i.e., it holds among small firms that rely on MFIs as well as among small firms that rely on traditional banks. Finally, we compare the allocation of guarantees across lenders. We find that, while MFIs distribute 50 percent of their guarantees to smaller, highly-sensitive, borrowers, traditional banks distribute only 20 percent of their guarantees towards this segment of firms. A back of the envelope calculation, using our estimated elasticity and observed allocation, indicates that the program reduced aggregate delinquency by 5 percentage points. However, if all guarantees would have been allocated by traditional banks, aggregate delinquency would decline by 3.5 percentage points only.

Motivated by our empirical evidence, we build a thoretical model that rationalizes these patterns and allows us to do counterfactual analysis. We build on recent work by Joaquim and Netto (2022) and incorporate lender heterogeneity into this framework. Firms are heterogeneous in their initial debt and cash-in-hand, and face idiosyncratic liquidity shocks. These variables determine firms' survival probability conditional on participating in the program. There are

[3] It is worth mentioning that we recently received access to the tax reports data and our analysis of real outcomes is still in revision by the Central Bank for release.

two types of lenders, MFIs and traditional banks, who maximize expected profits and face different distributions of clients. MFIs are specialized in smaller firms with low levels of debt and cash-in-hand, while traditional banks tend to serve larger firms. We calibrate the distribution of traditional banks and MFIs clients over debt and cash-in-hand to match key moments of the corresponding empirical distributions. The value of lending relationships, from the bank perspective, is proportional to firm size. Lenders face poaching threats only among those clients that do not receive guarantees. Thus, financial institutions trade-off between client size and responsiveness, which leads to misallocation of financial stimulus. Poaching threats are calibrated to match the observed share of unattended firms switching lenders after the program, and the liquidity shock distribution matches our size-dependent treatment effects.

Our model highlights the role of lender incentives and lender specialization in determining the allocation of financial stimulus in recessions. 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 financial stimulus towards firms with high treatment effect, lenders trade-off between firm size and treatment effect. Second, the optimal participation of lenders depends on the actual distribution of clients and our estimated size-dependent treatment effects. We define the optimal participation of MFIs as the one that maximizes non-defaulting debt.

We use our model to conduct two counterfactual analysis. First, we estimate how far is the private allocation relative to the social planner in terms of non-defaulting debt. We find that, private lenders distribute more guarantees towards bigger firms with higher probability of surviving the recession without the program. Thus, the private allocation saves 82 percent of the social planner's non-defaulting debt. Second, we measure the optimal participation of Micro-Finance Institutions. We find that if the whole program were distributed by traditional banks, the private allocation would have saved only 53 percent of the social planner non-defaulting debt. Thus, the observed participation of MFIs generated an additional 29 percent of non-defaulting debt. Finally, the effects are highly non-linear, and the optimal level of MFIs participation of 40 percent would lead to an additional 5 percent of non-defaulting debt.

Overall, our paper documents that microfinance institutions can play a key role in improving the allocation of financial stimulus by targeting small, highly sensitive borrowers. Through this channel, MFIs can amplify the aggregate impact of financial policy during economic downturns in emerging markets.

Literature Our paper is related to three main strands of literature. First, we contribute to the literature studying the effects of microfinance institutions in emerging markets. A first set of papers has used randomized controlled trials (RCTs) to document small real effects of micro-credit in normal times (Angelucci et al. (2015), Augsburg et al. (2015), Tarozzi et al. (2015), Attanasio et al. (2015)). However, RCTs have limitations such as the small-scale interventions and the inherent partial equilibrium analysis. More recent studies have documented that general equilibrium adjustments and large-scale shocks can lead to significant real effects of micro-credit (see, for example, Kaboski and Townsend (2011) and Buera et al. (2020) for theoretical work, and Breza and Kinnan (2021) for an empirical analysis).

Our contribution to this literature is threefold. First, we contribute by studying a novel angle through which MFIs might affect the real economy, named by shaping the allocation of financial stimulus in recessions. We document that MFIs play a crucial role in distributing loan guarantees towards smaller, highly sensitive borrowers, strengthening the aggregate impact of this policy. Second, we use detailed micro-data to trace the effects of MFIs on a large set of financial and real outcomes. To the best of our knowledge, this is the first paper to combine such detailed administrative micro-data on MFIs operations with a quasi-experimental research design. Finally, we contribute by developing a theoretical model where lender incentives determine the allocation of financial subsidy, and then, lender specialization becomes critical to target smaller, more sensitive firms. Even though it is still a preliminary model, to the best of our knowledge, this is the first attempt to provide a framework where lender incentives and lender specialization can shape the aggregate impact of financial policy.

Second, our paper is related to the literature studying the effects of loan guarantees, a widely used policy in developing and developed countries (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 focus on the role of micro-finance institutions, local lenders that are specialized in smaller borrowers. We document that smaller firms are more responsive to financial conditions, and depend heavily on MFIs to obtain loan guarantees. This result is similar to that reported by Haas-Ornelas et al. (2021), who find that private banks in Brazil tend to allocate public guarantees to bigger clients. Our paper shows that policymakers can improve the effectiveness of financial stimulus programs by promoting, to some extent, the participation of specialized lenders. In this line, we also contribute to the recent literature on lender specialization (Paravisini et al. (2023)). Our second contribution is to study the effects of loan guarantees in recessions. We find that this program is effective in improving firm performance measured by delinquency rates. Our findings contrast with those documented by Lelarge et al. (2010) in France. We interpret this discrepancy as evidence that financial needs in recessions can offset risk-shifting incentives associated with increasing firm leverage or weaker incentives on lender screening.

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 twofold. 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 financial institutions provided loan guarantees to more sensitive firms or not. In this line, our paper is related to Joaquim and Netto (2022) who document that bigger 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 firm responsiveness to the actual allocation of guarantees.

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 combine two types of administrative data that include information on financial and real outcomes for the universe of formal small firms in Peru.

1. Credit registry 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 in which 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 the loans are originated. On the firm side, we observe industry, an assessment of firm credit risk reported by lenders, and the year when firms obtained their first loan.

2. Tax reports data. We use firm-level data from tax files, including annual information on sales, capital, and employment from 2018 to 2022. This dataset includes a unique firm tax ID that allows us to combine financial and real outcomes. In addition, we observe the city where firms are located and the industry where they operate. We use this dataset to estimate the real effects of the policy.

2.2 The Market of Business Loans

The Peruvian banking sector contains 52 financial institutions in the market of business loans, including 15 traditional banks and 37 microfinance institutions. Business loans are divided into five groups based on a combination of firms' sales and outstanding debt: micro-firm loans, small business loans, medium-size firm loans, large firm loans, and loans to corporations. For example, micro-firm loans are those provided to firms whose total debt in the banking sector is below USD 6 thousand, while loans to corporations are those granted to firms whose total sales in the past two years were above USD 60 million.

Table 1 provides summary statistics of bank-level characteristics using data of December 2019. Columns (1) and (2) report the average and median lender size, measured by total credit. We can see that the size distribution is highly skewed to the right. The average lender size is around USD 1 billion, while the median is only USD 169 million. Columns (3) and (4) report broad measures of competition in the banking sector. There are 52 banks competing in the market of business loans, and only 5 of them account for almost 80 percent of the market. Finally, column (6) reports the relevance of MFIs in the market of business loans, where they provide 13 percent of credit.

