Financial Stimulus and Microfinance Institutions in Emerging Markets*

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Abstract

This paper quantifies how microfinance institutions (MFIs) shape the allocation and aggregate effect of financial stimulus policies in emerging markets. We analyze a large-scale loan guarantee program implemented in Peru during the COVID-19 recession. Using administrative data covering the universe of small business loans, we document that the program expanded credit supply with substantial heterogeneous effects on small firm performance. A 10 percent increase in credit reduced delinquency rates by 5 percentage points for the smallest borrowers versus just 1 percentage point for larger ones (top quintile). MFIs played a crucial distributional role, allocating 50 percent of their guarantees to the smallest, most responsive firms—compared to traditional banks' 20 percent. We develop a theoretical model where MFIs and traditional banks serve distinct clients and allocate guarantees to maximize expected profits. Our calibrated model shows that MFIs' participation increased debt saved from default by 30 percent relative to a counterfactual scenario with only traditional banks. Our results show that lender composition is a critical determinant of financial stimulus effectiveness during recessions.

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1 Introduction

Small firms face severe credit constraints in emerging markets, with informational frictions playing a key role. When hard information is scarce—as is typically the case for these firms—financial institutions must invest in relationship lending to gather soft information. While traditional banks predominantly rely on hard information, microfinance institutions (MFIs) are often structured to address these frictions: their local presence, in-person interactions, and tailored products (e.g., microcredit) may facilitate building lending relationships in segments where traditional banks cannot. Over the past decades, many developing economies have promoted MFI expansion to improve small-firm credit access. Yet, whether they can generate meaningful long-term development impacts or foster recovery during economic downturns are open questions.

This paper examines how microfinance institutions shape the allocation of financial stimulus and, through this channel, the aggregate effectiveness of financial policy during recessions. The potential for MFIs to improve the allocation of financial stimulus is theoretically ambiguous. On one hand, small borrowers may exhibit greater sensitivity to financial conditions during downturns. If MFIs—with their specialization in small business lending—can effectively target these high-sensitivity firms, they could amplify the macroeconomic impact of financial policy. On the other hand, the opacity of small firms combined with moral hazard concerns (e.g., risk-shifting behavior under higher debt ratios) suggests that MFI-led stimulus allocation could increase financial sector fragility, potentially dampening the effectiveness of financial interventions. This tension underscores why the net impact of MFIs on stimulus allocation remains fundamentally an empirical question.

We analyze this question in the context of *Reactiva Perú*, a large-scale loan guarantee program implemented by the Peruvian government during the COVID-19 pandemic. This setting offers unique advantages for studying MFIs in emerging markets. First, Peru represents a leading example of microfinance development, ranking consistently among the top markets for MFIs according to the Inter-American Development Bank.[1] The Peruvian microfinance sector is particularly mature, accounting for over 50 percent of all small-firm lending. Second, comprehensive regulatory reporting requirements provide loan-level data on firm debt across both traditional banks and MFIs, enabling precise measurement of credit balances. Third, the

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

program's scale—equivalent to 8% of GDP—might lead to important general equilibrium effects, while the Central Bank's adjustments to the policy design to incentivize MFIs' participation created additional variation in lender behavior. This combination of institutional features and data quality allows us to cleanly estimate the causal effect of loan guarantees on small firms, and quantify how MFI participation shapes aggregate effectiveness of financial stimulus.

We use monthly loan-level data covering the universe of small firms' lending relationships with traditional banks and MFIs operating in Peru from 2019 to 2021. For each lender-firm pair, we observe outstanding loan balances, days past due, and geographic location of loan origination. Firm-level characteristics include industry classification, age, and lender-reported risk ratings. These financial data are merged with annual tax records containing sales, wage bills, and capital stock for all formally registered small firms. This comprehensive dataset provides three key features: First, it captures the entire formal credit market, eliminating sampling concerns. Second, the combination of financial and real outcomes allows us to precisely measure firm performance. Third, the granularity of our data enables us to trace how loan guarantee allocations vary across lender types.

We estimate the program's causal effects using a difference-in-differences design that exploits variation in the intensity of loan guarantee uptake across financial institutions, adapting the reimbursement shock framework of Granja et al. (2022)[2]. We compare small firm credit with high- versus low-exposure lenders, before and after the intervention. Our design saturates the model with firm fixed effects to absorb demand shocks, as in Khwaja and Mian (2008), isolating the supply-side response to loan guarantees.

Our identifying assumption is that, absent the program, credit supply would have followed parallel trends across lenders with different treatment intensities. We provide evidence supporting our identification in two ways. First, we plot event study graphs confirming null effects of our treatment measure on credit outcomes during pre-treatment periods. Second, while our identification does not necessarily require banks to be similar in levels, we compare banks within size quartiles, effectively controlling for time-varying shocks that might differentially affect larger banks. By doing so, we mitigate concerns about endogenous matching between bank size and firm resilience (e.g., larger banks serving more resilient firms).

[2]Specifically, we define bank treatment as their share of small business loan guarantees relative to their pre-recession small business loan market share

A remaining concern is that guarantee uptake might correlate with borrower-specific shocks (e.g., lenders seeking more guarantees precisely because their clients were harder hit by the recession). We exploit a three-month delay in program implementation—a period with COVID-19 restrictions but no guarantees—to test this possibility. We find zero correlation between our treatment measure and both loan balances and repayment delays during this window. Our result suggests that the impact of the past recession was difficult to predict, especially for small firms where information frictions are severe. While we cannot rule out all possible confounders, this pattern is consistent with lenders' guarantee uptake being orthogonal to borrower-specific trends.

We present our empirical results in two main blocks. First, we estimate the program's average effects on credit and firm performance. Following the Khwaja and Mian (2008) framework with firm-time fixed effects, we find that financial institutions with one standard deviation greater uptake intensity increased credit supply by 11 percent while reducing non-guaranteed lending by 22 percent, consistent with partial crowding out of private credit. These results only reflect relative effects across lenders, i.e., they indicate that the program expanded credit supply of highly treated lenders, relative to less treated ones, for the same firm. To estimate 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 compute a firm-level treatment measure by weighting bank treatment with pre-crisis lending shares (Jimenez et al. 2020). A one standard deviation increase in firm exposure leads to a 10 percent expansion in total credit and a 24 percent contraction in non-guaranteed loans, highlighting how pre-existing lending relationships determined access to guaranteed credit.

We then estimate the effect of the program on delinquency rates using a difference-in-differences instrumental variable approach, where our firm-level treatment serves as instrument to estimate the elasticity of delinquency to credit. Our instrumental variable analysis reveals that a 10 percent increase in credit reduces delinquency rates by 3 percentage points. This effect suggests that easing financing constraints played a dominant role in improving firm performance during the crisis, outweighing potential alternative channels like risk-shifting or weakened screening incentives.

The second part of our analysis examines the allocation of loan guarantees and how treatment effects vary in the cross section of small firms. First, we document striking differences in lender specialization over firm size bins: traditional banks concentrate 98 percent of small firm loans in the top debt decile, while MFIs allocate just 59 percent of their portfolio to these larger firms. These patterns are robust to controlling for industry and location. We then document that treatment effects vary dramatically with firm size. A 10 percent credit expansion reduces delinquency by 5 percentage points for smallest firms (bottom 80 percent of the debt distribution) versus just 1 percentage point for larger firms (top 20 percent).[3]

This size-dependent pattern holds consistently across both MFI and traditional bank clients, and are not driven by industry nor location specific characteristics. Finally, we document that the allocation of guarantees is consistent with lender specialization. MFIs allocate 50 percent of guarantees to smaller, more sensitive borrowers compared to traditional banks' 20 percent allocation to this segment. A back-of-the-envelope calculation suggests that the program reduced aggregate delinquency by 12 percentage points, under the observed participation of MFIs, compared to 8 percentage points under a counterfactual scenario where only traditional banks distributed guarantees. Our results indicate that lender participation shapes the allocation of financial stimulus and, through this channel, the aggregate impact of the policy.

Motivated by our empirical findings, we develop a theoretical model that rationalizes the observed patterns and enables counterfactual policy analysis. Building on the framework of Joaquim and Netto (2022), we incorporate lender heterogeneity by modeling two distinct financial intermediaries who maximize expected profits facing different distributions of clients: MFIs that specialize in smaller firms with limited debt and cash reserves, and traditional banks that predominantly serve larger firms. Firms in our model are heterogeneous in their initial debt and cash-on-hand, and face idiosyncratic liquidity shocks that jointly determine their survival probabilities with and without loan guarantees.

The model includes two key features that create strategic incentives in loan guarantee allocation: lenders face poaching threats only among clients who do not receive guarantees, and the value of lending relationships is proportional to borrower size. We calibrate the joint distribution of firm characteristics separately for MFI and bank clients to match empirical moments from our data. The liquidity shock distribution is disciplined by our estimated size-dependent treatment effects, and poaching threats are calibrated to match the observed share of unattended firms switching lenders after the program. The resulting framework generates the following trade-

[3] It is worth noticing that here we refer to smaller or larger firms within the market of small business loans. All firms included in our analysis are small firms.

off: lenders balance treatment effect against probability of survival without the program when allocating guarantees

Our model reveals how lender incentives are not necessarily aligned with those of the social planner, leading to potential misallocation of guarantees. While a social planner would allocate guarantees to maximize aggregate treatment effects, private lenders distort this allocation by overweighting the probability of survival without the program, due to poaching threats. The model also highlights how different lender participation shapes stimulus effectiveness during recessions. Because of their clients' type, traditional banks disproportionally serve bigger firms with relatively larger probability of survival without guarantees. The optimal participation of MFIs maximizes non-defaulting debt, relative to the social planner equilibrium, by appropriately weighting MFIs' comparative advantage in serving smaller, more responsive firms against banks' scale advantages.

We use our model for two main purposes. First, we study the allocation of guarantees in the market equilibrium and compare it to the social planner's. We find that for a given level of cash, firms with very low debt are not attended by the social planner as they can survive without guarantees. Similarly, highly indebted firms are not attended because they have a low probability of survival even with assistance. In the market equilibrium, lenders disproportionately serve larger clients compared to the social planner because such clients are relatively more profitable than smaller ones in the market equilibrium, relative to the social planner's.

