Loan Guarantees and Microfinance Institutions in Emerging Markets*

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Abstract

This paper estimates the effect of small business loan guarantees on firm performance and examines the role of Microfinance Institutions (MFIs) in shaping the allocation and aggregate impact of these guarantees. We analyze a large-scale program implemented in Peru during the COVID-19 recession. Using administrative data covering the universe of small business loans, we document that the program improved small firm performance by alleviating liquidity needs among micro-firms and high-contact industries. MFIs not only distribute more guarantees towards high sensitive borrowers, but conditional on firm size and industry, MFI clients are more responsive to the program. We develop a model where lenders specialize in different types of borrowers due to their comparative advantage. Our model shows that the observed MFIs' participation reduced defaulting debt by 30 percent more relative to a counterfactual scenario where traditional banks distribute all guarantees.

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1 Introduction

Loan guarantees are a widely used policy tool for sustaining small business credit during recessions. A key feature of these programs is their distribution through private lenders, a design intended to prevent political interference and promote efficient allocation. Yet, it remains unclear whether private lenders actually direct guarantees to the most sensitive, credit-constrained firms. Instead, they may prioritize inframarginal clients–such as existing large borrowers–to strengthen these relationships, even if these firms do not represent the program's intended beneficiaries.

This paper investigates how lender incentives shape the allocation and aggregate impact of small business loan guarantees, and whether specialized lenders such as microfinance institutions (MFIs) can improve the allocation of these programs in developing countries and thereby enhance the program effectiveness.

Whether lenders will distribute guaranteed loans to the most sensitive firms is a priori ambiguous. Allocating guarantees to sensitive borrowers could secure their survival, preserving the value of a relationship that might otherwise be lost. Conversely, offering guaranteed loans to large, inframarginal clients can serve as an easy way to strengthen ties with valuable, stable borrowers, even if the financial aid is less critical for them.

Similarly, the capacity of MFIs to improve the allocation of loan guarantees is a priori unclear. A potential benefit is their specialization in serving micro-firms that are likely more sensitive and credit-constrained, allowing them to effectively target the intended beneficiaries. However, a possible drawback lies in that MFIs' business model relies on building relationships and gathering soft information through costly, in-person monitoring. The safety of a government guarantee could distort these incentives, reducing monitoring and encouraging risk-taking, which could undermine financial stability and produce negative aggregate consequences. Thus, understanding how lender incentives shape the effectiveness of loan guarantees and whether specialized lenders can improve the allocation of financial aid are critical empirical questions.

We address these questions 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 three key advantages for analyzing lender incentives in an emerging market context. First, the program size, equivalent to 8% of GDP, operated in a financial system where the microfinance sector is exceptionally mature, accounting for over 50% of all small-firm lending.[1] This allows us to study the role of MFIs at scale, which is likely to generate spillovers and general equilibrium effects that can amplify the transmission of micro-credit shocks (Breza and Kinnan 2021). Second, comprehensive regulatory reporting provides loan-level data on firm debt across traditional banks and MFIs, enabling us to measure credit balances and loan guarantee allocation by type of lender. Third, the Central Bank adjusted the program's conditions to specifically incentivize MFI participation, allowing us to study the reasons of MFIs' limited participation in government programs. These features allow us to cleanly identify the causal effects of loan guarantees and quantify how MFI participation shapes the aggregate effectiveness of these programs in developing economies.

We use monthly loan-level data covering the universe of small firm 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. The combination of financial and real outcomes allows us to uncover the mechanisms through which loan guarantees impact small business performance. Moreover, the granularity of our data is crucial

[1]Peru represents a leading example of microfinance development, ranking consistently among the top markets for MFIs according to the Inter-American Development Bank. See, for example `https://graphics.eiu.com/assets/images/public/Microscope_on_Microfinance_2014/EIU-Microscope-Dec-2015.pdf`.

to trace the allocation of guarantees for each type of lender. By directly observing which firms are prioritized, and linking this to estimated firm-level elasticities, we can quantify how the composition of lenders shapes the allocation and aggregate effectiveness of the program.

Our analysis proceeds in three steps. First, we estimate the effects of loan guarantees on credit supply and small firm performance. Second, we examine how the sensitivity of firms varies by size and industry exposure to the recession; this heterogeneity allows us to study the mechanisms through which loan guarantees improve firm performance. Having identified the most sensitive firms, we compare the allocation of guarantees distributed by traditional banks versus MFIs towards sensitive versus inframarginal clients. Third, we incorporate our reduced-form estimates into a theoretical model to determine the optimal participation of MFIs and perform counterfactual analysis.

In the first part of the paper, we use a difference-in-differences design to estimate the effects of the loan guarantee program on credit supply and firm performance. We leverage cross-sectional variation in the intensity of guarantee uptake across financial institutions to define a measure of treatment.[2] Our specification compares the credit supply from high- versus low-treated lenders to the same firm, before and after the program's implementation. The key identifying assumption is that, absent the program, credit supply would have evolved in parallel trends across lenders with different treatment intensities.

We provide evidence supporting our identifying assumption in three ways. First, we plot event-study graphs that show no evidence of pre-trends in credit outcomes. Second, we control for time-varying, lender-size-dependent shocks by comparing financial institutions within the same size quartile, thereby mitigating concerns that endogenous matching could drive our results (e.g., larger banks serving more resilient firms). Third, we exploit a three-month delay in the program's implementation–a period of COVID-19 restrictions without

[2]For a given institution, we define treatment as its share of small firm loan guarantees relative to its pre-recession share of small firm loans, similar to Granja et al. (2022).

loan guarantees–as a placebo test. Our treatment measure is uncorrelated with credit during this window, suggesting that the impact of the recession was difficult to predict for small firms. While identifying assumptions are untestable, this evidence is consistent with lenders' guarantee uptake being orthogonal to borrower-specific trends. We complement this evidence with a covariate balance test showing that lender takeup is uncorrelated with pre-COVID characteristics such as delinquent portfolio, leverage ratio, ROA, and dependence on foreign liabilities.

We find that financial institutions with one standard deviation higher treatment increase credit supply by 10 percent while reducing non-guaranteed lending by 30 percent, consistent with the program partially crowding out private credit. These results 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 aggregate our data at the firm-level and construct a corresponding measure of treatment using pre-COVID bank-firm lending shares (Jimenez et al. 2020). One standard deviation higher treatment leads to a 14 percent expansion in firm total debt and a 36 percent contraction in non-guaranteed credit. We also estimate bank-level regressions showing that the value of loans to new borrowers increased by 42 percent among highly treated banks.

We then estimate the effect of the program on small firm performance, measured by delinquency rates, using a difference-in-differences instrumental variable approach. We use our firm-level treatment as an instrument for firm participation in the program. We find that firm participation reduces delinquency by 11 percentage points. We then estimate the elasticity of delinquency to credit, which is crucial to measure the effectiveness of one Peruvian Sol distributed by the program. Our analysis reveals that a 10 percent increase in credit reduces delinquency rates by 1.4 percentage points. Overall, our results suggest that alleviating liquidity needs played a dominant role in improving small firm performance during the crisis, outweighing potential alternative channels like risk-shifting or weakened screening incentives.