Lender characteristics vary substantially across different types of credit, as reported in the bottom panel of Table 1. We can see that the size distribution is more right-skewed for bigger loans. While the average value of micro-credit provided by banks is USD 77 million, less than three times the median of USD 28 million, the average value of loans to corporation provided by banks is USD 1.3 billion, more than seven times the average value of USD 166 million.[4]

Additionally, we can observe that competition is limited among banks, specially as loans get bigger. For example, there are 42 institutions operating in the segment of micro-credit. On the other hand, only 13 banks provide corporate loans. Moreover, the five largest banks represent around 95 percent of corporate loans, while the same share is less than 60 percent in micro-credit. Finally, we report the share of microfinance institutions for each type of loan. We can notice that MFIs play a key role in micro and small firm loans, representing 68 and 47 of loans, respectively. However, they provide a small share of bigger loans. Our paper focuses on micro and small firm loans, named small business loans throughout the text.

Table 1: Lender Characteristics by Loan Type

	Total Loans		Number of	Share Top 5	Share of
	Mean	Median	Banks	Banks	MFIs
	(1)	(2)	(3)	(4)	
Total	1 106	169	52	77	12.9
Loans to:					
Micro-credit	77	28	42	58	68.2
Small firms	190	50	45	56	47.3
Medium-size firms	263	13	48	86	5.8
Large firms	491	8	27	87	0.3
Corporations	1 272	166	13	94	0.5

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 business loans. Total loans are expressed in USD million. Shares are expressed in percentage.

Table 2 reports summary statistics of firms with positive debt by December 2019. Column (1) and (2) show the average and median value of firm debt. Similar to the bank size distribution, the distribution of borrowers' debt is highly skewed to the right. The average firm debt is around USD 6 thousand, while the median is around USD 500. The distribution gets more right-skewed for bigger firms. Column (3) shows the share of firms facing more than 30 days of repayment

[4]Throughout the text, we use banks to refer to both traditional banks and microfinance institutions.

delay. In the whole market of business loans, 12 percent of borrowers exhibit more than 30 days of repayment delay in December 2019. This share is bigger among borrowers relying on medium-size loans. Finally, column (4) shows that our sample is composed of around 3 million of firms. Most of them are in the segment of micro-credit, around 2.3 million firms, and only 500 firms obtain corporate loans.

Table 2: Borrower Characteristics by Loan Type

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

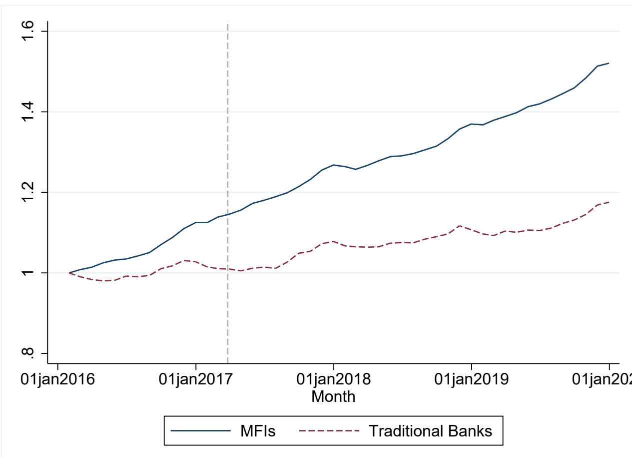
This table reports firm-level summary statistics as of December 2019. We report the mean and median of the distribution of total loans across firms. Repayment delay denotes the share of firms exhibiting more than 30 days of repayment delay. Total loans are expressed in USD thousand, and number of firms is expressed in thousand.

2.3 Traditional Banks and MFIs before Covid-19

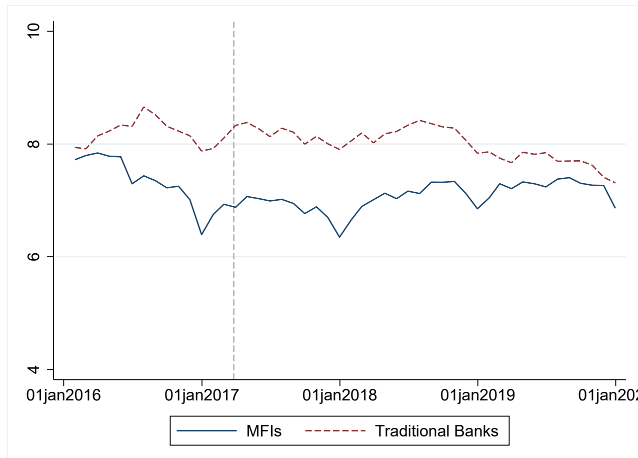
Microfinance institutions experienced a significant growth over the past decades in Peru, promoted mainly by deregulation policies and increasing foreign direct investment. The industry has matured over time and plays a key role in the segment of small business loans nowadays. Figure 1 plots the evolution of credit and delinquency rates among traditional banks and microfinance institutions, considering only small business loans, from January 2016 to December 2019.

Panel (a) shows credit growth rates, measured as the value of credit in a given point in time relative to its value in January 2016. We can see that small business loans provided by both types of lenders exhibited a steady increase over time. However, growth rates differ substantially. While traditional banks register a cumulative growth rate of 20 percent in the four years of our sample, microfinance institutions grew by 50 percent. This led to a 7 percentage points increase in MFIs' participation, from 46 to 53 percent of the market. The rapid expansion of microfinance institutions was coupled with stable delinquency rates. Panel (b) shows that the average delinquency rate among small business loans provided by microfinance institutions remained at around 7 percent, which is slightly smaller than that of traditional banks.

Figure 1: Credit Growth and Delinquency by Type of Lender before Covid-19



(a) Total Loans



(b) Delinquency Rates

This figure plots the evolution of credit and delinquency rates for traditional banks and microfinance institutions in the segment of small business loans. Panel (a) plots credit growth rate measured by the value of credit in a given point in time relative to the corresponding value in January 2016. Panel (b) plots delinquency rates measured by the share of outstanding debt with more than 30 days of repayment delay.

In December 2019, there were 15 traditional banks and 37 microfinance institutions. Table 3 provides summary statistics for these two types of lenders. Columns (1) and (2) consider traditional banks and columns (3) and (4) include all MFIs. The top panel considers the whole activities of banks, while the bottom panel focus on small business loans only. The average traditional bank is 20 times bigger than the average microfinance institution in terms of total assets, and 16 times bigger in terms of total credit. Delinquency rates are smaller among traditional banks, as they provide bigger loans where repayment delays are rare. The average traditional bank exhibits a return on assets of 1.7 percent, which is very close to that of the average MFI. Finally, traditional banks attend, on average, more cities than microfinance institutions, but their geographical concentration of loans[5] is twice as large as that of the

[5] We compute the geographical concentration of bank loans as the Herfindahl-Hirschman index of bank portfolios across locations.

average MFI.

Columns (5) and (6) compute the same statistics for the 10 biggest MFIs. These institutions are also smaller than traditional banks in terms of total assets and credit, and exhibit higher delinquency rates. However, the average MFI is now more profitable, attend more markets, and exhibit a much lower degree of loan geographical concentration than the average traditional bank. Finally, the bottom panel reports size measured by small business credit. There are 10 banks with an average size of USD 420 million, while the average size of the top 10 MFIs is USD 360 million.