Second, we conduct two counterfactual analysis. We start by quantifying the optimal MFI participation. The decentralized allocation, under the observed MFI participation, achieves 80 percent of the social planner's non-defaulting debt, with the gap reflecting excessive focus on larger, less responsive firms. In a bank-only scenario, this would fall below 50 percent, indicating that traditional banks are more sensitive to overweighting larger firms. At the optimal level, MFIs should distribute 57 percent of guarantees and the decentralized allocation saves the same amount of debt as the social planner's. Moving to a MFI-only scenario, the decentralized allocation would achieve only around 50 percent of the social planner's non-defaulting debt, cautioning over-reliance on MFIs, because at high participation rates, they would serve firms with either low treatment effects or insufficient debt to improve the aggregate impact of the program.

Overall, our paper demonstrates that MFIs can significantly enhance the aggregate impact of financial stimulus in emerging markets by channeling resources to smaller, more responsive borrowers. This lender specialization channel represents an important determinant of financial policy effectiveness during economic downturns.

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), documenting small real effects of microcredit in normal times (Angelucci et al. (2015), Augsburg et al. (2015), Tarozzi et al. (2015), Attanasio et al. (2015)). More recent studies have documented that general equilibrium adjustments and large-scale shocks can lead to significant real effects of microcredit (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, namely, 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 stimulus, and then, lender specialization becomes critical to target smaller, more sensitive firms. 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 microfinance 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 administrative datasets covering financial and real outcomes for the universe of formal small firms in Peru.

1. Credit registry data. This is a loan-level data from the *Reporte Crediticio de Deudores*, provided by the Central Bank of Peru. This quarterly panel spans 2019–2021 and includes outstanding loan balances, days past due, and the city of loan origination for each firm-bank relationship. Firm-level characteristics include industry classification, lender-reported credit risk ratings, and the year of first loan origination. On the lender side, we observe a unique ID used for bank regulation purposes, the type of lender (traditional bank or microfinance institution) and balance sheet information. We use this data to estimate the effects of government guarantees on credit and delinquency rates.

2. Tax reports data. The second dataset comprises firm-level tax records from 2018–2022, containing annual sales, capital stock, and employment. These records include a unique firm tax ID, enabling precise merging with credit registry data. Geographic location and industry classification are also observed, allowing us to control for local economic conditions and sector-specific trends when estimating the policy's effects.

2.2 The Peruvian Credit Market

The Peruvian banking sector has 52 financial institutions offering business loans: 15 traditional banks and 37 microfinance institutions (MFIs). Loans are categorized into five segments based on firm size, measured by sales and outstanding debt: micro-credit, small business loans, and loans to medium-size firms, large firms, and corporations. For example, micro-credit is defined as loans to businesses whose total debt in the banking sector is below \$6 thousand. On the other hand, loans to corporations are defined as credit to businesses whose total sales in the past two years were above \$60 million.

Table 1 provides summary statistics of lender characteristics as of December 2019. The size distribution is highly skewed: columns (1) and (2) show the average credit is \$1 billion, while the median is \$169 million. The market is highly concentrated, as reported in columns (3) and (4). The top 5 lenders holding 80 percent of total credit. MFIs account for 13 percent of aggregate lending but play a predominant role in smaller loans—they originate 68 percent of micro-credit and 47 percent of small business loans. The number of lenders declines with loan size; only 13 banks serve the corporate segment, compared to 42 in micro-credit.

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

Table 2 reports summary statistics for firms with positive debt in December 2019. Column (1) and (2) reveal similar skewness in firm debt. The average value is around $6 thousand, while the median is around $500. Column (3) shows the share of delinquent firms (more than 30 days of repayment delay) equal to 12 percent in December 2019. Finally, column (4) shows that our sample is composed of around 3 million of firms, most of them in the segment of micro-credit (around 2.3 million). Only 500 firms qualify for corporate loans, highlighting the prevalence of small businesses in Peru's credit market.

2.3 Lender Specialization: Traditional Banks versus MFIs

MFIs expanded significantly in Peru over the past two decades, driven by deregulation of geographical presence. The industry has matured and plays a key role in the segment of small business loans nowadays.

Figure 1 plots credit growth and delinquency rates for small business loans in a more recent period between 2016 and 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. MFI credit grew 50 percent cumulatively, outpacing traditional banks' 20 percent growth, and raised their market share from 46 to 53 percent in the market of small business loans. The rapid expansion of microfinance institutions was coupled with stable delinquency rates. Panel (b) shows that delinquency rates remained stable at 7% for MFIs, slightly below traditional banks' rates, suggesting a better MFIs' technology in this segment.

Table 3 compares the two types of lenders. Columns (1) and (2) consider traditional banks,

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

while columns (3) and (4) consider MFIs. Additionally, the top panel considers the whole activities of lenders, while the bottom panel only considers small business loans. Traditional banks are larger, with 20 times bigger assets and 16 times more credit. The average traditional bank serves more cities but exhibits higher geographical concentration.[5].

MFIs are more profitable, especially the top 10 with a ROA of 1.7 percent, reported in columns (5) and (6). The average top 10 MFI attends more markets than the average traditional bank, and also exhibit a much lower geographical concentration. Moreover, considering only small business loans, the average top 10 MFI provides $360 million in loans, while the average traditional bank provides $420 million.

Figure A1 highlights cities where traditional banks and micro-finance institutions have active branches in December 2019.[6] Around 80 percent of cities are *financial deserts*, and only 9 percent of banked locations have only traditional banks. In contrast, one third of banked cities have only MFIs' branches. Moreover, while the average city served by traditional banks has 2,442 individuals per square kilometer, the average city where only MFIs are present has 243 individuals per square kilometer.[7] Thus, MFIs play a key role in expanding access geographically.

2.4 The Program of Loan Guarantees

Reactiva Perú, launched in May 2020 by the Ministry of Finance and the Central Reserve Bank, provided loan guarantees to firms in order to mitigate Covid-19 restrictions. The Ministry of Finance served as collateral, while the Central Bank provided liquidity. Of 52 eligible lenders, 28 participated in the program.

Guarantees covered between 80 and 98 percent of loan value (higher for smaller loans), and were allocated via first-price auctions where lenders bid on interest rates. There were separate auctions for each type of business loans. Private lenders were in charge of screening borrowers and allocating loan guarantees. These loans had an average duration of 36 months and were

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

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

[7] The average financial deserts has 69 individuals per square kilometer, the average city with only bank branches has 1,407 individuals, and the average city with both lenders has 2,612 individuals per square kilometer.

granted between May and December 2020. The repayment period started 12 months after the loan was originated. Firms with poor credit rating, exhibiting more than 60 days of repayment delays, were not allowed to participate.

Table 4 provides summary statistics on the program's scale. Column (1) shows the value of guarantees distributed by the program, and column (2) shows the ratio of this value relative to total credit in December 2019, before the recession. Similarly, column (3) shows the total number of clients attended by the program, and column (4) shows the ratio of this number relative to the total number of borrowers in 2019. The program provided \$16 billion of guaranteed loans (29 percent of 2019 credit) and reached 473 thousand firms (16 percent of borrowers). In micro-credit, the program represented 37 percent of outstanding debt but only benefited 14 percent of borrowers, while in large firm loans, the program served 82 percent of eligible firms and represented 34 percent of outstanding credit. Guarantee rates varied by loan size, from 97 percent on micro-credit to 80 percent on loans to corporations.

2.5 Program Participation and Lender Outcomes

Initially, traditional banks dominated in the majority of auctions, even in the segment of small business loans, mainly due to MFIs' higher operational costs, which make their bids uncompetitive. Thus, to ensure small-firm access to loan guarantees, the Central Bank introduced separate MFI-specific auctions, leading to an expansion in MFIs participation in the program.

Figure 2 plots the evolution of credit and delinquency around the intervention and relative to their corresponding pre-recession period. While traditional banks expanded small business loans by 50 percent peak-to-trough, MFIs grew 20 percent with a lag. Credit growth converged among both types of lenders one year after the program. Delinquency fell sharply during the one-year grace period, following the expansion of credit. However, it rose in the post-grace period, with traditional banks reaching a 2 percentage points higher delinquency relative to MFIs.

These patterns suggest that MFIs allocated guarantees more efficiently to sensitive borrowers—a hypothesis we test rigorously in subsequent sections, where we also quantify their role in shaping the aggregate impact of the policy.

3 Empirical Framework

We exploit differences in lenders uptake 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 small business loans as follows:

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

Figure 3 plots the distribution of Treatment_f across lenders. We can see large heterogeneity in take-up. 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, providing evidence that treatment was uncorrelated with aggregate 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 is also uncorrelated with delinquency before the program. Finally, highly treated banks exhibit a reduction in delinquency rates during the recession. The difference of 3 percentage points at the peak is economically meaningful since aggregate delinquency is 11 percent among small firms.

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 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

[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.

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 or include fixed effects as reported in columns 1 to 4.

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 up to the first quarter of the policy, when a negligible 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.

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 loan guarantees, as shown by our estimated total credit response.

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.

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.

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.

Overall, our results show that lending relationships 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.

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 Microfinance institutions and allocation of guarantees

We now study the allocation of guarantees across smaller and bigger firms by type of financial institution. We define microfinance 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 independent of whether they borrow from MFIs or banks. Moreover, the elasticity of each group of firms is not statistically different across financial institutions.

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.

We conduct a back-of-the-envelope calculation, explained in more detail in Appendix C, to measure the gains from the observed MFIs participation using our reduced-form evidence. Given our estimates and the observed participation of MFIs and traditional lenders, the program reduced delinquency by 12 percentage points. Instead, if all guarantees would have been allocated through traditional banks, aggregate delinquency would have declined by 8 percentage points. We further explore this question in the next section, exploiting our micro-data to calibrate the whole distribution of treatment effects across firms and financial institutions.