In the second part of the paper, we examine heterogeneity in treatment effects across small firms, providing further support to the role of liquidity needs in driving the net effect of the program. We test whether firm size and industry exposure to in-person contact, two proxies for liquidity needs during the COVID-19 recession, shaped the impact of loan guarantees. Our hypothesis is that the smallest firms and those in high-contact industries suffered more severe liquidity shocks and would thus be more sensitive to a credit expansion. Our results are consistent with this hypothesis: a 10 percent credit increase reduces delinquency by 1.5 percentage points for the smallest firms (bottom 90% of the debt distribution) versus just 0.4 percentage point for larger small firms (top 10%).[3] Similarly, a 10 percent credit expansion reduces delinquency by 1.6 percentage points for firms in high-contact industries, and only 0.9 percentage points for the remaining firms. These findings are consistent with our hypothesis that loan guarantees helped small firms to alleviate the liquidity shock from pandemic restrictions.

We examine tax records to uncover how liquidity needs affect small firm real outcomes. We consider small firms with pre-existing debt in 2019 and follow their sales, wage-bill, and stock of capital from 2016 to 2023. We find that one standard deviation higher treatment allows firms to accumulate 2 percent more capital. Similarly, wages and total sales increased by 2 percent, while the number of workers expand by 1 percent. Furthermore, the program reduced small firm exit by 1 percent in 2020, and 2 percent in 2021. Finally, our results indicate that higher treatment reduced the probability of liquidating assets by 1.9 percent.

We then analyze how lender composition shapes the allocation of loan guarantees to the most sensitive firms. We compare the lending patterns of MFIs and traditional banks and document that MFIs prioritized more sensitive borrowers: they allocated 65 percent of

[3] All firms in our analysis fall within the “small firm” category; these comparisons are within that market segment.

their guarantees to the smallest firms, compared to only 29 percent from traditional banks. Furthermore, 60 percent of MFI guarantees went to firms in high-contact industries, versus 46 percent for traditional banks. A back-of-the-envelope calculation suggests these allocation differences had aggregate consequences: the program reduced aggregate delinquency by 12 percentage points under the actual mix of lenders, compared to a counterfactual reduction of only 8 percentage points if only traditional banks participated.

These allocation patterns closely mirror lenders' pre-existing specialization. Prior to the pandemic, traditional banks concentrated 74 percent of their small-firm lending in the largest firms, while MFIs allocated just 50 percent of their portfolio to this segment. Similarly, MFIs had 64 percent of their pre-crisis portfolio in high-contact industries, compared to 59 percent for traditional banks. We also find that this specialization enabled better targeting within borrower segments: among highly sensitive firms, those that received guarantees from MFIs exhibited better performance than those funded by traditional banks. While a 10 percent increase in credit reduced the probability of delinquency by around 4 percentage points for smaller firms and those in high-contact industries attached to MFIs, the decline was statistically insignificant for those attached to traditional banks. This evidence confirms that lender composition critically shapes the allocation of financial stimulus and, through this channel, its aggregate impact. Thus our findings suggest that specialization allows for a bigger share of guarantees distributed over sensitive borrowers and better targeting within more responsive firms.

Motivated by our empirical findings, we develop a theoretical model that rationalizes the observed patterns and enables counterfactual analysis. Our economy includes a continuum of firms that choose whether to pay a fixed cost to become hard-information or remain as soft-information upon observing a productivity signal. Firms are heterogeneous in productivity and risk and operate a Cobb-Douglas technology. There are two financial intermediaries, MFIs and traditional banks, that maximize expected profits and have different technologies.

While MFIs face lower costs at originating loans to soft-information firms, traditional banks exhibit lower costs when originating loans to hard-information borrowers. Such lender-specific comparative advantage leads to two different distributions of clients for each lender. We model the recession as a liquidity shocks, and firms have different survival probabilities, with and without loan guarantees, depending on their net cash-in-hand before the recession.

The model includes two key features that create strategic incentives in loan guarantee allocation: lenders face more severe poaching threats among clients who do not receive guarantees, and the value of lending relationships is proportional to borrower size. Our calibrated model yields an equilibrium distribution of clients form MFIs and traditional banks that matches key empirical moments from our data related to market shares and lender specialization. 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. In equilibrium, 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. Thus, the optimal participation of MFIs maximizes non-defaulting debt by properly weighting MFIs' comparative advantage in serving smaller firms versus 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 more profitable, in expectation, than smaller ones.

Second, we quantify the optimal MFI participation in the program. 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 risky firms with low treatment effect.

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

Related Literature

This paper contributes to two primary strands of literature. First, it connects to research on government credit guarantees, a common tool for sustaining small business lending during crises (Lelarge et al. 2010; Bach 2014; Brown and Earle 2017; Mullins and Toro 2018; Bachas et al. 2021; González-Uribe and Wang 2022; Bonfim et al. 2023; Barrot et al. 2024; Core and De Marco 2024). While existing work establishes the average effects of such programs, we focus on their optimal design to ensure financial stimulus reaches the most sensitive, credit-constrained borrowers. We show that private lender incentives can diverge from social objectives, making the composition of lenders a critical determinant of the program effectiveness.

In this line, we contribute to recent work examining how private intermediaries distribute financial stimulus (Haas-Ornelas et al. 2021; Joaquim and Netto 2022). We provide novel evidence by tracing the exact allocation of guarantees across different lender types–specifically, traditional banks versus MFIs–and linking these patterns to borrower sensitivity. This allows us to quantify how the participation of specialized lenders improves the allocation and aggregate effectiveness of loan guarantees. Our findings contribute to the literature on lender specialization (Blickle et al. 2023; Paravisini et al. 2023). We provide evidence that the pre-existing expertise and business models of MFIs enable them to improve the allocation of a large-scale financial stimulus, ensuring it reaches more sensitive borrowers.

Second, our paper contributes to the literature on the role of microfinance institutions in emerging markets. While early randomized controlled trials found modest real effects of microcredit (Angelucci et al. 2015; Augsburg et al. 2015; Tarozzi et al. 2015; Attanasio et al. 2015), recent work highlights that general equilibrium forces (Kaboski and Townsend 2011; Buera et al. 2020) and large-scale interventions (Breza and Kinnan 2021) can generate significant aggregate impacts.

Our contribution to this literature is threefold. First, we identify a novel channel through which MFIs affect the economy: by shaping the allocation of financial stimulus during a recession. We show that MFIs are effective at distributing government guarantees to highly sensitive, smaller borrowers that traditional banks overlook, thereby crucially strengthening the program's aggregate impact. This finding relates to recent work that studies how different lenders allocate financial stimulus in the context of the Paycheck Protection Program

(Balyuk et al. 2021; Griffin et al. 2023). Second, we combine detailed administrative data on the universe of MFI operations with a quasi-experimental design to trace the causal effects of a large-scale shock. Third, we integrate these findings into a theoretical framework where lender incentives determine the allocation of financial stimulus. By modeling why MFIs target smaller, sensitive firms, this framework enables us to measure their optimal participation in loan guarantee programs.

The remaining of this paper is organized as follows. Section 2 describes our data and the institutional background, and section 3 presents our conceptual framework. Section 4 discusses our empirical approach and we report the average effect of loan guarantees on financial outcomes in section 5. We explore the heterogeneous effects of the program and the role of MFIs in section 5 and section 6 presents our model and 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. Crucially, we focus on micro and small-firm credit, which are the segments where MFIs compete with traditional banks, and call them small business loans throughout the paper.

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 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 A1 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.

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

2.3 Traditional Banks versus Micro-Finance Institutions

MFIs expanded significantly in Peru over the past two decades, driven by continuus deregulations. The industry is mature 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 2018 and 2012. Panel (a) shows credit growth rates, measured as the value of credit in a given point in time relative to its value in January 2018. Before the recession, MFI credit grew 20 percent cumulatively, outpacing traditional banks' 10 percent growth. Panel (b) shows that the rapid expansion of microfinance institutions was coupled with stable delinquency rates of 7% for MFIs, slightly below traditional banks' rates.

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.