Table 3: Traditional Banks and Micro-Finance Institutions

	Traditional Banks		Micro-Finance Inst.		Top 10 MFIs	
	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)
Total Assets	7.89	1.78	0.39	0.16	1.04	0.98
Total Credit	5.45	1.25	0.33	0.16	0.94	0.86
Delinquency Rate	3.57	3.02	7.81	5.46	6.18	4.71
ROA	1.70	2.00	1.64	1.41	1.89	2.23
Num. of Cities	61	46	46	40	99	94
Geographical loan concentration	.48	.32	.21	.05	.03	.03
Num. Institutions	15		37		10	
In small business loans:						
Total Credit	0.42	0.12	0.12	0.05	0.36	0.36
Num. Institutions	10		35		10	

This table reports bank-level summary statistics of institutions participating in the segment of small business loans as of December 2019. Columns (1) and (2) consider all traditional banks, columns (3) and (4) include all microfinance institutions, and columns (5) and (6) focus on the 10 biggest MFIs according to their total value of credit. The value of assets and credit are expressed in USD billion, while delinquency and ROA are expressed in percentage. Geographical concentration for bank b is computed using bank b loans in city c, L_{cb}, as follows: $\sum_c (L_{cb}/L_b)^2$

We conclude this section by describing the geographical footprint of traditional banks and micro-finance institutions. Figure A1 in the Appendix plots the map of Peru, highlighting the cities[6] where traditional banks and micro-finance institutions have active branches in December 2019. First, we can observe that the majority of cities, around 80 percent, are *financial deserts*. Second, only 9 percent of the 382 cities with bank branches have only traditional banks. In contrast, one third of these cities have only MFIs' branches. Moreover, these are typically rural low-population-density locations. While the average city served by traditional banks has 2442 individuals per square kilometer, the average density of cities where only MFIs are present is 243 individuals per square kilometer.[7] Thus, a significant part of the role of microfinance institutions in expanding credit access is related to their geographical operations.

2.4 The Program of Loan Guarantees

Reactiva Perú is the program of loan guarantees implemented by the Ministry of Finance and the Central Reserve 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 lenders 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 financial institutions. There were separate auctions for each type of business loans. Out of the 52 financial institutions established in Peru, 28 participated in the program.

Guarantees ranged from 80 to 98 percent of loan value, with higher rates among smaller loans. Private lenders were in charge of screening borrowers and allocating loan guarantees. 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 originated. Firms with poor credit rating, exhibiting repayment delays of more than 60 days, were not allowed to participate.

Table 4 provides summary statistics of loan guarantees. Column (1) shows the value of guarantees distributed by the program in USD billion, and column (2) shows the ratio of this value relative to total credit in December 2019. Similarly, column (3) shows the total number of clients attended by the program, in thousand of firms, and column (4) shows the ratio of this number relative to the total number of borrowers in 2019. The program provided around USD 16 billion of guaranteed loans, equivalent to 29 percent of outstanding debt in 2019, and

[6]The term *cities* is used here to denote *districts*, which represents the most granular level of geographical classification in Peru.

[7]In the remaining categories, population density varies as follows. The average financial deserts has 69 individuals per square kilometer, and the average city with only bank branches has 1407 individuals. Finally, the average city with both lenders has 2612 individuals per square kilometer.

benefited 473 thousand firms, equal to 16 percent of existing borrowers. The bottom panel shows that the relevance of the program varied across different types of loans. For example, in the segment of micro-credit, the program represented 37 percent of outstanding debt, and benefited clients represented 14 percent of existing borrowers. On the other hand, the program was equivalent to 34 percent of outstanding debt in the segment of large-firm loans, and attended 82 percent of clients. Finally, column (5) shows that the guaranteed rate of loans distributed by the program also varies across different types of credit. In micro-credit, 97 percent of loans distributed by private banks are guaranteed by the government, while this share is 80 percent for loans to corporations.

Table 4: Guaranteed Loans by Type of Credit

	Guaranteed Loans		Benefited Clients		Guaranteed
	Value	Ratio	Number	Ratio	Rate
	(1)	(2)	(3)	(4)	(5)
Total	15.5	29	473.1	16	91
Loans to:					
Micro-credit	1.2	37	319.9	14	97
Small firms	3.6	42	121.8	22	95
Medium-size firms	5.9	46	28.8	81	91
Large firms	4.5	34	2.6	82	85
Corporations	0.4	3	0.2	36	80

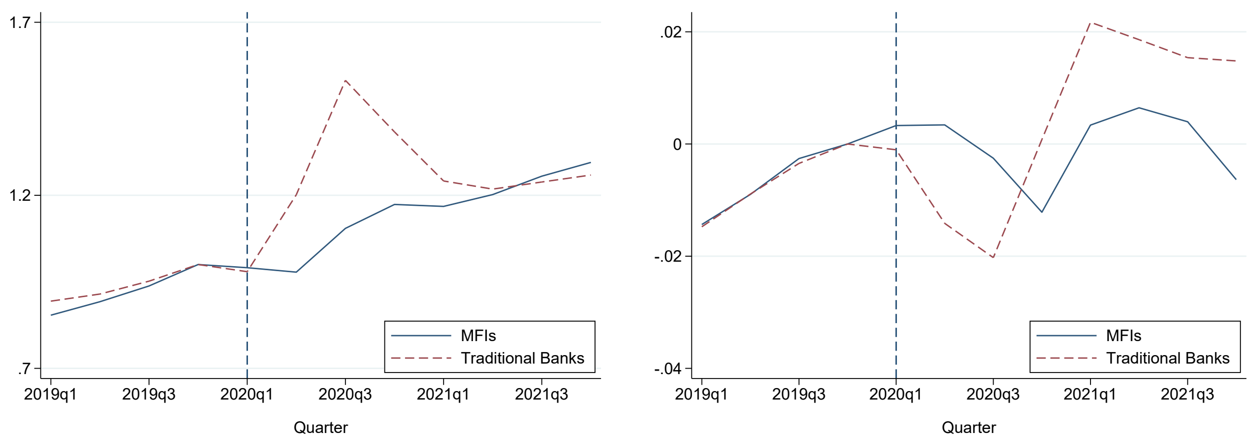
This table reports summary statistics of guaranteed loans in different segments of the business loan market. Column (1) reports the value of loans, in USD million, distributed by the program, and column (3) reports the number of clients, in thousand, obtaining a guaranteed loan. Columns (2) and (4) are ratios computed relative to the corresponding value as of December 2019. Column (5) shows the share of the value reported in column (1) that is guaranteed by the program.

2.5 Traditional Banks and MFIs in the Program

During the first months of the program, traditional banks won the majority of auctions in all types of loans, distributing a big share guarantees, even in the segment of small business loans. This was mainly due to the high operational costs faced by MFIs, which led to non-competitive bids relative to traditional banks. Given the relevance of MFIs in reaching out small firms in distant locations, the Central Bank promoted their participation by launching separate auctions for these institutions.

Figure 2 plots the evolution of credit and delinquency rates among traditional banks and micro-finance institutions using quarterly data around the Covid-19 recession from 2019 to 2022. The dotted lines denote the quarter prior to the program. Panel (a) shows credit growth rates, measured as the value of outstanding debt in a given point in time relative to its value in December 2019. We can observe a rapid increase of traditional banks' small business loans, reaching a 50 percent growth at the peak. On the other hand, MFIs' credit exhibited a delayed and smaller expansion of around 20 percent. Both institutions converged in terms of credit growth one year after the program. Panel (b) plots the evolution of delinquency, defined as the difference between the current value and that of December 2019. We observe a sharp decline that mimics the timing of credit expansion. Most of this decline is mechanical, as loans had a one-year grace period. Once this grace period ends, we observe that traditional banks exhibit 2 percentage points higher delinquency than MFIs, relative to the pre-Covid period.

Figure 2: Credit Growth and Delinquency by Type of Bank



(a) Total Loans (b) Delinquency Rates

This figure plots the evolution of credit and delinquency rates for traditional banks and microfinance institutions in the segment of small business loans. Panel (a) plots credit growth rate measured by the value of credit in a given point in time relative to the corresponding value in 2019q4. Panel (b) plots delinquency rates growth measured by the share of outstanding debt with more than 30 days of repayment delay in a given point in time minus the corresponding value in 2019q4. The dashed line corresponds to 2020q1, the quarter prior to the program.

Overall, these aggregate trends are suggestive evidence that, despite the smaller and delayed credit expansion, MFIs seems to be more efficient in distributing guarantees to highly sensitive clients. In the following sections, we explore this in more detail, and study the role of MFIs in shaping the allocation and aggregate impact of loan guarantees.