6 Model

We develop a theoretical model with two primary objectives. First, we aim to rationalize the observed allocation of loan guarantees by showing that the client composition of traditional banks and microfinance institutions' portfolios drives the heterogeneous distribution of credit documented in our empirical analysis. Second, we seek to quantify the optimal participation of MFIs in guarantee programs. To achieve this, we extend the framework of Joaquim and Netto (2022) in two key directions: (i) introducing heterogeneity among financial intermediaries by modeling two distinct lenders, each serving different client segments; and (ii) calibrating the model using micro-level data and our reduced-form estimates.

6.1 Firms

Firms are heterogeneous in their initial debt obligations (b) and cash-in-hand (ρ). We model a recession as a liquidity shock ν that reduces firm cash flows, drawn from the distribution:

$$\tilde{\Phi}(\nu;\eta) = \begin{cases} 0, & \text{if } \nu < 0 \\ \left(\frac{\nu}{c_0}\right)^{\eta}, & \text{if } \nu \leq c_0 \\ 1, & \text{if } \nu > c_0 \end{cases} \tag{6}$$

where $\eta > 0$ determines the shock's distribution. Firms may borrow φb if they participate in the guarantee program. A participating firm i survives the recession if its net cashflow is positive:

$$\rho_i - b_i + \varphi b_i > \nu_i \tag{7}$$

Thus, we can define the effect of the program on firm i's survival probability as follows:

$$T_i \equiv \Pr\left(\nu \leq \rho_i - b_i + \varphi b_i\right) - \Pr\left(\nu \leq \rho_i - b_i\right) \equiv \Phi_i(\varphi) - \Phi_i(0) \tag{8}$$

where $\Phi_i(z) = \widetilde{\Phi}(\rho_i - b_i + z b_i)$. We use delinquency as the empirical counterpart for these survival probabilities.

6.2 Lenders

The model features two types of financial intermediaries, traditional banks and microfinance institutions, indexed by j, serving distinct clients characterized by distributions $G^j(b,\rho)$. MFIs provide an exogenous fraction γ_{MFI} of loan guarantees. When lender j extends a guaranteed loan to firm i, the firm survives with probability $\Phi_i(\varphi)$, repays its debt, and preserves the lending relationship, yielding continuation value $\psi_F b_i$. Without guarantees, the survival probability falls to $\Phi_i(0)$ and the relationship persists only with probability ψ_C due to poaching risks. In both cases, lenders recover a fraction δ of the debt if the firm fails.

Thus, lenders' expected profits from client i depend on guarantee provision decisions $\ell_i^j \in \{0, 1\}$, where $\ell_i^j = 1$ indicates lender j provides a guarantee, as follows:

$$\begin{aligned} \Pi_i^j = {} & \ell_i^j \left\{ \Phi_i(\varphi) \left(1 + \psi_F\right) + \left(1 - \Phi_i(\varphi)\right) \delta \right\} b_i \\ & + \left(1 - \ell_i^j\right) \left\{ \Phi_i(0) \left[\left(1 - \psi_C\right) \left(1 + \psi_F\right) + \psi_C\right] + \left(1 - \Phi_i(0)\right) \delta \right\} b_i \end{aligned} \tag{9}$$

where ψ_F represents the relationship value, ψ_C captures poaching risks, and δ is the recovery rate. This simplifies to $\Pi_i^j = \ell_i^j \Omega_i^j b_i + \Theta_i^j b_i$, with $\Omega_i^j \equiv T_i[(1 - \delta) + \psi_F] + \Phi_i(0)\psi_C\psi_F$ capturing the net benefit of guarantee provision. Lenders solve:

$$\max_{\ell_i^j \in \{0,1\}} \int \ell_i^j \Omega_i^j b_i dG^j(\rho_i, b_i) \qquad \text{s.t.:} \quad \int \ell_i^j \varphi b_i dG^j(\rho_i, b_i) = \gamma_j M \tag{10}$$

The solution reveals a key trade-off: while guarantees improve survival probabilities, lenders must balance firm sensitivity (T_i) and survival probability without guarantees ($\Phi_i(0)$), weighting the latter by poaching threats (ψ_C) and relationship values (ψ_F). This can lead to allocative inefficiencies when lenders prioritize less sensitive firms with higher survival probability without guarantees.

6.3 Constrained First-Best

We define the constrained first-best as the allocation implemented by a social planner who faces the same capacity constraints as private lenders – limited by the total value of guarantees M, the client distribution $G(\rho_i, b_i) = G^{TB}(\rho_i, b_i) + G^{MFI}(\rho_i, b_i)$, and individual debt increase of φ among participants. The planner maximizes total debt saved from default by solving:

$$\max_{\ell_i^{SP} \in [0,1]} \int \ell_i^{SP} T_i b_i dG(\rho_i, b_i) \qquad \text{s.t.:} \quad \int \ell_i^{SP} \varphi b_i dG(\rho_i, b_i) = M \tag{11}$$

where $T_i \equiv \Phi_i(\varphi) - \Phi_i(0)$ measures the treatment effect of guarantees on firm survival. The solution allocates guarantees to firms with the highest $T_i b_i$ product, prioritizing those where guarantees yield maximal social benefit.

Thus, the decentralized equilibrium generates misallocation when private lenders' profitability metric Ω_i^j deviates from the social planner's criterion T_i. As shown above, this distortion depends on the baseline survival probability $\Phi_i(0)$ weighted by poaching risk ψ_C and relationship value ψ_F. Since $\Phi_i(0)$ varies with firm characteristics (b, ρ), the extent of misallocation and optimal lenders' participation depends on the client composition of traditional banks versus MFIs.

6.4 Calibration

We build our calibration in three blocks, each targeting distinct features of the data. Table 10 summarizes the calibrated parameters and their empirical targets.

Client Distributions. We model the joint distribution of firm characteristics (b, ρ) for each lender type $j \in \{\text{TB}, \text{MFI}\}$ using Pareto marginal distributions coupled via Frank's copula. For characteristic $k \in \{\rho, b\}$ and lender j, the marginal CDF follows:

$$G_k^j(x) = \Pr(k \leq x) = \begin{cases} 1 - \left(\frac{x_{\min}^{kj}}{x}\right)^{\alpha^{kj}} & , \text{ if } x \geq x_{\min}^{kj} \\ 0 & , \text{ if } x < x_{\min}^{kj} \end{cases} \tag{12}$$

The dependence between debt (b) and cash flow (ρ) is governed by the copula parameter ζ^j. For MFIs, we calibrate shape parameters $\alpha^{b,\text{MFI}}$ and $\alpha^{\rho,\text{MFI}}$ to match the share of loans and revenue held by their top 20% clients, while ζ^{MFI} targets the debt-revenue correlation among MFI clients. For traditional banks, parameters $\alpha^{b,\text{TB}}$, $\alpha^{\rho,\text{TB}}$, and ζ^{TB} are calibrated to corresponding moments. We normalize average bank client revenue to unity, which determines $x_{\min}^{\rho,\text{TB}}$. The remaining parameters $x_{\min}^{b,\text{TB}}$, $x_{\min}^{b,\text{MFI}}$, and $x_{\min}^{\rho,\text{MFI}}$ are set to match aggregate debt-to-sales ratios (for banks and MFIs' clients, separately) and MFIs' share of small business loans.

Institutional Parameters. We match key features of Peru's financial sector. The MFI client share $s_{\text{MFI}} = 0.75$ reflects the pre-recession market composition, while the recovery rate $\delta = 0.1$ aligns with regulatory estimates. The relationship value $\psi_F = 0.013$ replicates the ratio of bank profits to GDP. The program size M equals 25% of outstanding debt, with MFI participation $\gamma_{\text{MFI}} = 0.2$ matching the actual share of guarantees distributed by MFIs.

Reduced-Form Estimates. The shock distribution parameters (c_0, η) are calibrated to match our estimated treatment effects of 0.45 for bottom-quintile firms and 0.15 for top-quintile firms. The parameter φ targets the observed average debt expansion among program participants. Finally, we estimate the poaching probability ψ_C from regressions of bank-switching behavior on guarantee receipt.

6.5 Equilibrium and Counterfactual Analysis

We use our model to quantify how MFIs' participation shape the allocation and effectiveness of loan guarantees during recessions. We proceed in three steps: we first compare guarantee allocations in the social planner and the decentralized equilibrium, then we compute the optimal MFI market share, and finally, we explore how the severity of recessions affects these results.

Allocation of Guarantees. Our calibrated model compares guarantee allocations under two regimes: the constrained first-best (social planner) and market equilibrium. The social planner's allocation, shown in the top panel of Figure 8, reveals a key trade-off. For a given level of cash ρ, firms with very low debt levels are excluded from the program as they can survive without guarantees. Similarly, highly indebted firms receive no guarantees due to their low survival probabilities even with assistance. The planner concentrates guarantees on intermediate-debt firms, for any given level of revenue ρ, where the marginal benefit is highest.

In the market equilibrium, shown in the middle and bottom panels of Figure 8, allocations diverge significantly by lender type. Traditional banks disproportionately serve larger clients relative to the social planner, as profit maximization leads them to overweight baseline survival probabilities $\Phi_i(0)$ against treatment effects T_i. Their specialization in larger clients, as captured by $G^{\text{TB}}(\rho, b)$, reinforces this bias. In contrast, microfinance institutions focus on smaller borrowers, align more closely with the planner's allocation for smaller firms, reflecting their comparative advantage in this segment.

Figure 10 illustrates this tension by plotting the average treatment effect T_i and the average expected lender profit Ω_i for different quintiles of the debt distribution. We can observe that firms at the bottom four quintiles exhibit a bigger treatment effect than firms at the top. The average expected lender profit is lower than the treatment effect, but this gap declines among bigger borrowers, highlighting lender incentives to provide more guarantees to bigger firms relative to the social planner.