Table A2 compares the two types of lenders. Columns (1) and (2) consider traditional banks, 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

[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.

borrowers and allocating loan guarantees. These loans had an average duration of 36 months and were 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 2: 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 2 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. 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.

We can observe in Figure 1 that, while traditional banks expanded small business loans by 50 percent peak-to-trough around the program implementation, MFIs grew only 20 percent and with a lag. Credit growth converged among both types of lenders one year after the program. Furthermore, 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 3 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 Conceptual Framework

We describe a stylized model to discuss the potential differences in lender incentives relative to social planner's when allocating guaranteed loans. Our framework includes heterogeneous firms with exogenous levels of cash and debt that we will endogenize in our quantitative analysis. On the lender side, there are two types of lenders that choose how to allocate guarantees over their exogenous set of clients which we will also endogeneize in the quantitative part.

3.1 Firms

There is a continuum of firms indexed by cash-in-hand y and debt obligations rb, with r denoting gross interest rate, that face a standard liquidity constraint to operate:

$$y_i - rb_i \geq 0$$

Pandemic restrictions generate an unexpected negative cash-flow shock ν_i drawn from a distribution $\tilde{\Phi}(\nu)$. The government implements a loan guarantee program distributed by private lenders to help firms dealing with this liquidity shock. If firm i obtains a loan, it obtains a liquidity injection proportional to its current debt φb_i. Thus, the firm liquidity constraint during the recession becomes:

$$y_i - rb_i - \nu_i + \ell_i \varphi b_i \geq 0$$

where ℓ_i is a dummy equal to one if firm i receives a loan guarantee. Then, we can define the treatment effect T_i as the impact of receiving a guaranteed loan on the probability of survival:

$$T_i = \widetilde{\Phi}(y_i - rb_i + \varphi b_i) - \widetilde{\Phi}(y_i - rb_i) \equiv \Phi_i(\varphi) - \Phi_i(0)$$

where $\Phi_i(z) = \widetilde{\Phi}(\rho_i - rb_i + zb_i)$.

The first implication of our model is that the average treatment effect of participating in the program $\mathrm{E}[T_i]$ depends non-linearly on the severity of the shock, which is captured by the shape of the distribution Φ. If it is a soft recession such that the distribution of liquidity shocks is concentrated among low values (e.g., the shock faced by large firms in low-contact industries), the average effect will be small. On the other hand, if the economy face a deeper recession such that the shock distribution is concentrated among higher values (e.g., the recession faced by micro-firms in high-contact industries), the average effect might be large. However, if the recession is very tough, and the shock distribution is concentrated among the highest values, the average treatment effect will be again close to zero.

3.2 Social Planner

Since the goal of the program was preserving financial stability, we assume that the social planner will choose the allocation of guarantees that maximizes non-defaulting debt subject to a capacity constraint, as follows:

$$\max_{\ell(y,b)\in\{0,1\}} \int \ell T b \, dG(y,b) \qquad \text{subject to:} \quad \int \ell \varphi b \, dG(y,b) \leq M$$

where M represents the total value of guaranteed loans to be distributed.

The resulting allocation is the constrained first-best, i.e., the allocation implemented by a social planner who faces the same capacity constraints as private lenders – limited by the total value of guarantees M and the individual debt increase φ among program recipients. The solution allocates guarantees to firms with the highest T_i.

3.3 Private Lenders

We consider a representative bank serving an exogenous pool of clients characterized by (y, rb). Following Joaquim and Netto 2022, we assume that our representative bank face poaching threats over borrowers that do not get guarantees. For simplicity, we assume that poaching threats come from an outside lender.

Thus, if the bank provides a loan guarantee to a client, there are two possible scenarios. If the firm survives, it repays its debt and the bank preserves this relationship, which gives a net present value equal to $\psi_F b$ that represents profits from future interactions with the borrower. If the firm does not survive, the bank recovers a fraction δ of the outstanding debt

b. On the other hand, if the bank does not provide the loan guarantee, the two scenarios are as follows. If the firm survives, banks get repaid but preserves the lending relationship with probability $1 - \psi_C$ due to poaching threats. If the firm does not survive, the bank recovers a fraction δ of outstanding debt.

Thus, the bank expected profit from a givem client i is:

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

This expression simplifies to $\Pi_i = \ell_i \Omega_i b_i + \Theta_i b_i$, with $\Omega_i \equiv T_i \left(r + \psi_F - \delta\right) + \Phi_i(0)\psi_C\psi_F$. Then, the representative bank solves:

$$\max_{\ell(y,b)\in\{0,1\}} \int \ell \left[T \left(r + \psi_F - \delta\right) + \Phi(0)\psi_C\psi_F\right] b \, dG(y, b) \qquad \text{subject to:} \quad \int \ell\varphi b \, dG(y, b) \leq M$$

The second implication of this model is that private lenders weight firm sensitivity T_i versus survival probability without guarantees $\Phi_i(0)$ due to the existence of poaching threats ψ_C and relationship value ψ_F. This can lead to allocative inefficiencies when treatment effects do not correlate perfectly with the probability of survival without guarantees.

3.4 Loan Guarante Misallocation

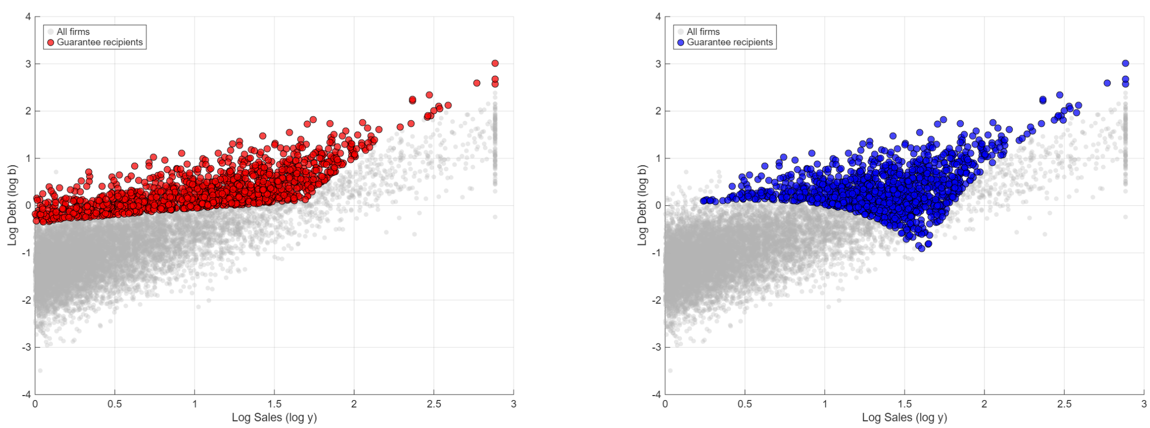
To illustrate qualitatively the role of lender incentives, we consider the following set of parameters. We assume the relationship lending parameter is 0.1/0.04 meaning that banks make 10% returns every year, on expectation, upon preserving the relationship and assuming a discount rate of 4%. We set the recovery rate to 10% and assume that poaching threats materialize with 10% probability.[8] We model sales as a Pareto with shape parameter 1.6

[8]We do not consider recovery on guaranteed loans as the guaranteed rate was between 95 to 98% in this segment.

over the support $[1, \infty)$ and assume that debt follows $b = 0.25y \times u$, where u is distributed as a log-normal with mean zero and variance 0.5.[9] Finally, we set the size of the program to 25% of initial debt, $\varphi = 0.8$ coinciding with the average debt increase among program receipients, and a liquidity shock distribution $\tilde{\Phi}(x) = (x/5)^{0.8}$ over the interval $[0, 5]$.