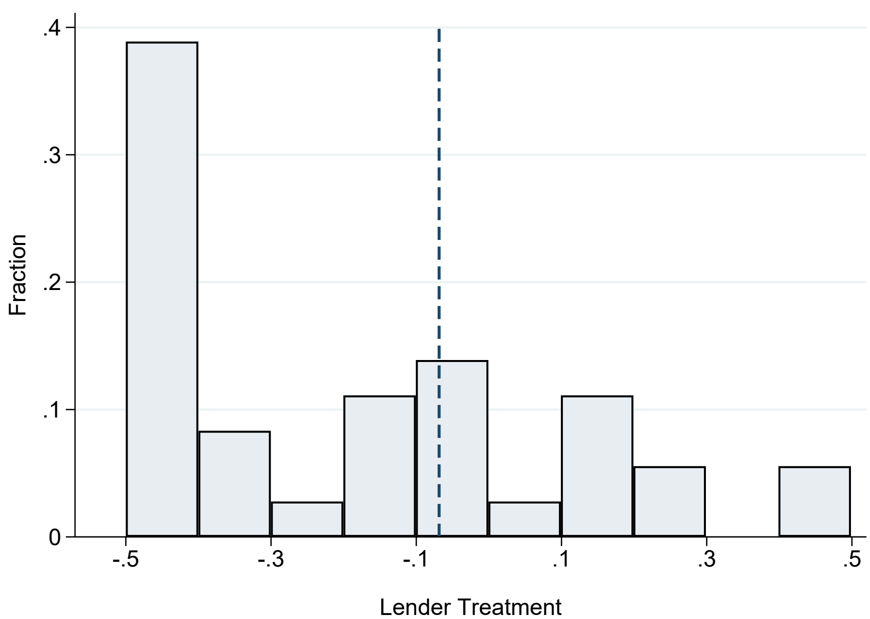
3 Empirical Framework

We exploit differences in lenders 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 financial institution f in the market of micro and small firm lending as follows:

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

where the shares are based on the value of loans.

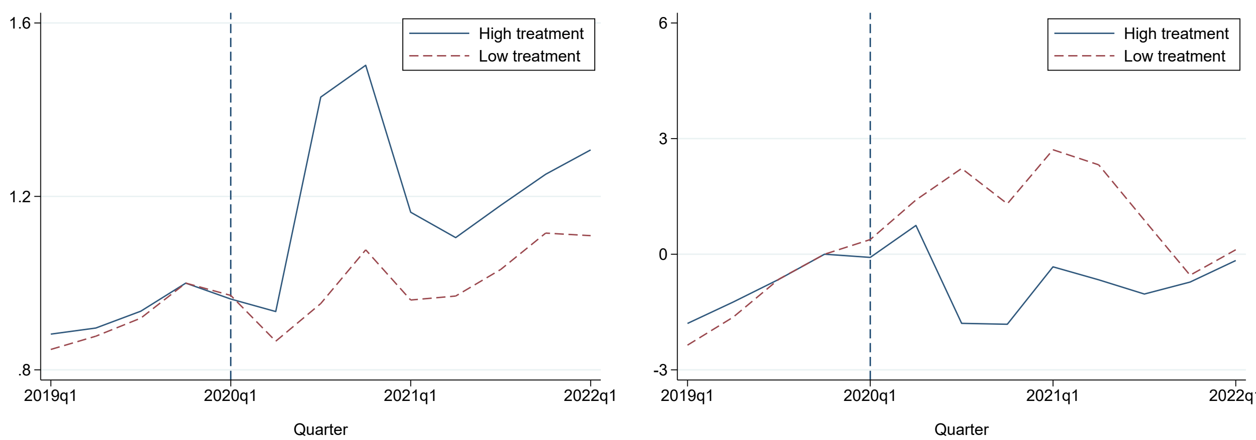
Figure 3: Distribution of Bank Treatment in Micro-credit



This figure plots the distribution of bank treatment measured by equation 1. The dashed line indicates the weighted-by-size median treatment.

Figure 3 plots the distribution of Treatment_f across lenders. We can see large heterogeneity in takeover. The dashed line indicates the median of bank treatment, weighted by pre-Covid market share. We use this value to split financial institutions into two groups and plot the corresponding evolution of credit and delinquency rates in Figure 4. Panel (a) shows the evolution of credit and provides evidence that treatment was orthogonal to credit growth before the program. It also shows that treatment predicts a rapid and persistent expansion of credit. Panel (b) shows the evolution of delinquency. We can observe that treatment does not determine the evolution of delinquency before the program. Finally, highly treated banks were capable of reducing delinquency rates during the recession. The difference of 3 percentage points at the peak is economically significant since aggregate delinquency is 11 percent among small firms.

Figure 4: Credit, Delinquency and Bank Treatment



(a) Total Loans

(b) Delinquency Rates

This figure plots the evolution of credit and delinquency rates for high and low treated banks according to our measure of treatment defined by equation (1). Panel (a) plots credit growth rate measured by the value of credit in a given point in time relative to the corresponding value in 2019q4. Panel (b) plots delinquency rates growth measured by the share of outstanding debt with more than 30 days of repayment delay in a given point in time minus the corresponding value in 2019q4. The dashed line corresponds to 2020q1, the quarter prior to the program.

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 normal loans, i.e., those not guaranteed by government, by estimating the following equation:

$$Y_{ift} = \theta \times \text{Treatment}_f \times \text{Post}_t + \delta_{if} + \delta_{it} + \delta_{q(f),t} + u_{ift} \tag{2}$$

where Y_{ift} denotes the balance of total loans and normal loans (in logs) that firm i has with lender f in period t, and Treatment_f is the standardized treatment defined by equation (1). We include firm-bank fixed effects δ_{if} to control for match-specific time-invariant characteristics such as lender specialization in a given industry. δ_{it} denote firm-by-period fixed effects and remove any time-varying shock at the firm level. A potential concern is that bigger lenders might be more likely to serve bigger firms that are better prepared to deal with Covid-19 restrictions using internal resources. Moreover, bigger lenders might be able to bid a lower interest rate and take more guarantees. We deal with this concern by including time-varying fixed effects for each quartile of the lender size distribution $\delta_{q(b),t}$, 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 small firm access to loan guarantees and to estimate the response of small firm performance measured by delinquency rates. We do so by constructing the following treatment:

$$\text{Treatment}_i = \sum_f \frac{L_{if}}{L_i} \times \text{Treatment}_f \tag{3}$$

where L_{if} denotes the outstanding debt that firm i holds with lender f in December 2019 and Treatment_f is defined in equation (1). Then we estimate the following equation for multiple firm-level outcomes:

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

where Y_{it} denotes the balance of total loans and normal loans (in logs), and delinquency rate[8] of firm i 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, and size-bin measured by pre-Covid

[8] 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.

debt. 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 main-lender level.

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 to 4 in Table 5. We find that one standard deviation higher treatment leads to a 11% increase in credit supply in our benchmark specification reported in column 3. Our results are robust to different specifications that partially exclude fixed effects as reported in columns 1 to 4.