Optimal MFIs' Participation. We conduct a counterfactual analysis shifting the share of guarantees distributed by MFIs to find the optimal participation. We define debt saved by the program as the debt saved from default. For example, if firm i is attended, the program saves $T_i b_i$ from default. Thus, we quantify allocative efficiency through the debt-saved ratio relative to the first-best benchmark:

$$\mathcal{R} \equiv \frac{\int \ell_i^{\mathrm{B}} T_i b_i dG^{\mathrm{B}} + \int \ell_i^{\mathrm{MFI}} T_i b_i dG^{\mathrm{MFI}}}{\int \ell_i^{\mathrm{SP}} T_i b_i dG} \tag{13}$$

Figure 9 plots this ratio for different levels of MFIs participation γ_{MFI}. We can see that, when MFIs do not participate in the program, $\gamma_{\mathrm{MFI}} = 0$, the debt-saved ratio equals 0.5, indicating a 50 percent efficiency loss from excluding MFIs. On the other hand, at the observed MFIs participation, $\gamma_{\mathrm{MFI}} = 0.2$, the debt-saved ratio is 0.8, showing that the Central Bank of Peru recovered 30 percentage points of the efficiency loss. Notice that the optimal participation rate is $\gamma^*_{\mathrm{MFI}} = 0.58$, while full MFI participation reduces the debt-saved ratio to 52 percent. The non-monotonic relationship highlights two critical forces: misalignment of lender incentives and specialization. Private lenders overweight $\Phi_i(0)$ relative to social planner's focus on T_i. In this context, MFIs' advantage in small, sensitive borrowers attenuates traditional banks' specialization in bigger, less sensitive firms.

Loan Guarantees in Soft and Deep Recessions. We conduct a second counterfactual by changing the severity of our recession, governed by the liquidity shock parameter η. Panel (a) of Figure 11 plots the debt-saved ratio in a soft recession with $\eta = 0.001$, i.e., a recessions where small-size shocks are more likely. MFIs play a more important role because small firms are more likely to survive with loan guarantees in mild recessions. Panel (a) in Figure 12 shows that treatment effects are bigger in mild recessions, specially for small borrowers, making MFIs' specialization critical. Thus, the optimal MFI's participation increases the debt-saved ratio in 60 percentage points relative to a traditional bank only scenario.

Panel (b) of Figure 11 plots the debt-saved ratio in a deep recession with $\eta = 2$, i.e., a recession where large shocks are more likely. Lender composition is less important when big shocks are more likely due to a lower treatment effect that increases with debt size, as shown in Panel (b) of Figure 12.

Our model provides three key insights. First, market allocations diverge from the first-best due to lenders' incentives to overweight survival probabilities without the program. Second, MFIs attenuate this distortion by channeling guarantees to smaller, more responsive firms—optimal policy thus requires balancing their participation against traditional banks' scale. Third, the gains from MFIs' specialization are largest in mild downturns, where heterogeneous firm sensitivities are more important.

7 Conclusions

The global expansion of microfinance institutions in emerging markets has raised important questions about their capacity to support long-term economic development and facilitate short-term recovery. This paper examines a large-scale loan guarantee program implemented in Peru during the last recession, providing new evidence on how MFIs shape the allocation and effectiveness of financial stimulus in developing economies.

We show that loan guarantees significantly increased credit supply and improved firm performance, with particularly strong effects for smaller borrowers. The reduction in delinquency rates for smaller firms is five times bigger than for larger recipients, with MFIs playing a critical role in channeling guarantees to this high-sensitivity segment. We develop a model where lenders face different distributions of clients and calibrate it with our micro-data and reduced form estimates. Our model shows that traditional banks alone would have achieved only 50 percent of the constrained first-best non-performing debt, while the actual MFI participation boosted this effectiveness to 80 percent.

These results carry important policy implications. MFIs emerge as complementary actors in financial stabilization efforts, particularly valuable for reaching small entrepreneurs who are most responsive to credit interventions but often underserved by traditional banks. However, our findings caution against over-reliance on MFIs, because at high participation rates, MFIs would necessarily serve firms with either low treatment effects or insufficient debt to improve the aggregate impact of the policy. Our results contribute to a growing literature on how lender specialization shapes macroeconomic outcomes.

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Appendix A: Tables

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 as percentages.

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.

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 as percentages. Geographical concentration for bank b is computed using bank b loans in city c, L_{cb}, as follows: $\sum_c \left(L_{cb}/L_b\right)^2$

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.

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.

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.

Table 7: Elasticity of Delinquency Rates to Total Credit

	All firms	Bottom Quintiles	Top Quintil
	(1)	(2)	(3)
ln total loans	-0.304***	-0.463***	-0.143***
	(0.053)	(0.088)	(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.

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.

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.

Table 10: Model Calibration

Panel A: Distribution of Clients - Micro Data

	Description	Value	Target Moments
$\alpha^{\rho,\mathrm{TB}}$, $x_{\min}^{\rho,\mathrm{TB}}$	Distribution of k (debt or cashflow)	1.02 and 1.3	Share of top 20% (agg. revenue is normalized)
$\alpha^{b,\mathrm{TB}}$, $x_{\min}^{b,\mathrm{TB}}$	for clients attached to lender j	0.9 and 1.5	Share of top 20% and agg. leverage of TB clients
$\alpha^{b,\mathrm{MFI}}$, $x_{\min}^{b,\mathrm{MFI}}$	(TB or MFI) is fully represented	1.4 and 0.7	Share of top 20% and MFI share of SBL
$\alpha^{\rho,\mathrm{MFI}}$, $x_{\min}^{\rho,\mathrm{MFI}}$	by parameters α^{kj}, $x_{\min}^{kj}$, and ρ^j	1.02 and 0.6	Share of top 20% and agg. leverage of MFI clients
ρ^{MFI} and ρ^{TB}		0.3 and 0.3	Empirical correlation between b and ρ

Panel B: Financial Sector - Observable Moments

	Description	Value	Observable Moments
s_{MFI}	MFI share of clients	0.75	Number of clients before Covid
δ	Recovery rate	0.1	Bank supervisor estimates
ψ_F	Lender share of firm future profits	0.013	Financial sector net profits to GDP ratio
M	Size of the program	$0.08 \times$ Tot. Revenue	Guaranteed loans to pre-Covid GDP
γ_{MFI}	MFI share of guarantees	0.2	Guarantees distributed by MFIs

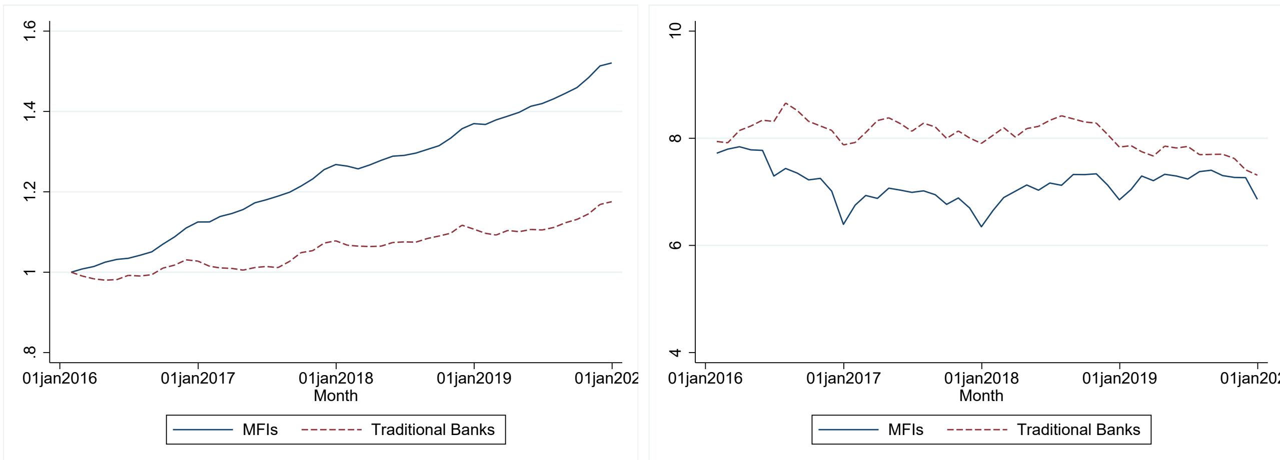
Panel C: Model Calibration - Estimated Moments

	Description	Value	Target Moments
c_0, η	Covid-19 shock distribution	10 and 0.1	Average treatment effects at both quintiles
φ	Guaranteed loans to pre-Covid debt	0.5	Credit growth of participants
ψ_C	Poaching probability	0.01	Prob. of switching main bank if not attended

This table shows the calibrated parameters. Panel A provides the set of parameters calibrated to match the empirical distribution of revenue and debt of MFIs and traditional banks' clients. Specifically, we target the share of debt and revenue held by the top 20 percent of clients, the aggregate leverage ratio, and the correlation between debt and revenue. Additionally, we match the share of debt provided by MFIs. Panel B presents the set of parameters calibrated to match observable moments such as the share of MFIs clients, the recovery rate, financial sector profits relative to GDP, size of the program relative to GDP, and share of MFIs' guarantees. Panel C describes the set of parameters calibrated to match our reduced form estimates such as average treatment effect, treatment effect on smaller and bigger firms, and probability of switching lender for unattended borrowers.

Appendix B: Figures

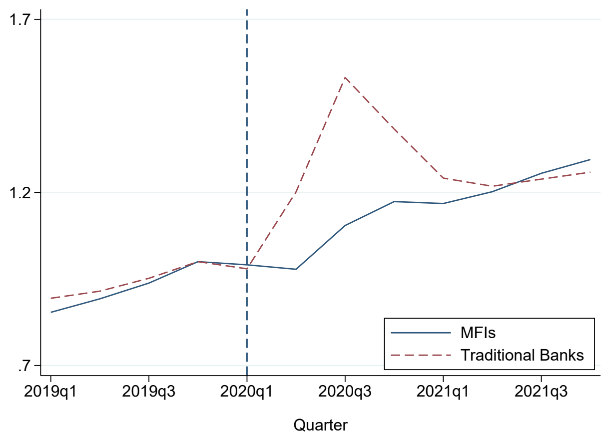
Figure 1: Credit Growth and Delinquency by Type of Lender before Covid-19



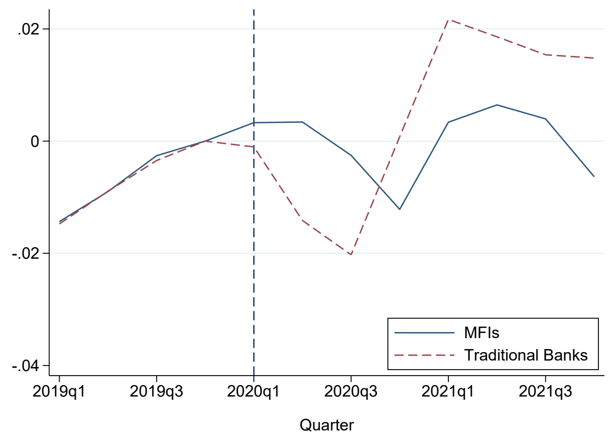
(a) Total Loans (b) Delinquency Rates

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.