Figure 2 plots the distribution of borrowers and highlights those receiving loan guarantees in different equilibria. Panel (a) focuses on the social planner allocation and Panel (b) shows the private market equilibrium. We can observe that our representative bank tends to choose clients with higher probability of survival without the program, compared to the social planner, such as those at the bottom part of the mid-part of Panel (b). On the other hand, the social planner prefers to provide guarantees to highly indebted firms with high treatment effect such as those at the north-west part of Panel (a).

Figure 2: Allocation of Loan Guarantees: Social Planner versus Private Lender



(a) Social Planner (b) Private Lender

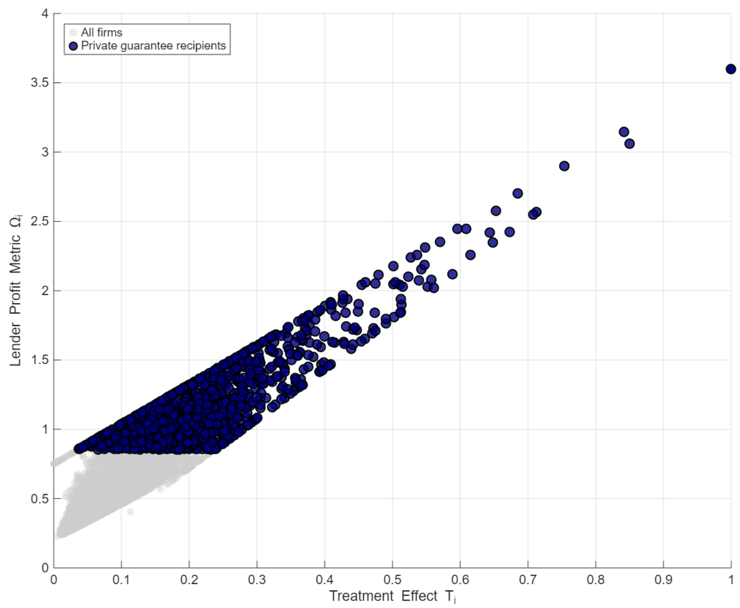
This figure plots the allocation of guarantees implemented by the Social Planner in Panel (a), and the private lender in Panel (b). See the main text for further details on the parameter values.

Figure 3 plots the relationship between treatment effect T_i and lender profit function Ω_i in a simulated set of borrowers using the parametrization described above. The figure highlights

[9] We can think of a revenue function $y = k^{0.3}$ with interest rate of 20%

the firms that are selected by the private lender to get a guaranteed loan. We observe that the allocation departs from maximizing treatment effects, as shown at the bottom part of the selected borrowers. The private bank chooses a set of very low treatment effect firms with relatively high values Ω.

Figure 3: Private Allocation of Guarantees: Lender Profit versus Treatment Effect



This figure plots the lender profit metric Ω and treatment effect T for a simulated set of borrowers. Gray dots represent the full set of borrowers and blue dots are those who receive a loan guarantee in the private equilibrium. See the main text for further details on the parameter values.

In the next sections we describe our empirical framework and estimate the effects of loan guarantees. We then extend our model in Section 6 to capture endogenous sorting of different types of firms across different lenders, quantify the aggregate effect of the program, and conduct counterfactual analysis.

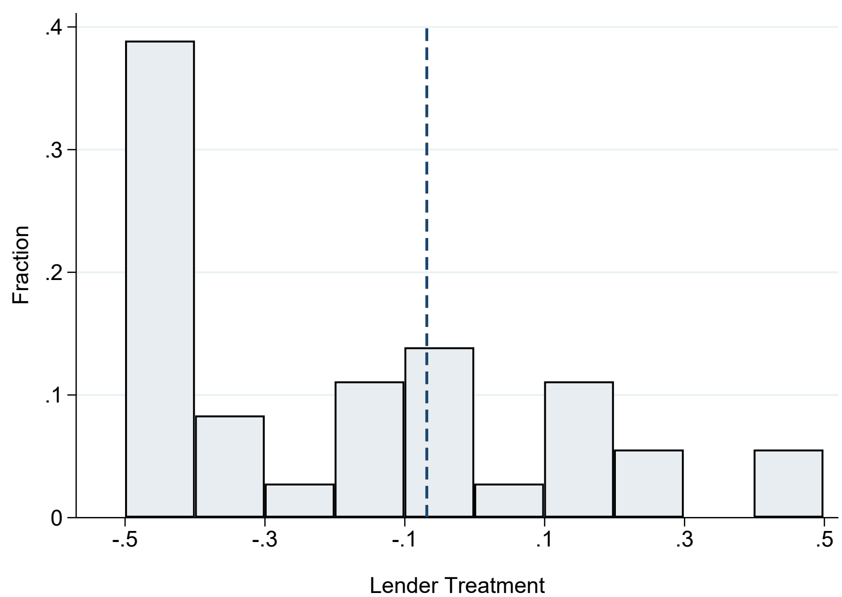
4 Empirical Framework

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:

$$\text{Treatment}_f = \frac{\text{Share of Covid-19 Loans}_{f,2020} - \text{Share of Total Loans}_{f,2019}}{\text{Share of Covid-19 Loans}_{f,2020} + \text{Share of Total Loans}_{f,2019}} \times 0.5 \qquad (2)$$

Figure 4 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.

Figure 4: Distribution of Bank Treatment in Micro-credit



This figure plots the distribution of bank treatment measured by equation 2. The dashed line indicates the weighted-by-size median treatment.

We use the median exposure to split financial institutions into two groups and plot the corresponding evolution of credit and delinquency rates in Figure A2. 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 for traditional banks and MFIs. Panel (b) shows the evolution of delinquency. We can observe that treatment is also uncorrelated with delinquency before the program. Finally, highly treated MFIs exhibit a strong and persistent reduction in delinquency rates that persists after the recession. The difference of 3 percentage points at the peak is economically meaningful since aggregate delinquency is around 10 percent for small business loans.

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:

$$Y_{ift} = \theta \times \text{Treatment}_f \times \text{Post}_t + \delta_{if} + \delta_{it} + \delta_{q(f),t} + u_{ift} \tag{3}$$

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 (2). 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:

$$\text{Treatment}_i = \sum_f \frac{L_{if}}{L_i} \times \text{Treatment}_f \tag{4}$$

where L_{if} denotes the outstanding debt that firm i holds with lender f in December 2019 and Treatment_f is defined in equation (2). Then we estimate the following equation for multiple firm-level outcomes:

$$Y_{it} = \beta \times \text{Treatment}_i \times \text{Post}_t + \delta_i + \delta_{x(i)t} + u_{it} \tag{5}$$

where Y_{it} denotes the balance of total loans and normal loans (in logs), and delinquency rate[10] 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

[10] 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.

at the main-lender level.

5 Results

5.1 Guaranteed Loans and Credit Supply

We start by estimating the effect of the program on credit supply. We estimate equation (3) using the log of total loans as the dependent variable. Our results are reported in columns 1 to 4 in Table 3. 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.