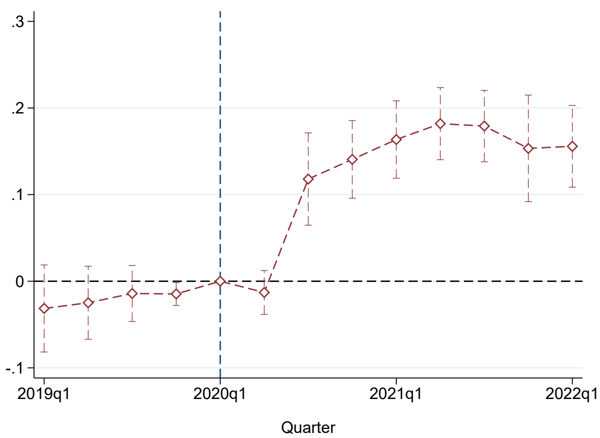
Table 5: Effect of Loan Guarantees on Credit Supply

	Total Loans				Non-Covid-19 Loans			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Treatment}_{bk} \times \text{Post}_t$	0.161***	0.095**	0.107***	0.093***	-0.515***	-0.301***	-0.218***	-0.147***
	(0.039)	(0.047)	(0.022)	(0.023)	(0.156)	(0.110)	(0.053)	(0.045)
Observations	37.8M	22.1M	22.1M	19.4M	37.1M	21.5M	21.5M	18.9M
Fixed Effects								
Firm	✓	✗	✗	✗	✓	✗	✗	✗
Bank	✓	✗	✗	✗	✓	✗	✗	✗
Time	✓	✗	✗	✗	✓	✗	✗	✗
Firm-time	✗	✓	✓	✗	✗	✓	✓	✗
Firm-bank	✗	✓	✓	✓	✗	✓	✓	✓
Bank type-time	✗	✗	✓	✗	✗	✗	✓	✗
Firm-bank type-time	✗	✗	✗	✓	✗	✗	✗	✓
Bank size-time	✗	✗	✗	✓	✗	✗	✗	✓

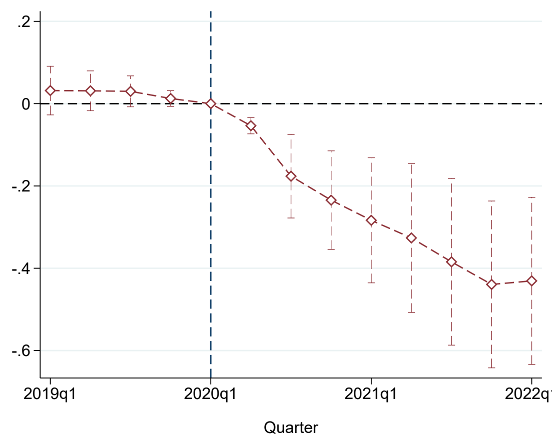
This table shows the effect of the program on the balance of total loans and non-Covid-19 loans at the bank-firm level. Treatment is standardized. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the bank level. Observations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

Panel (a) in figure 5 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 guarantees were distributed. The balance of loans experience a significant and persistent increase since the third quarter of 2020. Figure A2 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.

Figure 5: 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. Confidence intervals at 95%.

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 normal loans. We estimate equation (2) using the log of normal loans as our dependent variable. We report our results in columns 5 to 8 of Table 5. We estimate that one standard deviation higher treatment leads to a decline of 22% in the supply of normal loans.

We plot the event study graphs for the response of normal loans in Panel (b) of figure 5. We include the same fixed effects used in our benchmark specification. We find no evidence of pre-trends. The balance of normal loans exhibit a steady decline after the program. Figure A3 in the Appendix plots event-study graphs for the other specifications. Our results indicate that the program reduced the supply of normal loans, consistent with the crowding out hypothesis. However, this reduction in normal loans is more than compensated by the expansion of guaranteed loans as we showed above.

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 imply 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.

Table 6: Lending Relationships, Credit, and Delinquency Rates

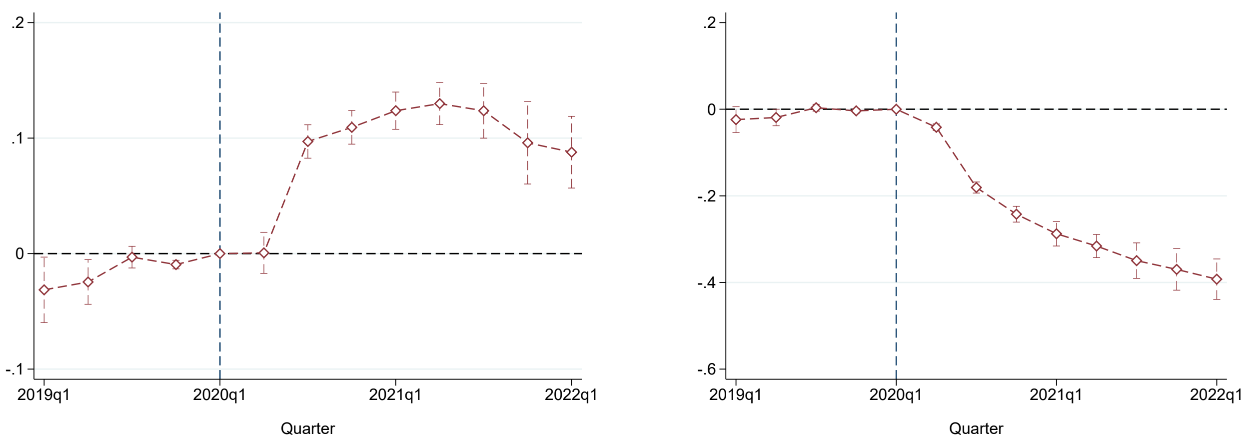
	Total (1)	Non-Covid-19 (2)	Delinquency (3)
$\text{Treatment}_i \times \text{Post}_t$	0.103***	-0.242***	-0.031***
	(0.022)	(0.016)	(0.005)
Fixed Effects			
Firm	✓	✓	✓
City-period	✓	✓	✓
Industry-period	✓	✓	✓
Risk group-period	✓	✓	✓
Age group-period	✓	✓	✓
Debt size bin-period	✓	✓	✓
Observations	12.4M	12.2M	12.4M

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.

Our results are reported in column 1 of Table 6. 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 6. 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. Figure A4 in the Appendix shows quarterly treatment effects for other specifications that partially exclude fixed effects, we find similar patterns. Our results indicate that lending relationships play a key role in shaping the ability of firms to obtain guaranteed loans.

While this result shows that better connected firms obtain more credit, it does not tell us whether normal loans can partially help worse connected firms or not. We address this question by estimating equation (4) using the balance of normal loans as our dependent variable. We report our results in column 2 of Table 6. One standard deviation better connected firms have a 24% 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 6 reports quarterly treatment effects, showing no evidence of pre-trends.

Figure 6: Lending Relationships and Credit



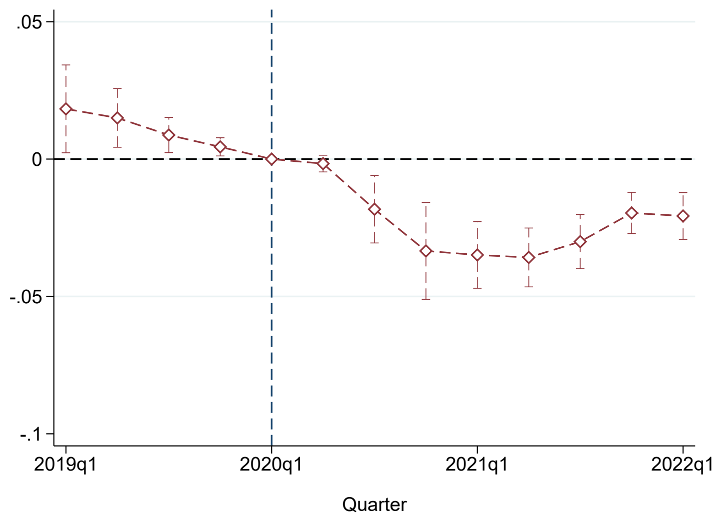
(a) Total Loans

(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 6. 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 7 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. Figure A5 in the Appendix shows quarterly treatment effects for other specifications that partially exclude fixed effects, we find similar patterns and no evidence of pre-trends.