Figure 2: Credit Growth and Delinquency by Type of Bank



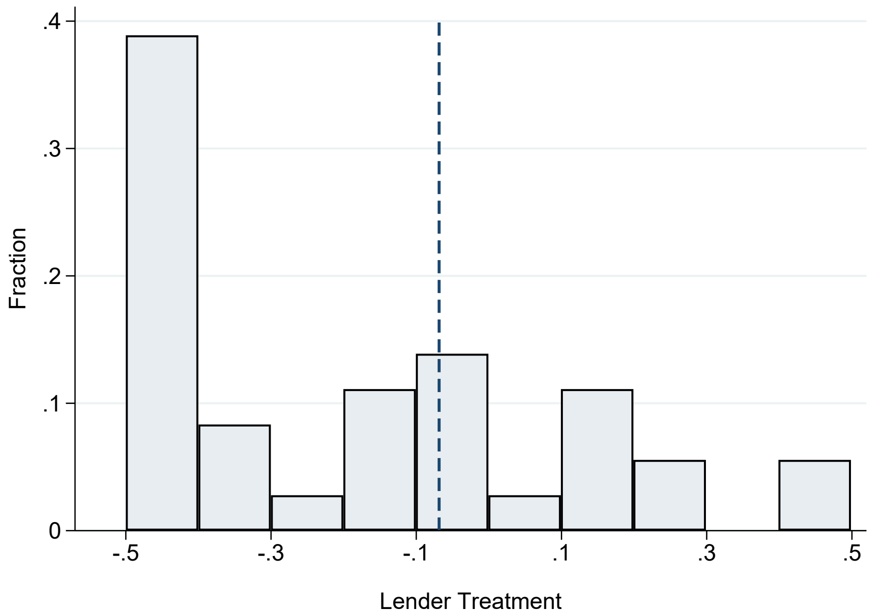
(a) Total Loans



(b) Delinquency Rates

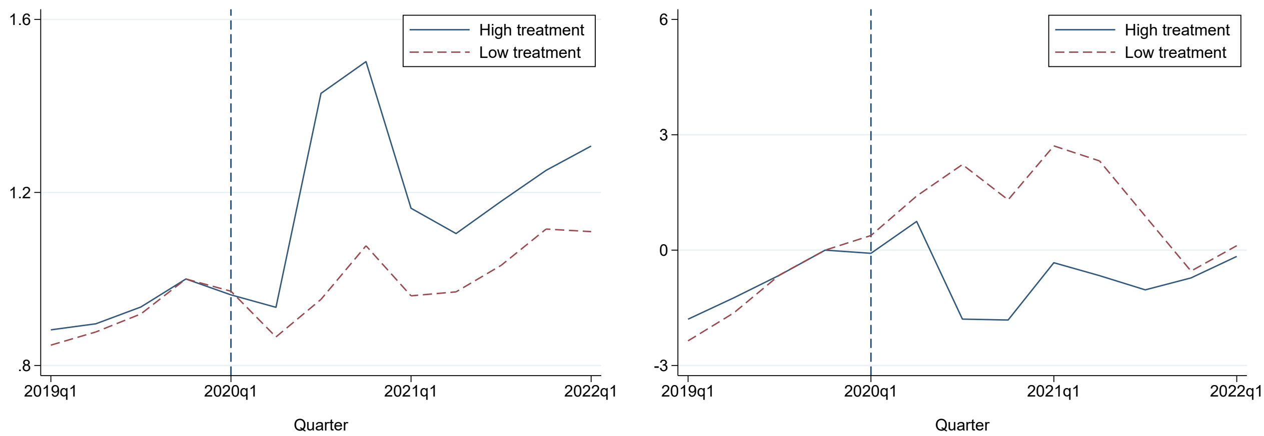
This figure plots the evolution of credit and delinquency rates for traditional banks and microfinance institutions in the segment of small business loans. Panel (a) plots credit growth rate measured by the value of credit in a given point in time relative to the corresponding value in 2019q4. Panel (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.

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.

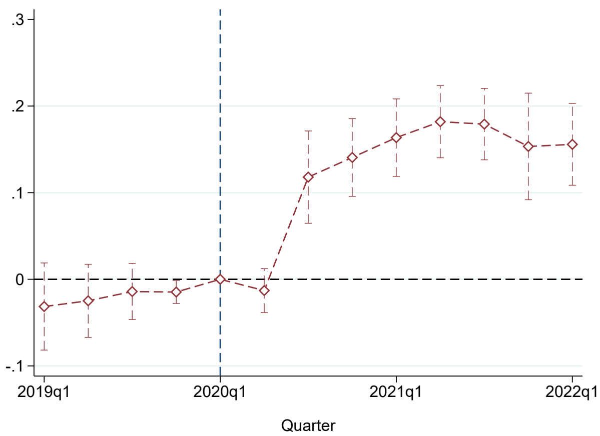
Figure 4: Credit, Delinquency and Bank Treatment



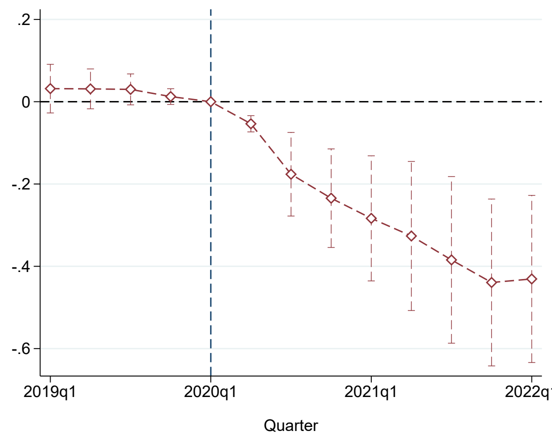
(a) Total Loans (b) Delinquency Rates

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.

Figure 5: Effect of the Program on Credit



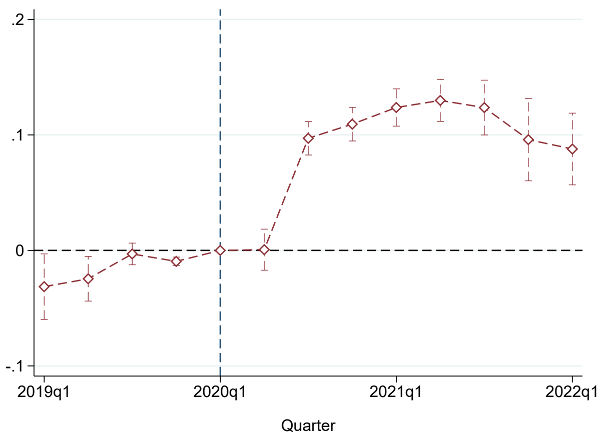
(a) Total Loans



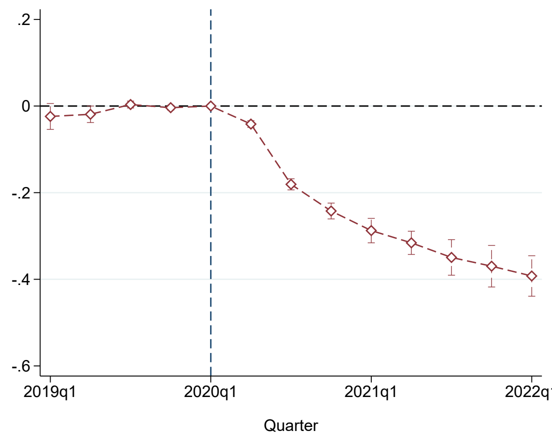
(b) Non-Covid-19 Loans

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%.