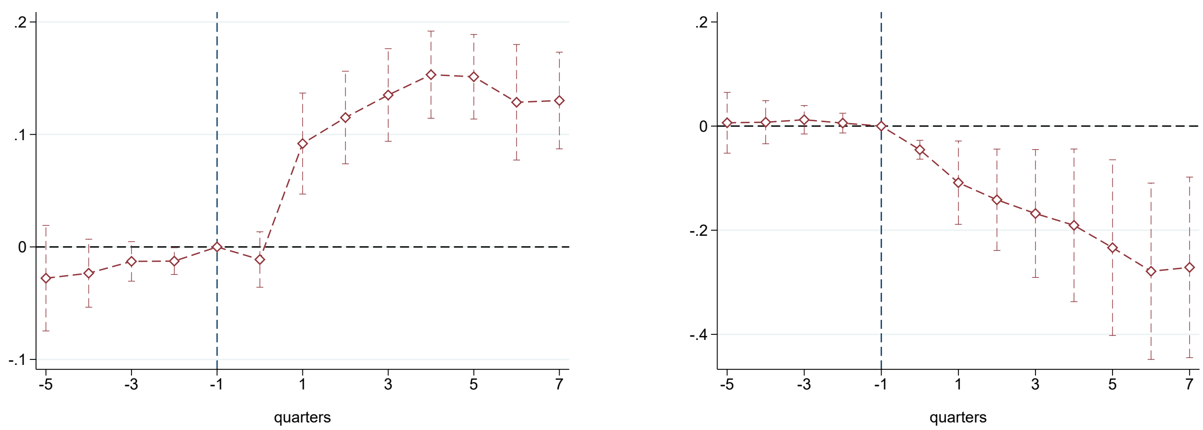
Table 3: Effect of Loan Guarantees on Bank Credit Supply

	Total Loans			Non-Guaranteed Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_b \times \text{Post}_t$	0.163***	0.095**	0.088***	-0.501***	-0.300***	-0.133***
	(0.050)	(0.047)	(0.019)	(0.148)	(0.110)	(0.043)
Observations	37.4M	22.1M	22.1M	36.8M	21.5M	21.5M
Fixed Effects						
Bank-Firm	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	–	–	Yes	–	–
Firm × Quarter	No	Yes	Yes	No	Yes	Yes
$g(i) \times g(b) \times$ Quarter	No	No	Yes	No	No	Yes

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 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 5: Effect of the Program on Credit



(a) Total Loans (b) Non-Guaranteed 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 (3) using the log of normal loans as our dependent variable. We report our results in columns 5 to 8 of Table 3. 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. 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.

5.2 Guaranteed Loans and Small Firm Performance

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 (4). 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 (5) using total loans as our dependent variable.

Our results are reported in column 1 of Table 5. We find that one standard deviation better connected firms experience a 10% increase in total loans after the program. We report quarterly treatment effects in panel (a) of Figure A4. 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. 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 (5) using the balance of normal loans as our dependent variable. We report our results in column 2 of Table 5. 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 A4 reports quarterly treatment effects, showing no evidence of pre-trends.

Table 4: Effect of Loan Guarantees on Small Firm Borrowing

	Total Loans			Non-Guaranteed Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_b \times \text{Post}_t$	0.163***	0.141***	0.140***	-0.433***	-0.436***	-0.357***
	(0.038)	(0.022)	(0.024)	(0.074)	(0.076)	(0.080)
Observations	24.5M	24.5M	12.1M	24.2M	24.2M	12.0M
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Real}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f) \times$ Quarter	No	Yes	Yes	Yes	No	Yes

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.

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 (5) using this measure as a dependent variable. Our results are reported in column 3 of Table 5. We find that firms connected with highly treated banks perform better after the program. One standard deviation higher treatment reduces in 3 ppts the probability of experiencing repayment delays. Figure A5 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.

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.

Table 5: Effect of Loan Guarantees on Small Firm Financial Performance

	OLS			IV	
	(1)	(2)	(3)	(4)	(5)
Exposure$_i \times$ Post$_t$	-0.020***	-0.019***	-0.020***		
	(0.004)	(0.004)	(0.005)		
Treated$_i \times$ Post$_t$				-0.107***	
				(0.022)	
ln Loans$_{it}$					-0.135***
					(0.033)
Observations	24.6M	24.6M	12.1M	24.6M	24.6M
Fixed Effects					
Firm	Yes	Yes	Yes	Yes	Yes
$x^{\text{Real}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f) \times$ Quarter	No	Yes	Yes	Yes	Yes

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.

5.3 Allocation of Guaranteed 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:

$$
\begin{aligned}
\text{Delinquency}_{it} &= \beta_2 \times \ln L_{it} + \delta_i + \delta_{x(i)t} + u_{it} \\
\ln L_{it} &= \rho_2 \times \text{Treatment}_i \times \text{Post}_t + \delta_i + \delta_{x(i)t} + u_{it}
\end{aligned}
\tag{6}
$$

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 5. Column 5 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 1.4 percentage points. This is around a fourth 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 (6) for each group of firms. Bigger firms account for 60 percent of total debt in the pre-Covid period, while smaller clients account for the remaining 40 percent. Our estimation results are reported in columns (1) to (6) of Table 6. 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.

5.4 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 (6) for each group of firms. Our results are reported in Tables A10 to 7. Small firms and those operating in high-contact industries are more sensitive independent of whether they borrow from MFIs or banks. Indeed, those attached to MFIs are even more responsive, suggesting a better technology to target sensitive firms among these lenders.

Table 6: Heterogeneous Effect of Loan Guarantees on Small Firm Financial Performance - Pre-Covid Debt Deciles

	Bottom Deciles (40% of Loans)			Top Decile (60% of Loans)		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure$_i\times$ Post$_t$	-0.020***			-0.008*		
	(0.004)			(0.004)		
Treated$_i\times$ Post$_t$		-0.121***			-0.034*	
		(0.024)			(0.019)	
ln Loans$_{it}$			-0.151***			-0.039*
			(0.035)			(0.020)
Observations	21.7M	21.7M	21.7M	2.9M	2.9M	2.9M
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Real}}(f)\times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)\times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes

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.

Finally, we explore the allocation of guarantees across firms for both financial institutions. Table A8 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 7: Heterogeneous Effect of Loan Guarantees on Small Firm Financial Performance - Industry Contact

	High-Contact			Low and Non-Contact		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure$_i \times$ Post$_t$	-0.021***			-0.016***		
	(0.003)			(0.005)		
Treated$_i \times$ Post$_t$		-0.116***			-0.088***	
		(0.020)			(0.025)	
ln Loans$_{it}$			-0.162***			-0.093***
			(0.035)			(0.028)
Observations	16.5M	16.5M	16.5M	8.0M	8.0M	8.0M
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Real}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes

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.

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 Quantitative Analysis

We extend our paper to endogeneize the distribution of firms across revenue and debt, and the difference in lending portfolios of traditional banks and MFIs. In our setting, a continuum of firms choose their type, whether they want to be soft- or hard-information, and lenders have different technologies, with MFIs showing a comparative advantage in the cost of originating loans for soft-information firms, while banks exhibit a comparative advantage among hard-information ones. Thus, our model yields an endogenous distribution of clients for each lender.

6.1 Firms

We model the timing of firm type choice following Ulyssea (2018). First, each firm receives a signal ν about its future productivity potential, drawn from a Pareto distribution with parameter ξ over the support $[\nu_0, \infty)$, where ν_0 is normalized to one. This signal represents the firm's assessment of its own potential productivity. Upon observing this signal ν, firms choose their type f: they can either pay a fixed cost c_e to operate as a hard-information firm $f = h$, or operate as a soft-information, opaque firm $f = s$ without paying any fixed cost. After choosing its type, firm actual productivity is determined as $z = \epsilon \times \nu$, where ϵ is drawn from a log-normal distribution with mean zero and variance V. Firms face probability of failure σ which is drawn from a Beta distribution $\sigma \sim \text{Beta}(\alpha_\sigma, \beta_\sigma)$ over $[0, 0.5]$.[11]

Firms have access to the same Cobb-Douglas production technology $y = zk^\alpha$, where k denotes capital. After choosing their type and observing their productivity and risk, firms choose capital, fully financed with debt, to maximize expected profits $(1-\sigma)[zk^\alpha - rk]$, taking interest rates as given. The optimal capital demand function is:

$$k = \left(\frac{\alpha z}{r}\right)^{\frac{1}{1-\alpha}} \tag{7}$$

6.2 Banking Sector

The banking sector consists of two types of lenders, traditional banks and microfinance institutions (MFIs), with different technologies. Traditional banks are better equipped to serve hard-information firms captured by their marginal cost of loan origination c_h^T, while MFIs face a higher cost c_h^M in this segment. Conversely, MFIs specialize in relationship lending, giving them a cost advantage with soft-information firms, captured by the marginal cost c_s^M. Traditional banks face higher costs c_s^T in this segment due to their reliance on standardized, hard information.