Figure 7: 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. The decline of delinquency is consistent with the unprecedented need of external financing due to Covid-19 restrictions, which offsets firm risk-shifting incentives and lower lender screening. In the next section, we explore heterogeneity across firms 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:

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

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 7. 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.

Table 7: Elasticity of Delinquency Rates to Total Credit

	All firms (1)	Bottom Quintiles (2)	Top Quintil (3)
ln total loans	-0.304*** (0.053)	-0.463*** (0.088)	-0.143*** (0.010)
Observations	12.4M	9.5M	2.9M
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.

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 bigger firms and the rest as smaller borrowers. Then, we estimate equation (5) for each group of firms. Bigger 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 7. The elasticity of delinquency rates to credit among smaller firms is four times that of bigger borrowers, suggesting that smaller companies face higher needs of external financing during the Covid-19 recession.

5.1 Micro-finance institutions and allocation of guarantees

We now study the allocation of guarantees across smaller and bigger 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 8. Small firms are more sensitive than bigger 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 8: 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***	-0.200***	-0.629***	-0.127***
	(0.045)	(0.011)	(0.033)	(0.009)
Observations	6.2M	1.3M	3.3M	1.6M
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 9 reports the share of smaller and bigger firms in the portfolio of MFIs and traditional banks' pre-Covid debt and guaranteed loans. The first two rows report these shares for MFIs. We can observe that, despite bigger firms representing a higher share of MFIs portfolio of pre-Covid loans, they distribute guarantees equally across smaller and bigger clients. On the other hand, traditional banks portfolios of pre-Covid debt and loan guarantees are both concentrated towards bigger borrowers. Thus, MFIs play a critical role in reaching out small, more sensitive borrowers. However, their participation in the program was limited. They represent 52% of pre-Covid loans but obtained only 20% of guarantees. In the next section, we explore the gains from MFIs participation in the program.

Table 9: 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	.53
	Top Quintile	.71	.47
Banks	Bottom Quintiles	.09	.18
	Top Quintile	.91	.82

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

We conduct a back of the envelope calculation to measure the gains from the observed MFIs participation using our reduced-form evidence. Given our estimates, the program reduced delinquency by 5 percentage points. Instead, if all guarantees would have been allocated through traditional banks, aggregate delinquency would have declined by 3.5 percentage points. We further explore this question in the next section, exploiting our micro-data to calibrate the whole distribution of treatment effects and size across firms and financial institutions.

6 Model

We build a theoretical model to rationalize our empirical results and perform counterfactual analysis. Our framework extends recent work by Joaquim and Netto (2022), incorporating two types of financial intermediaries. We describe our building blocks and main results below.

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 a recession as a liquidity 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, and liquidity 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 as follows:

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

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

6.2 Lenders

There are two types of financial intermediaries, traditional banks and Micro-Finance Institutions, facing two different distributions of clients. Traditional banks tend to serve bigger 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 $G^{\text{MFI}}(b,\rho)$. MFIs distribute a given fraction γ_{MFI} of total guarantees, which denotes their participation in the program. When firms survive, loans are repaid and, additionally, banks obtain $\psi_F b_j$, which represents future profits from preserving the lending relationship with firm j. If firms survive without loan guarantees, the relationship ends with probability ψ_C and, while outstanding debt is still repaid, lenders do not get any future profits from this relationship. If firms do not survive, lenders get a fraction δ of outstanding debt. Thus, lender k gets the following expected profits from client j:

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

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

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

Then, 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 $\Phi_j(0)$. 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 $G(\rho_j, b_j) = G^B(\rho_j, b_j)/(1 - s^{\text{MFI}}) + G^{\text{MFI}}(\rho_j, b_j)/s^{\text{MFI}}$ 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 the value of lending relationships 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 size-dependent 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 traditional 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 10: Model Calibration

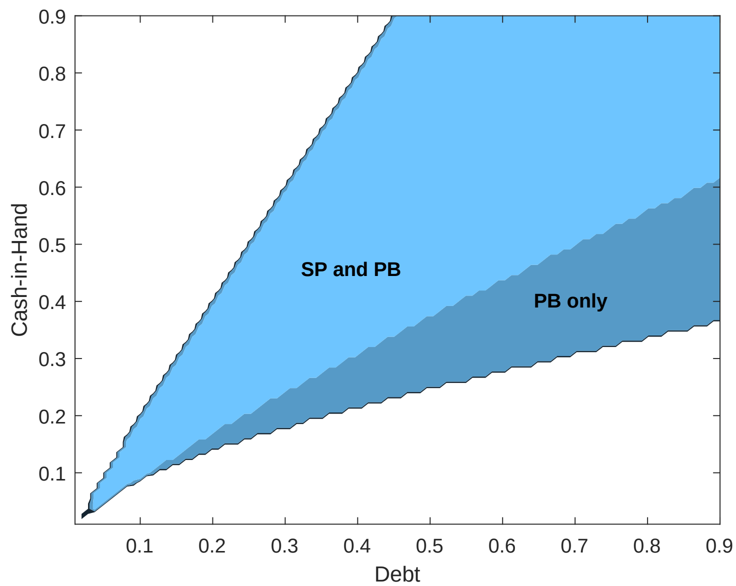
	Description	Value	Targeted Moments
α_b^{MFI}, μ_b^{MFI}	Debt distribution across MFI clients	1 and 16	Bank clients share of debt and cash-holdings,
α_b^{B}, μ_b^{B}	Debt distributi on across bank clients	2 and 18	aggregate leverage of bank and MFI clients,
α_ρ^{MFI}, μ_ρ^{MFI}	Revenue distribution across 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 8 plots the region of firms attended by the social planner and traditional 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.

Figure 8: 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.

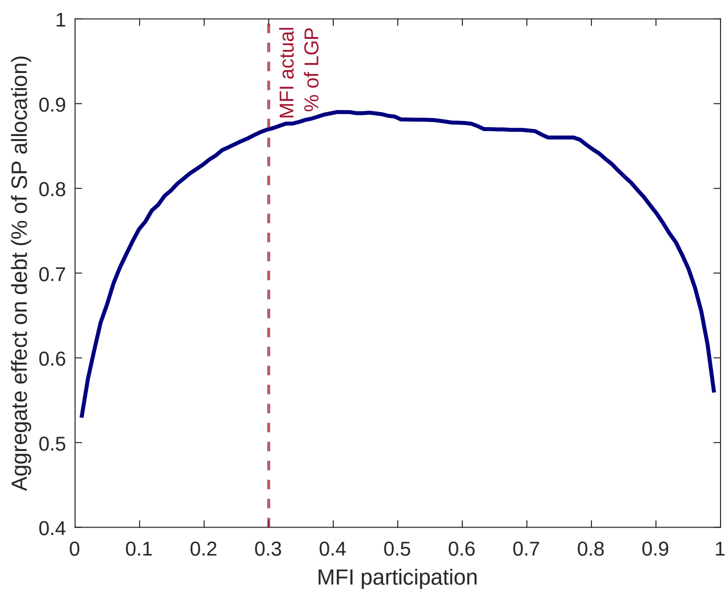
The dark blue area plots the region of firms attend in the market equilibrium only, where banks solve the problem in equation (10). We can notice that, in our calibrated model, traditional banks are more likely to attend bigger clients relative to the social planner. This is because of the second term 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.

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:

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

Figure 9 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 traditional 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 82%. Further increasing MFI's participation to the optimal level leads to small additional gains.

Figure 9: 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.

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).

7 Conclusions

Microfinance institutions have exhibited a steady growth in most emerging markets over the last decades. However, whether they can promote economic development in the long-run or foster economic recovery in the short-run remain open questions. In this paper we study a huge program of loan guarantees implemented in Peru during the last recession to shed light on the role of MFIs in shaping the allocation and aggregate impact of financial stimulus in developing countries.