Figure 6: Lending Relationships and Credit



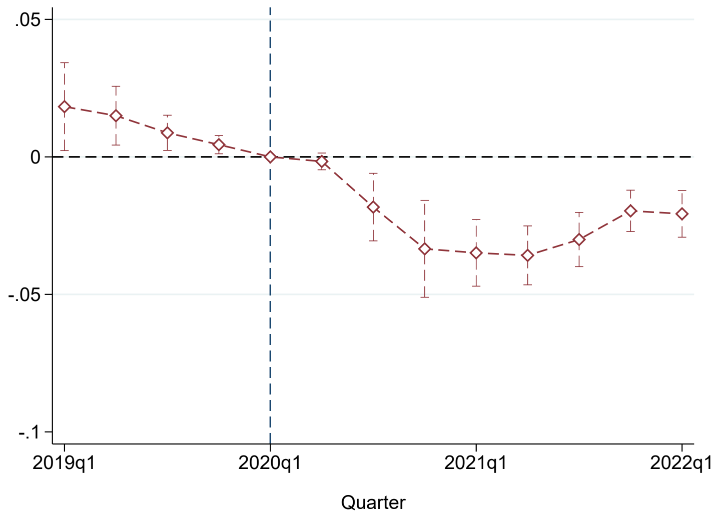
(a) Total Loans



(b) Non-Covid-19 Loans

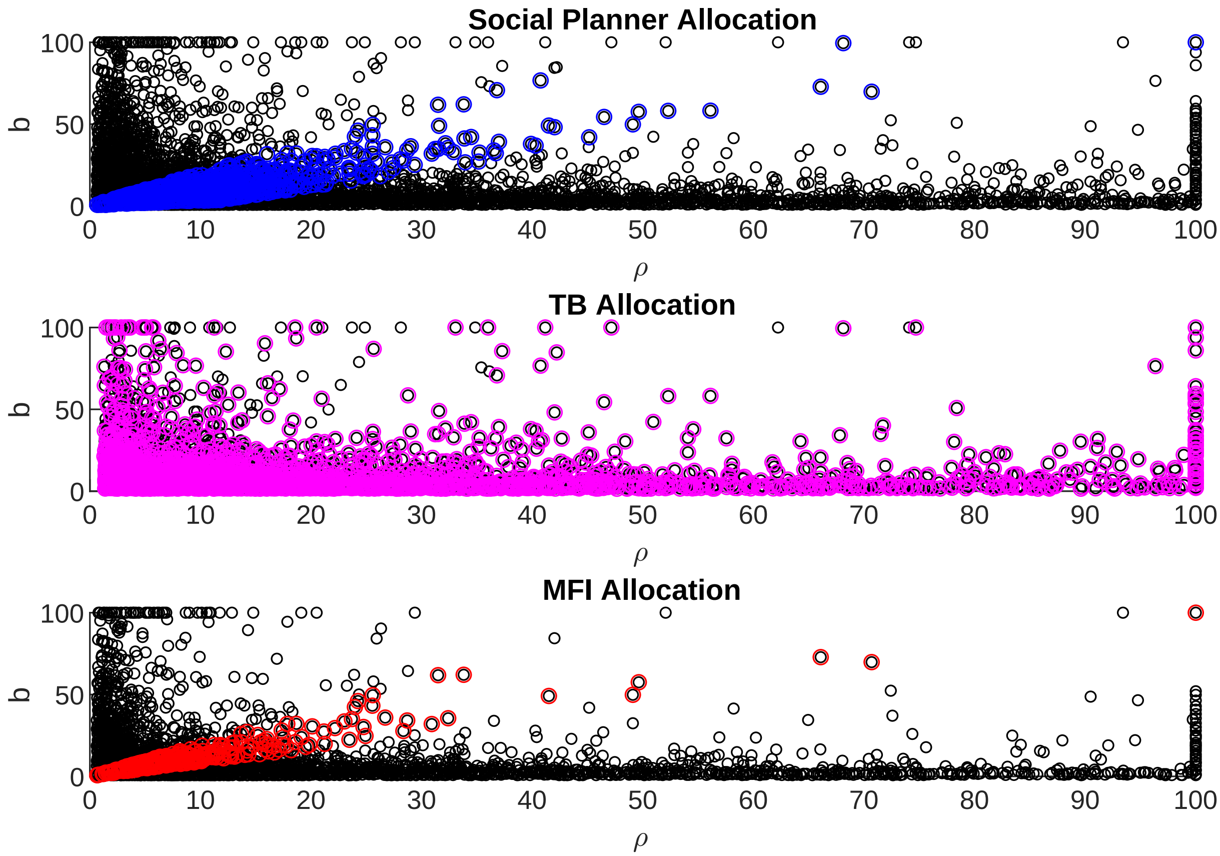
This figure plots the quarterly effects of being better connected to treated banks on total credit and non-Covid-19 loans at the firm level. The dependent variables are in logs. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter 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.

Figure 7: Lending Relationships and Delinquency Rates



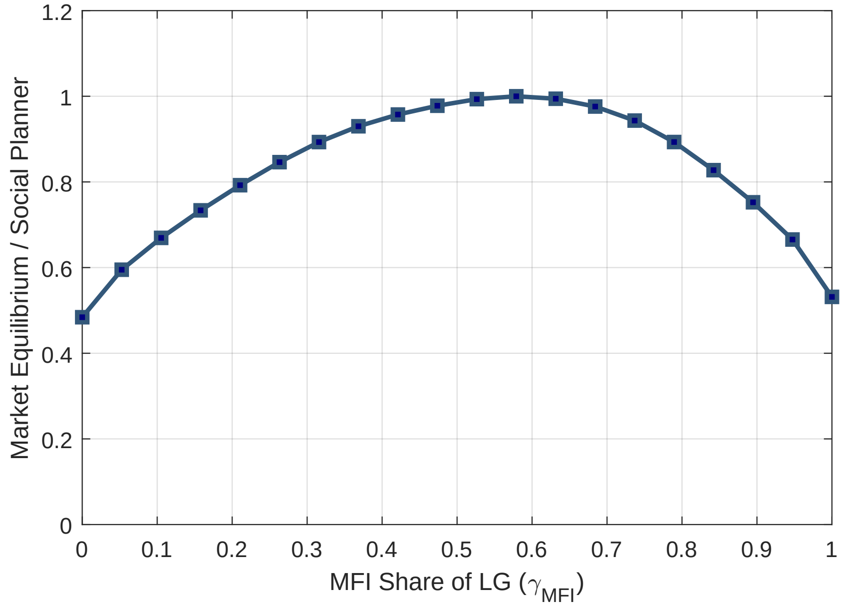
This figure plots the quarterly effects of being better connected to treated banks on delinquency rates, defined as an indicator variable of experiencing repayment delays. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter 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.

Figure 8: Social Planner and Market Equilibrium



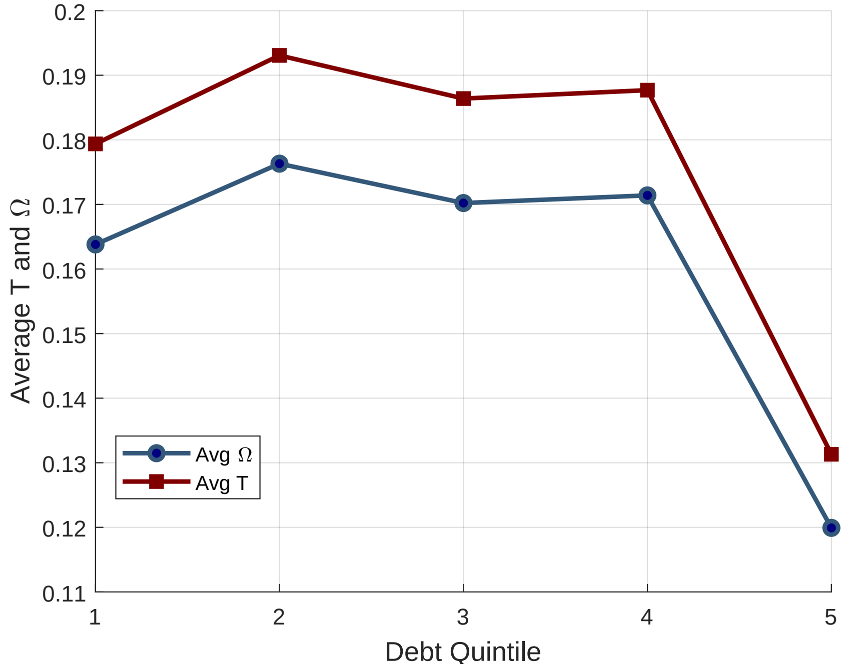
This figure plots the allocation of guarantees in the social planner and market equilibrium. Each circle is a firm and the blue circles in the top panel denote firms attended by the social planner. Purple and red circles in the middle and bottom panels represent firms attended in the market equilibrium, by traditional banks and MFIs, respectively.

Figure 9: Loss function by MFI participation



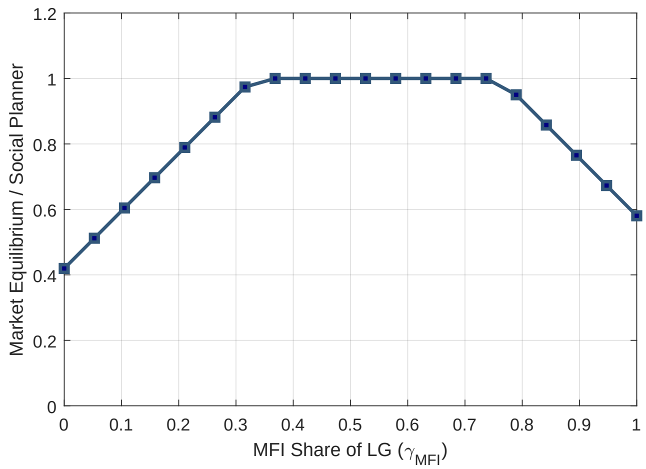
This figure plots the debt-saved ratio defined by equation (13) for different levels of MFI's participation. This ratio is equal to the debt saved by the program in the decentralized equilibrium divided by the ratio saved by the social planner.

Figure 10: Average Treatment Effect versus Average Lender Expected Profit

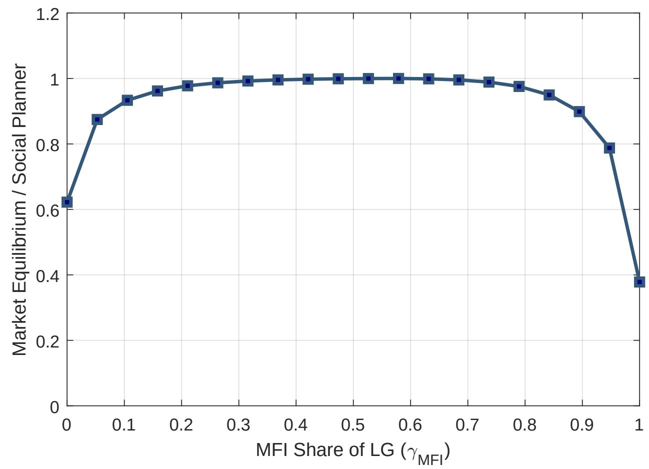


This figure plots the average treatment effect T_i and lender expected profit Ω_i for firms in different quintiles of the debt distribution.