There is one representative traditional bank and one representative MFI that compete à la Cournot for each firm.[12] Lender j takes competitors' strategies as given and chooses loan quantity k_b to solve:

$$\max_{k_j} \, (1-\sigma) r(k) k_j - c_f^j k_j$$

where $k = \sum_j k_j =$ represents total lending in the segment, and the inverse demand function derived from firm optimization is $r(k) = \alpha z k^{\alpha-1}$. The first-order condition for

[11] We can also relate the risk distribution to firm type, capturing the benefits of information and the inherent vulnerabilities of opaque firms. However, as we documented in previous sections, delinquency rates are similar across different lender types.

[12] Note that we can also model this as a Bertrand game assuming that firm capital is a composite input determined by a CES aggregator of differentiated bank debt products.

lender j is:

$$(1-\sigma)\left[r + k_j \frac{\partial r}{\partial k}\right] = c_f^j$$

Let $s_j = k_j/k$ denote bank j's market share. We assume a symmetric equilibrium such that all lenders charge the same interest rate r to the firm. Then, we have the following equilibrium interest rate:

$$r(\sigma; f) = \frac{c_f}{(1-\sigma)\left[1 + (\alpha - 1)\mathrm{HHI}_f\right]} \tag{8}$$

where $c_f = \sum c_f^j \times s_j$ and $\mathrm{HHI}_f = \sum (s_j)^2$. Since this interest rate only varies across firm type and risk, we compute equilibrium market shares across firms within the same type and risk category.

6.3 Equilibrium

Upon observing their signal ν, firms choose the type that maximizes expected profits:

$$\max_{\{\mathrm{s,h}\}} \left\{ \int\limits_{\epsilon,\sigma} \Lambda_s \left((1-\sigma)\epsilon\nu\right)^{\frac{1}{1-\alpha}} dF(\epsilon,\sigma)\,,\ \int\limits_{\epsilon,\sigma} \Lambda_h \left((1-\sigma)\epsilon\nu\right)^{\frac{1}{1-\alpha}} dF(\epsilon,\sigma) - c_e \right\}$$

where $\Lambda_f = (1-\alpha) \times \left(\alpha \left[1 + (\alpha - 1)\mathrm{HHI}_f\right]/c_f\right)^{\frac{\alpha}{1-\alpha}}$ and F is the joint distribution of ϵ and ν. In equilibrium, there exists a cutoff ν^* such that firms with signals $\nu \geq \nu^*$ find it profitable to pay the fixed cost and become hard-information firms, while those with $\nu < \nu^*$ remain opaque. This mechanism endogenously sorts firms into two segments based on their expected productivity and crucially generates an overlap in the productivity distribution of soft- and hard-information borrowers.

6.4 Loan Guarantee Program

We model the recession as a liquidity shock similar to Section 3. The guarantee program consists on providing liquitidy to help firms surviving the recession. The total value of guaranteed credit is M and MFIs provide an exogenous fraction γ_{M} of it. Thus, lender j solves:

$$\max_{\ell_i^j \in \{0,1\}} \int \ell_i^j \Omega_i^j k_i dG^j(y_i, k_i) \qquad \text{s.t.:} \quad \int \ell_i^j \varphi k_i dG^j(y_i, k_i) = \gamma_j M \tag{9}$$

Thus, the efficiency of the market equilibrium depends on the characteristics of borrowers attended by each type of lender, summarized by distributions G^j, and on lender participation γ_j. On the other hand, the social planner faces the aggregate distribution $G(y, k)$, which is consistent with the two distributions G^j, and we define the constrained first-best similar to section 2.

6.5 Calibration

We build our calibration in two blocks, each targeting distinct features of the data. First, we target specific moments of the small firm credit market. The parameter α is set to 0.6 to match the aggregate debt to sales ratio in the data. The fixed cost to become a hard-information firm matches the share of formal borrowers in the economy, and the truncated Pareto parameters match the share of debt held by large borrowers. We target the average delinquency rate to calibrate parameters α_σ and β_σ, while the set of parameters $\left\{c_f^j\right\}$ match average interest rates paid by informal and formal borrowers, where informality is proxied by the tax category “natural person with business”. We set the recovery rate δ equal to 0.1, which aligns with regulatory estimates, and the relationship value parameter ψ_F at 2.5, which is consistent with a 10% margin on a perpetuity of lending discounted at 4%. The top panel of Table 8 summarizes our calibration of parameters related to the small firm credit market.

Table 8: Model Calibration

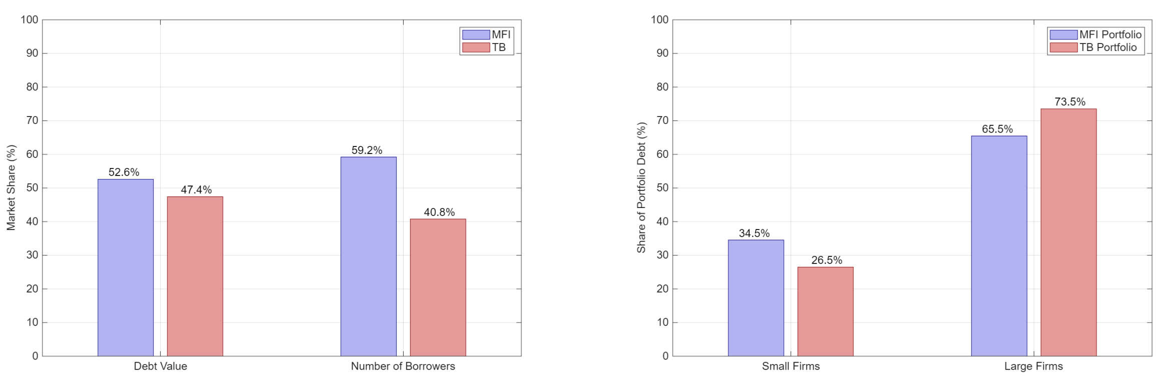
Parameter	Description	Value	Target
α	Capital share in production	0.6	Aggregate leverage ratio
c_e	Fixed cost for hard-info firms	0.045	Share of formal borrowers
ξ, $b_{\max}$	Truncated Pareto signal	2.5, 1.5	Large firm debt share
V	Log-normal productivity variance	0.2	Share of large informal firms
α_σ, β_σ	Beta distribution for firm risk	2, 8	Delinquency rate
c_s^{M}, c_s^{B}, c_h^{M}, c_h^{B}	Loan origination costs	1.07, 1.35, 1.07, 1.01	Lender specialization patterns
δ	Recovery rate	0.1	Recovery rate in default
ψ_F	Relationship value	2.5	10% returns and 4% discount
m	Guarantees over aggregate debt	0.25	Observed size of the program
γ_M	Guarantees distributed by MFIs	0.25	Observed MFI participation
ψ_C	Poaching probability	0.1	Unserved switching lender
φ	Credit growth with guarantees	0.8	Debt increase for recipients
c_0, η	Shock distribution	0.5, 0.4	Average treatment effects

This table presents the calibrated parameters for the endogenous banking model with loan guarantees. The top panel shows the parameters that govern the equilibrium distribution of firms across information types (soft vs hard) and lenders (MFIs vs traditional banks). The bottom panel shows the parameters that determine the allocation of government guarantees. Column (2) describes the parameters, column (3) shows the calibrated values, and column (4) outlines the targeted moment.