We find that loan guarantees increase credit and improve small firm performance with substantial heterogeneous effects. We document that the decline in delinquency rates is five times bigger for smaller borrowers, and MFIs play a key role in distributing guarantees to this group of firms. We build a stylized model where MFIs and traditional banks maximize expected profits, facing poaching threats and different types of clients, as observed in the data. Our model indicates that if all guarantees were distributed by traditional 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 82%. Further increasing MFI's participation to the optimal level leads to tiny additional gains.

Overall, our paper highlights the role of microfinance institutions in shaping the aggregate impact of financial stimulus policies in emerging markets. We provide evidence that MFIs can improve the effectiveness of financial policy by targeting small, highly sensitive entrepreneurs.

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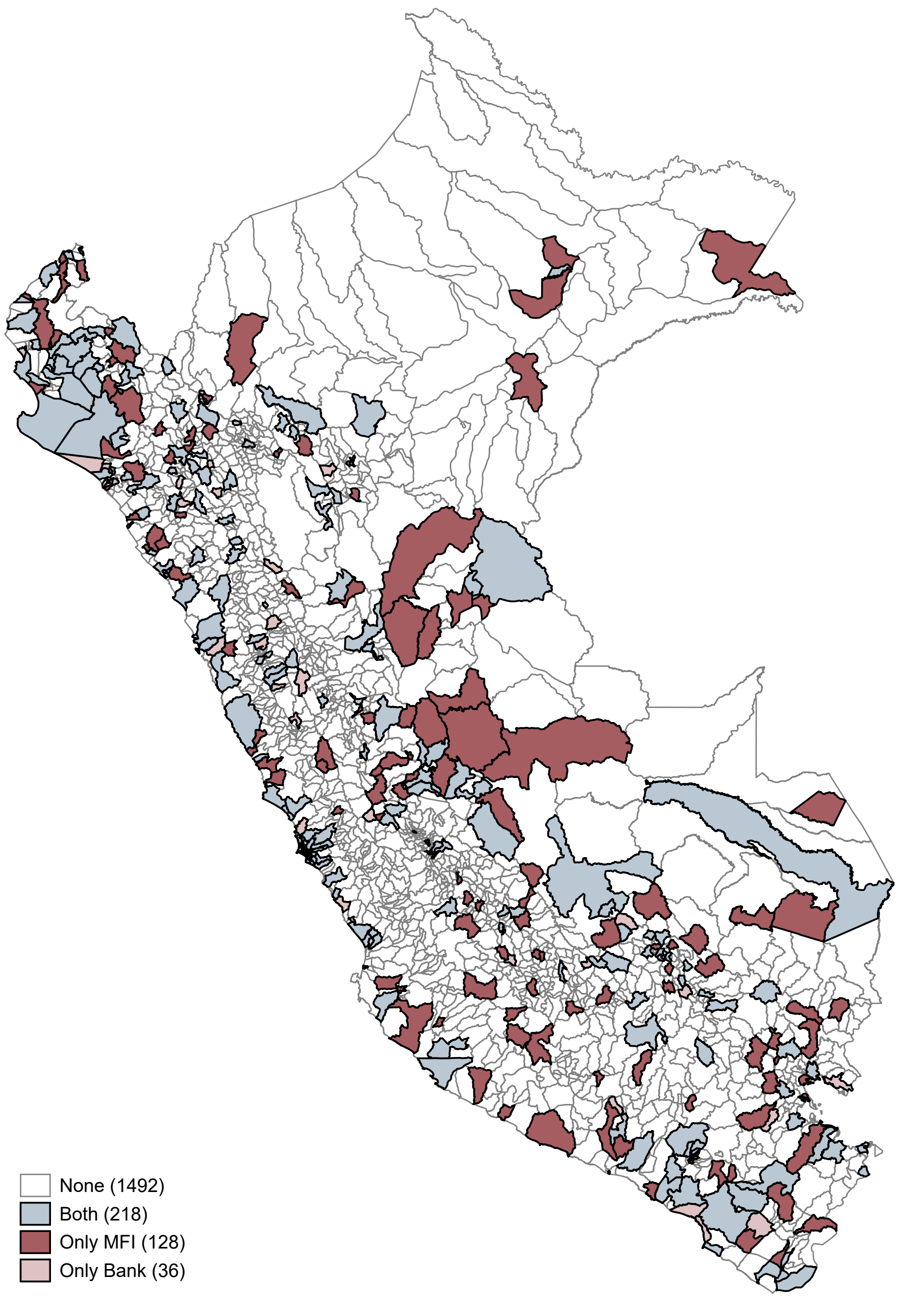
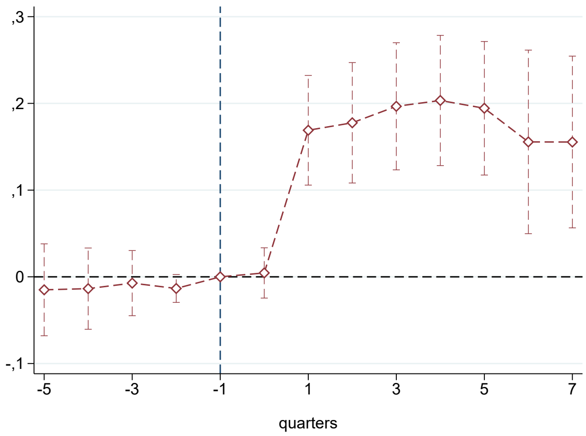
Appendix A

Figure A1: Geographical Distribution of Financial Institutions



Appendix B: Additional Specifications

Figure A2: Effect of Loan Guarantees on Total Credit



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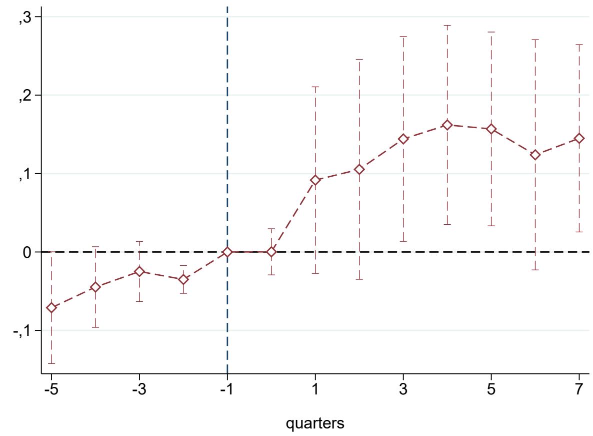

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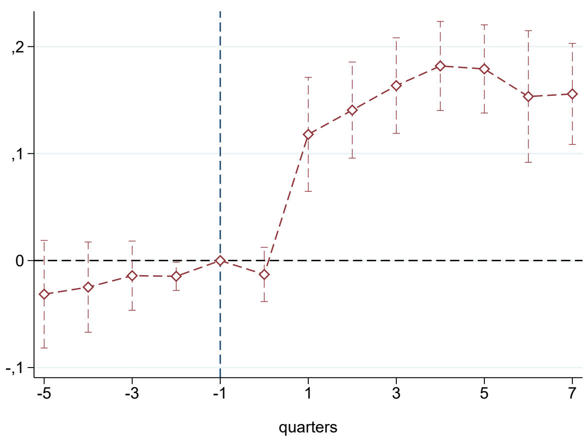