Figure 11: Loss function by MFI participation in two types of Recessions



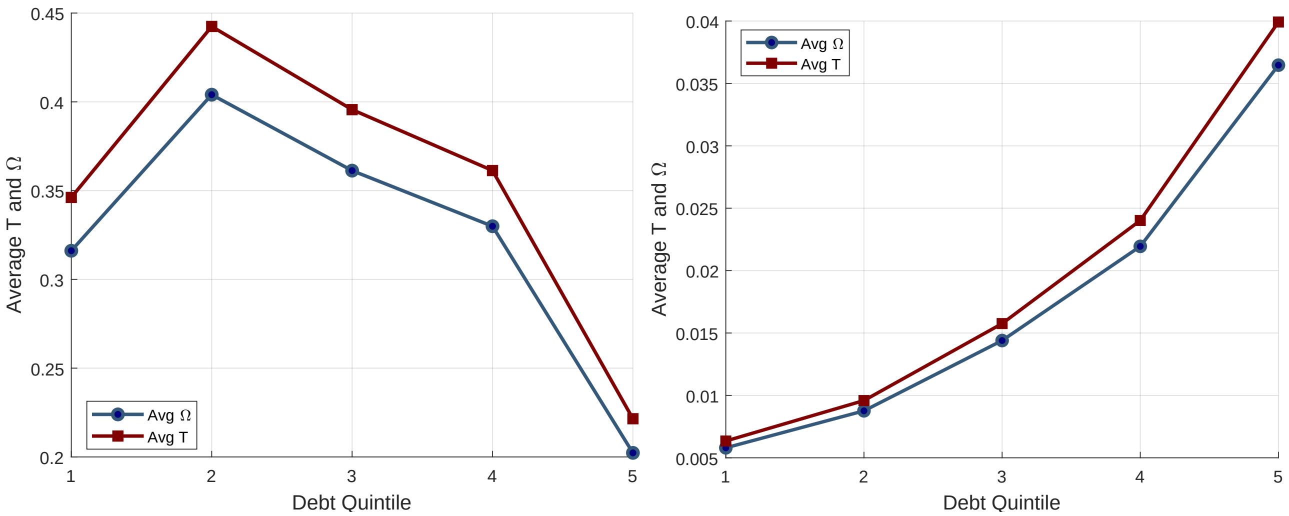
(a) Soft Recession



(b) Deep Recession

This figure plots the debt-saved ratio defined by equation (13) for different levels of MFI's participation in two types of recessions. This ratio is equal to the debt saved by the program in the decentralized equilibrium divided by the ratio saved by the social planner.

Figure 12: Average Treatment Effect T and Lender Expected Profit Ω in two types of Recessions



(a) Soft Recession (b) Deep Recession

This figure plots the average treatment effect T_i and lender expected profit Ω_i for firms in different quintiles of the debt distribution. The left panel considers a soft recession and the right panel a deep recession.

Appendix C: Back-of-the-Envelope Calculation

Consider we have the following stock of debt in period t, before the recession:

$$\overline{B}_t = B_t^n + B_t^d$$

Out of total debt $\overline{B}_t$, the non delinquent debt is B_t^n, while delinquent debt is B_t^d. Then, we have the following delinquent debt in $t+1$, after the recession, under the assumption that no program was implemented:

$$B_{t+1}^d = \Pr(d|n)\, B_t^n + \Pr(d|d)\, B_t^d$$

Where $\Pr(d|n)$ denotes the probability of being delinquent in $t+1$ conditional on being non delinquent in t, and $\Pr(d|d)$ denotes the probability of being delinquent in $t+1$ conditional on being delinquent in t.

Since the program was delivered only to non-delinquent borrowers, we assume that only $\Pr(d|n)$ was affected by the program. Thus, we have the following delinquent debt in $t+1$, under the program:

$$\tilde{B}_{t+1}^d = \Pr(d|n,T)\, B_t^{n,T} + \Pr(d|n,C)\, B_t^{n,C} + \Pr(d|d)\, B_t^d$$

Where $\Pr(d|n,T)$ denotes the probability of being delinquent in $t+1$ conditional on being non delinquent in t and being treated, and $\Pr(d|n,C)$ denotes the same probability for non-treated borrowers. $B_t^{n,T}$ and $B_t^{n,C}$ represent debt holdings of treated and non-treated firms.

Thus, the program saved the following share of debt from default:[9]

$$\frac{\tilde{B}_{t+1}^d - B_{t+1}^d}{\overline{B}_t} = \left(\Pr(d|n,T) - \Pr(d|n)\right) \times \frac{B_t^{n,T}}{\overline{B}_t}$$

Now, we can compute this using our reduced form estimates. Column (1) of Table 7 shows that the impact of credit growth on probability of default is 0.304. Thus, we can define:

$$\Pr(d|n,T) - \Pr(d|n) = -0.304 \times \text{Credit Growth} = -0.304 \times \frac{M}{B^{n,T}}$$

Since guaranteed loans represented 40 percent of current small business loans (see Table 4),

[9] Of course, we are implicitly assuming that $\Pr(d|n) = \Pr(d|n,C)$ and $\Pr(d|d)$ does not change because of the program, i.e., we are abstracting from any type of general equilibrium effects.

i.e., $\frac{M}{\overline{B}_t} = 0.4$, then:

$$\frac{\tilde{B}^d_{t+1} - B^d_{t+1}}{\overline{B}_t} = -0.304 \times 0.4 = -0.122$$

We can conclude that the program saved 12 percent of existing debt from default.

What if guarantees were distributed by traditional banks only? In this case, the elasticity would have been different. Columns (2) and (3) of Table 7 show that the impact of credit growth on probability of default is 0.463 among smaller borrowers and 0.164 among bigger ones. Since traditional banks distribute 18 percent of guarantees to the former and 82 percent to the latter, we have:

$$\Pr(d|n,T) - \Pr(d|n) = -(0.463 \times 0.18 + 0.164 \times 0.82) \times \text{Credit Growth} = -0.218 \times \frac{M}{B^{n,T}}$$

Finally, we have:

$$\frac{\tilde{B}^d_{t+1} - B^d_{t+1}}{\overline{B}_t} = -0.087$$

which means that the program would have saved 8.7 percent of existing debt if all guarantees were distributed by traditional banks.

Appendix D: Additional Tables and Figures

Figure A1: Geographical Distribution of Financial Institutions

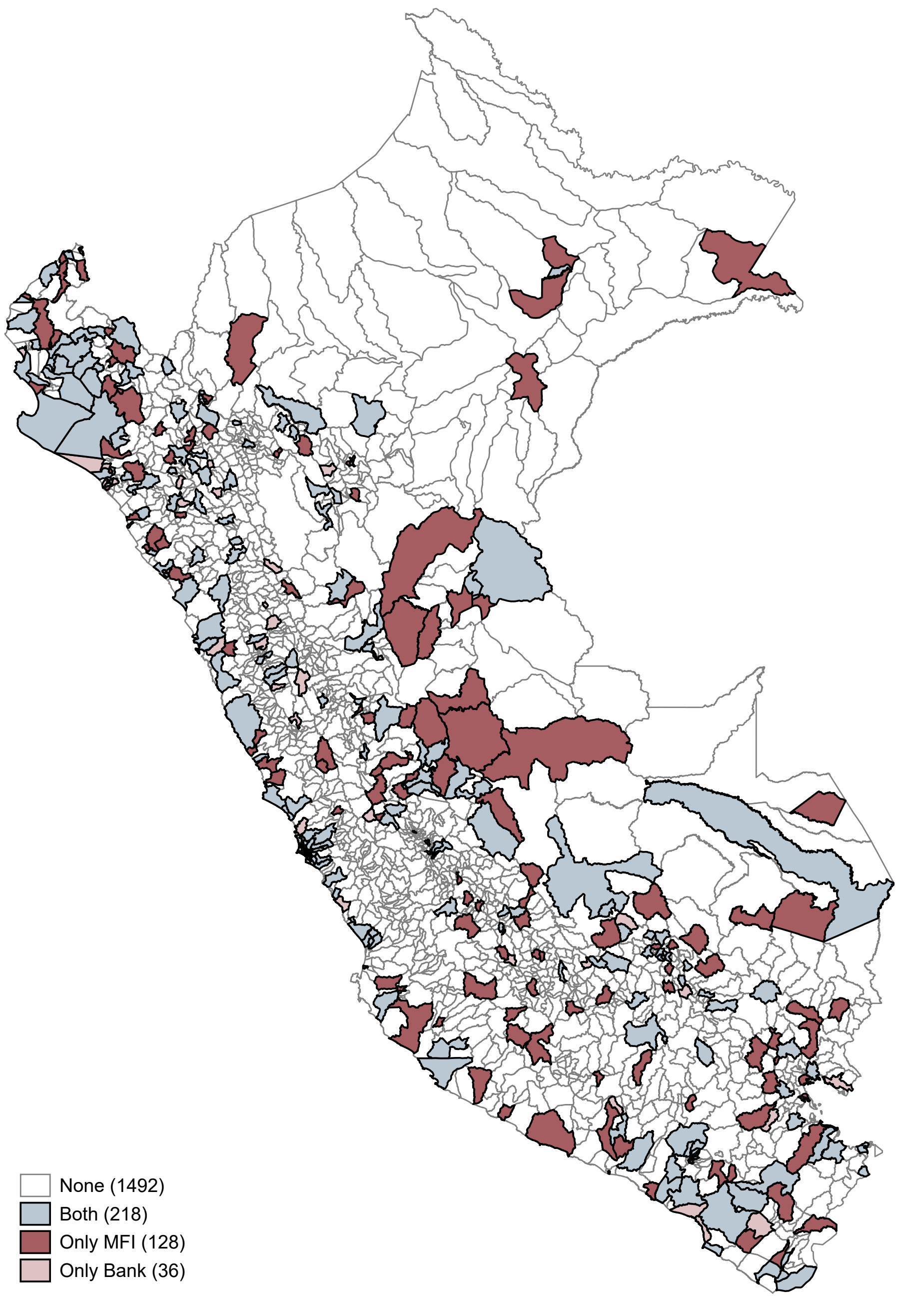
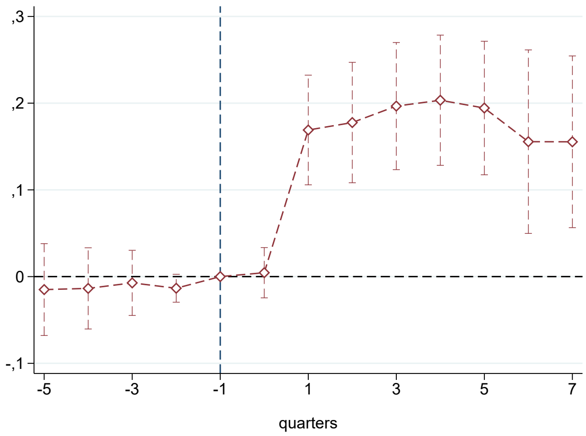
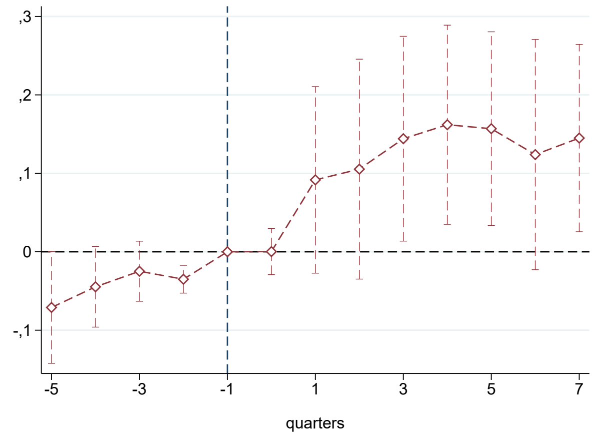