Second, we match key features of the program. The program size M equals 25% of outstanding debt, with the observed MFI participation γ_{MFI} equal to 20%. Our poaching probability parameter ψ is set at 0.1 to match the coefficient of a OLS regression that compares the probability of switching lenders for borrowers who received a guaranteed credit versus those who did not. The parameter φ targets the estimated average debt increase among program receipients. Finally, we model the recession as a liquidity shock ν that reduces firm cash flows and is drawn from the distribution $\tilde{\Phi}(\nu;\eta) = \left(\frac{\nu}{c_0}\right)^\eta$ over the interval $[0, c_0]$, where $\eta > 0$ determines the severity of the recession. We calibrate c_0 and η to match our estimated size-dependent treatment effects. The bottom panel of Table 8 provides a summary of the calibrated parameters related to the program and their empirical targets.

Figure 6 provides an assessment of our model goodness of fit. Panel (a) shows the market share of each lender type. Similar to our descriptive statistics reported in Section 3, MFIs represent around 53 percent of total debt, but since they are specialized in smaller firms, their share of clients is higher and reaches around 60 percent in our model. Panel (b) shows the composition of lenders' portfolios by firm-size. We define small firms as those in the bottom 9 deciles of the debt distribution and large firms as those at the top decile, similar to our empirical analysis. The model yields the specialization patterns described above. While traditional banks allocate 74 percent of their total lending toward large firms, micro-finance institutions only provide 66 percent of their portfolio to large firms.

Figure 6: Model Equilibrium Market Shares by Lender and Firm-Size

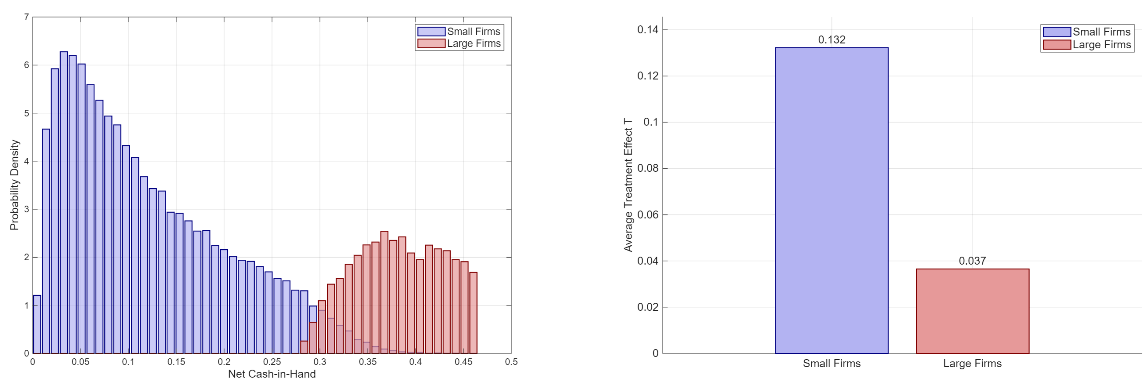


(a) Lender Market Shares **(b)** Portfolio Composition by Lender

This figure shows the equilibrium market shares of traditional banks and micro-finance institutions in our model. Panel (a) plots the market shares of micro-finance institutions (MFIs) and traditional banks (TBs) in the segment of small firm lending. The left-hand side bars measure market shares in terms of outstanding debt value and the right-hand side bars measure market shares in terms of number of borrowers. The blue bars refer to MFIs and the red bars refer to TBs. Panel (b) plots the market shares of MFIs and TBs by firm-size. Small firms are defined as those at the bottom 90 percent of the debt distribution and large firms are those at the top 10 percent. The blue bars refer to MFIs and the red bars refer to TBs.

Figure 7 shows firm-size-specific equilibium outcomes. Panel (a) plots the distribution of net cash-in-hand defined by $y - rk$ for small firms (blue bars) and large firms (red bars) in equilibrium. Two patterns emerge. First, we observe that small firms are more concentrated among low-net-cash values, which makes them more vulnerable to liquidity shocks. The potential effects of loan guarantees are non-linear. At the very bottom of the distribution of net cash-in-hand, firms may not survive even if they receive a guarantee, while at the middle part of the distribution, guarantees reach a maximum effect on the probability of firm survival. Second, large firms are concentrated among higher values, meaning that they are more likely to survive a liquidity shock without guarantees. Panel (b) shows the average treatment effect across firm-size groups. Consistent with our empirical estimates, treatment effects are 4 times bigger among smaller borrowers.

Figure 7: Net Cash Holdings and Treatment Effects by Firm-Size



(a) Net Cash Holding Distribution by Firm-Size **(b)** Average Treatment Effect by Firm Size

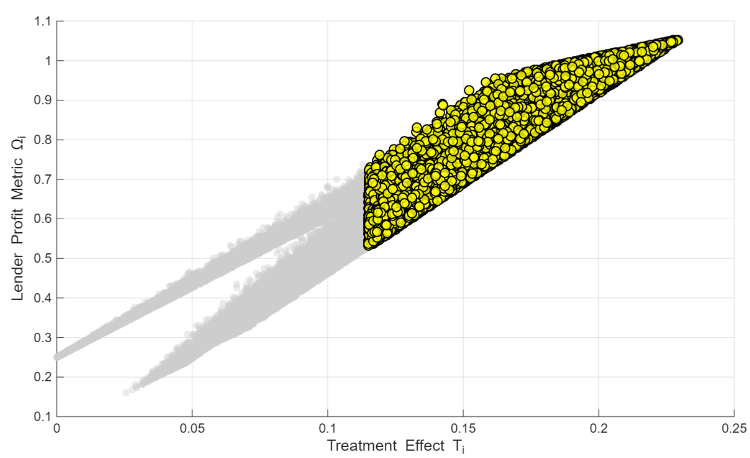
Panel(a) plots the distribution of net cash holdings across firms of different size. Net cash is defined by $y - rk$. Panel (b) plots the average treatment effect T_i by firm-size. Blue bars consider small firms and red bars consider large firms. Small firms are those at the bottom 90 percent of the debt distribution and large firms are at the top 10 percent.

6.6 Equilibrium and Counterfactual Analysis

We use our model to quantify how MFIs' participation shape the allocation and effectiveness of loan guarantees during recessions. We first compare guarantee allocations in the social planner and the decentralized equilibrium. Then, we compute the optimal participation of MFIs which minimizes the sare of debt in default.

Allocation of Guarantees. We compare the allocation of guarantees in the social planner constrained first-best versus the market equilibrium. Figure 8 plots the social planner's allocation across two firm characteristics: lender profit metric Ω_i and treatment effect T_i. Since the social planners wants to maximize the value of non-defaulting debt, the optimal allocation rule ranks firms based on their treatment effect and the social planner provides guarantees accordingly.