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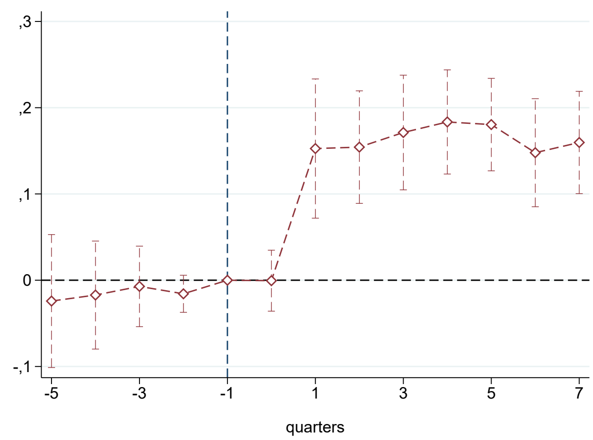
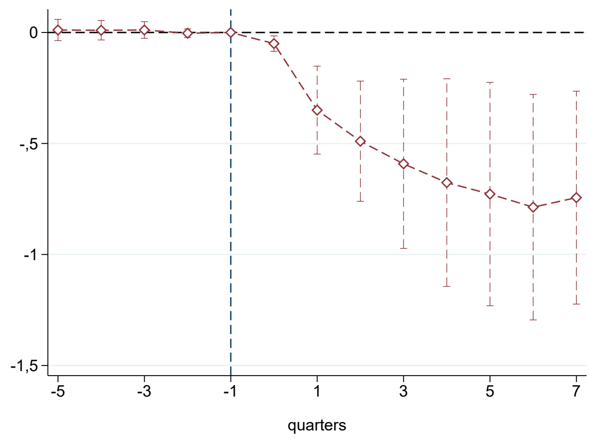


(b) Column (4)

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 A3: Effect of the Program on Non-Covid-19 Loans



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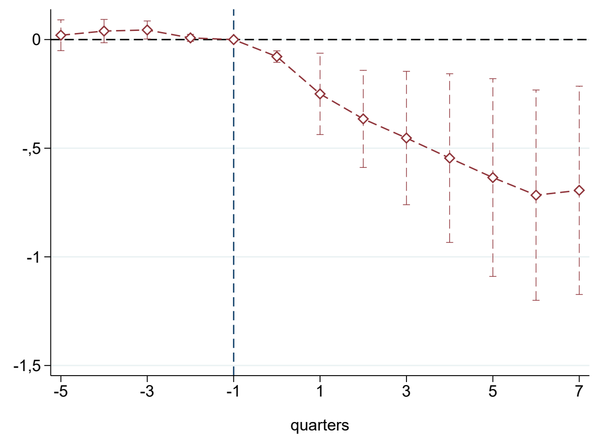

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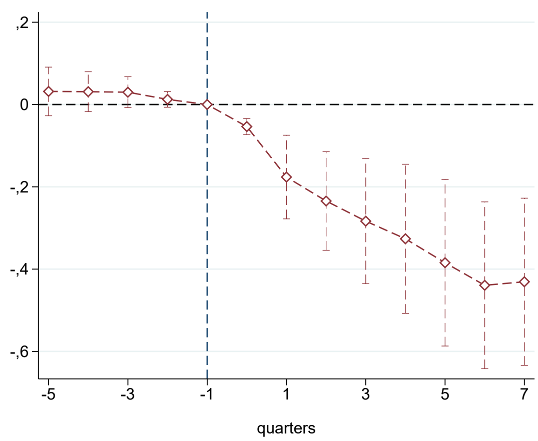

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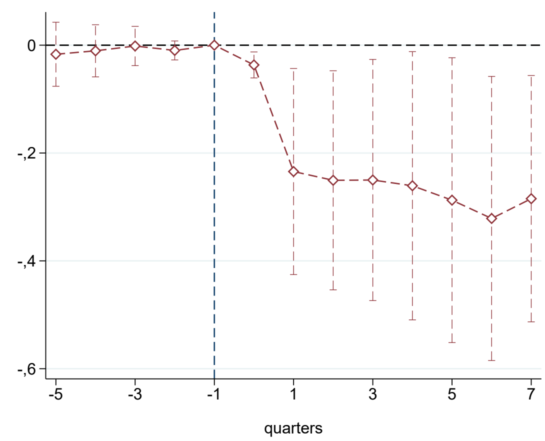
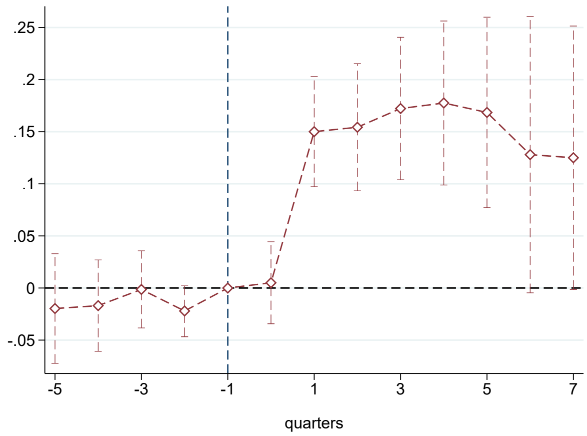


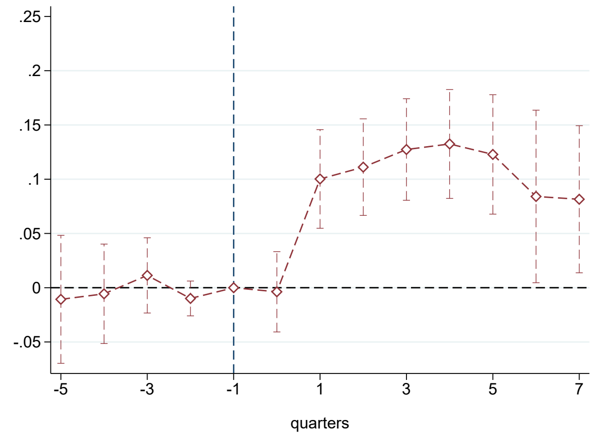
(b) Column (4)

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.

Figure A4: Effect of the Program on Firm-level Credit



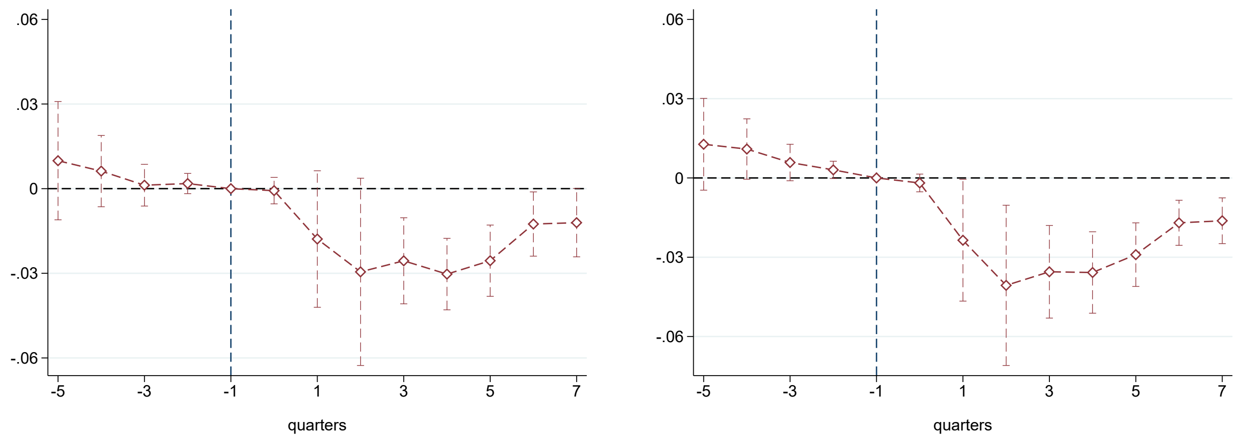
(a) Firm and Time FE



(b) Firm and Size×Time FE

This figure plots the quarterly effects of being better connected to treated banks on firm-level credit. 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.

Figure A5: Effect of the Program on Firm-level Delinquency



(a) Firm and Time FE

(b) Firm and Size×Time FE

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.