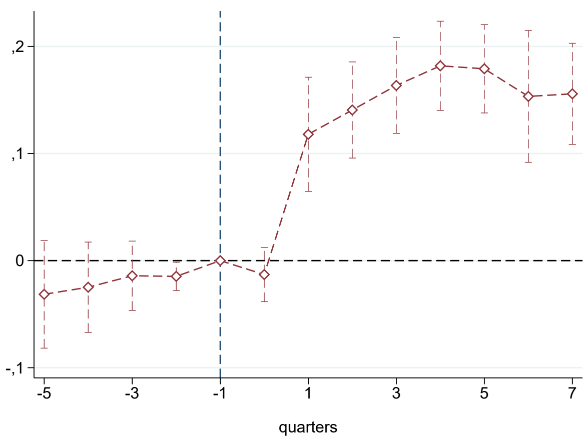
Figure A2: Effect of Loan Guarantees on Total Credit



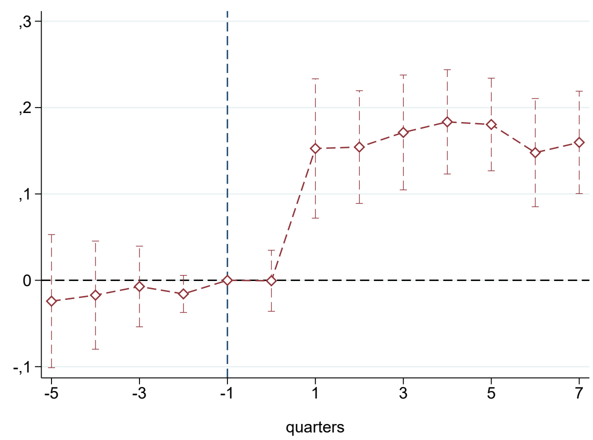
(a) Column (1)



(b) Column (2)



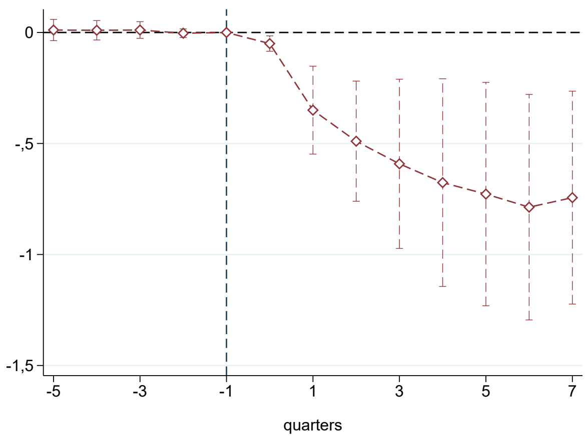
(a) Column (3)



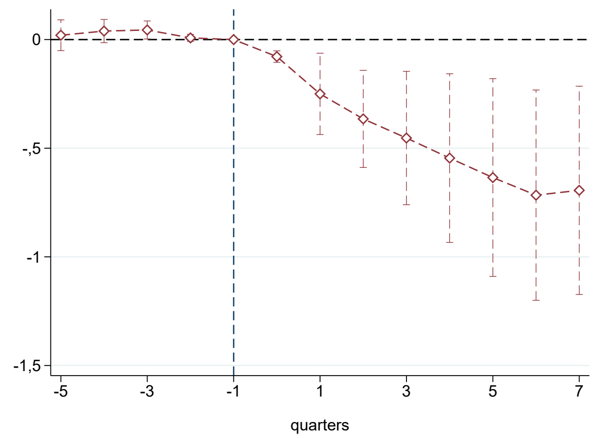
(b) Column (4)

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.

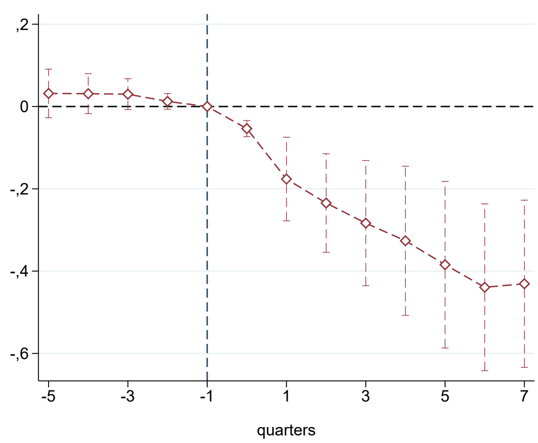
Figure A3: Effect of the Program on Non-Covid-19 Loans



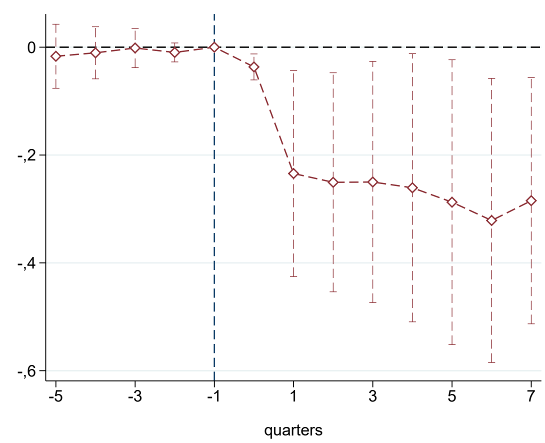
(a) Column (1)



(b) Column (2)



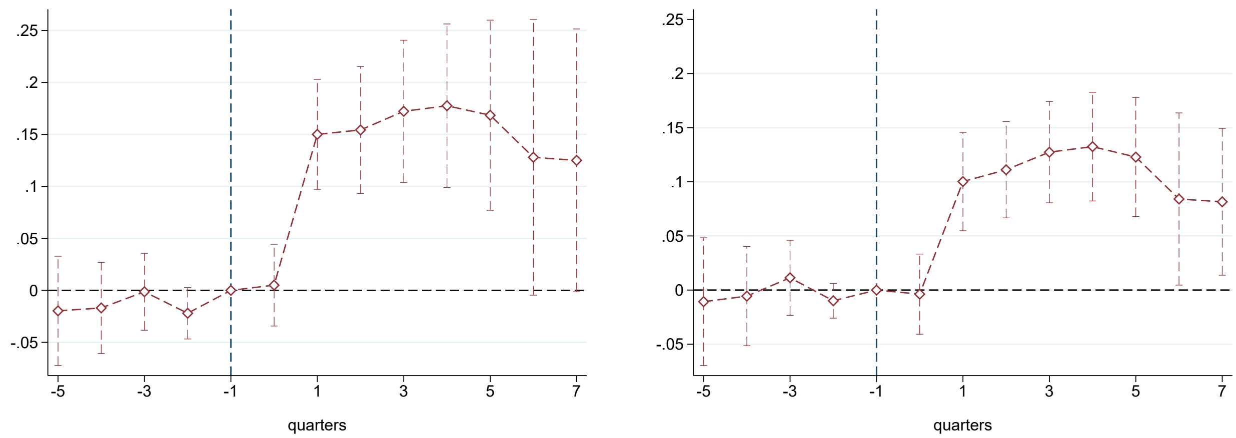
(a) Column (3)



(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

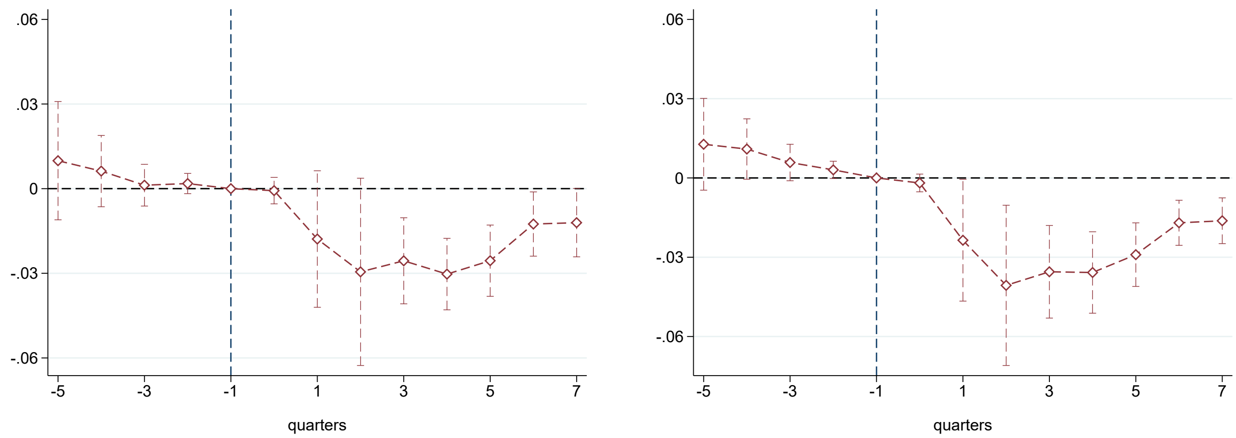


(a) Firm and Time FE

(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.