Figure 8: Social Planner Allocation of Guarantees

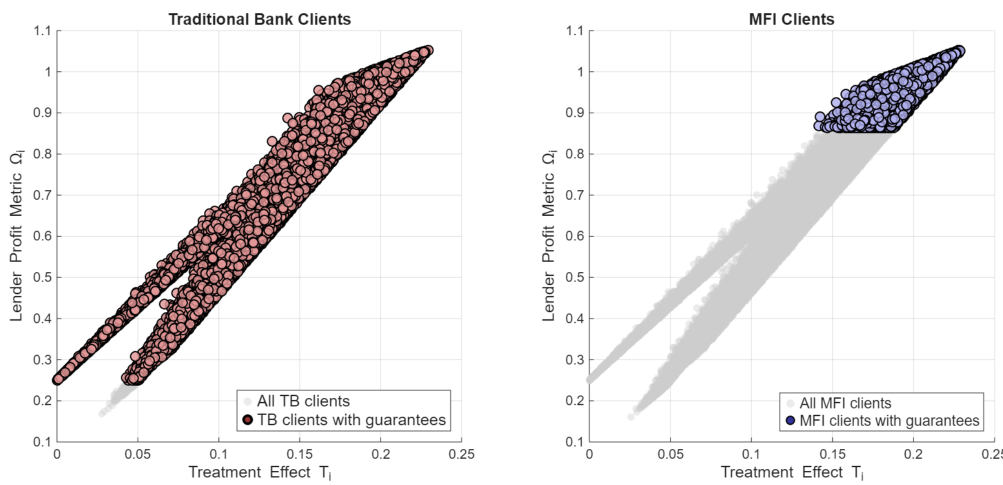


This figure plots the ditribution of lender profit metric Ω and treatment effect T across all borrowers. Each dot represents one borrower and yellow dots are those receiving a guarantee from the social planner.

Figure 9 plots the decentralized allocation and illustrates the key trade-off faced by private lenders. We assume that traditional banks distribute 75 percent of guarantees, as in the data. The left panel shows that firms are ranked based on the profit metric Ω, and banks provide guarantees accordingly. Red dots are firms who receive guarantees and grey dots are those who do not receive guarantees. We can observe that the allocation can improve if the bank shifts guarantees away from low-T-high-Ω firms located at the far-left part of the figure towards firms located at the lowest part of the figure.

The right panel shows the allocation of MFIs. Similar to traditional banks, MFIs rank their clients based on Ω and provide guarantees accordingly. However, since they obtain a smaller share of guarantees, they reach a smaller set of clients, and reallocating funds from traditional banks to MFIs can reach more sensitive clients, increasing the effectiveness of the program.

Figure 9: Private Allocation of Guarantees



This figure plots the allocation of guarantees by private lenders. Panel (a) shows the ditribution of lender profit metric Ω and treatment effect T across traditional banks (TBS) clients. The dots highlighted in red represent firms that receive a loan guarantee from TBs. Panel (b) shows the distribution of lender profit metric Ω and treatment effect T across micro-finance institutions (MFIs) clients. The dots highlighted in blue represent firms that receive a loan guarantee from MFIs.

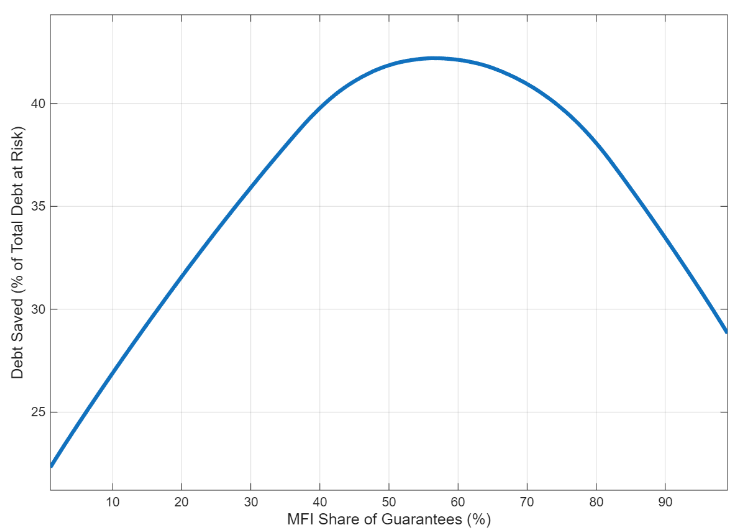
Optimal MFIs' Participation. We conduct a counterfactual analysis shifting the share of guarantees distributed by MFIs to find the optimal participation. We define the effectiveness of the program Δ as the value of debt that is saved in the private allocation divided by the total debt at risk due to the recession. This measure is given by:

$$\Delta \equiv \frac{\int \ell_i^{\mathrm{TB}}(\Phi_i(1) - \Phi_i(0))b_i di + \int \ell_i^{\mathrm{MFI}}(\Phi_i(1) - \Phi_i(0))b_i di}{\int \Phi_i(0) b_i di} \tag{10}$$

We compute this measure for different levels of MFI participation and plot the resulting function in Figure 10. We show that the function $\Delta(\gamma_{\text{MFI}})$ reaches its maximum at 54 percent of participation in the guarantee program, where the program saves around 45 percent of the total debt at risk of default. In the counterfactual scenario where only traditional banks distribute guarantees, the program only saves 22 percent of debt, while fully relying on MFIs leads to a ratio of 28 percent. The observed equilibrium generated a 34 percent of debt saved from default.

There are two forces playing a role. First, MFIs distribute a smaller share of guarantees compared to traditional banks, which make them more likely to serve high treatment effect firms if they get one more unit of guarantee. Second, conditional on the share of guarantees, the distribution of clients of MFIs is more oriented towards high treatment effect firms. This is because lender specialization makes traditional banks to have more infra-marginal borrowers in their portfolios that would very likely survive without guarantees.

Figure 10: Loss function by MFI participation



This figure plots the debt-saved ratio defined by equation (10) for different levels of MFI's participation. This ratio is equal to the total debt saved by the program in the decentralized equilibrium divided by the total debt in default absent the program.

Our model provides three key insights. First, market allocations diverge from the first-best due to lenders' incentives to overweight without-the-program survival probabilities. Second, MFIs attenuate this distortion by channeling guarantees to smaller, more responsive firms due to lender specialization. Third, optimal policy requires balancing MFI specialization versus traditional banks.

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 stronger effects among smaller firms and those in high-contact industries, consistent with their higher liquidity needs. MFIs played a critical role in channeling guarantees to these high-sensitivity segments. We develop a model where lenders specialize in different set of clients and calibrate it with our micro-data and reduced form estimates. Our model shows that traditional banks alone would have saved only 22 percent of debt at risk of default due to the recession, while the actual MFI participation boosted this measure of effectiveness to 43 percent.

Our results have important policy implications. Specialized lenders such as MFIs are key actors in financial policy, particularly valuable for reaching small entrepreneurs who are most responsive to credit conditions 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 low treatment effects and higher risk.

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Appendix A: Additional Tables

Table A1: 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 A2: 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: $\sum_c (L_{cb}/L_b)^2$

Table A3: Effect of Loan Guarantees on New Lending Relationships

	Value of New loans		Share of New Loans	
	(1)	(2)	(3)	(4)
Exposure$_b$ × Post$_t$	0.434**	0.415***	0.023*	0.029**
	(0.164)	(0.135)	(0.012)	(0.013)
Observations	334	334	478	478
Fixed Effects				
Bank	Yes	Yes	Yes	Yes
Quarter	Yes	-	Yes	-
Bank-size × Quarter	No	Yes	No	Yes

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 A4: Heterogeneous Effect of Loan Guarantees on Small Firm Financial Performance - Type of Credit

	Micro-Credit			Small Business Loan		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Exposure}_i \times \text{Post}_t$	-0.021***			-0.009*		
	(0.004)			(0.005)		
$\text{Treated}_i \times \text{Post}_t$		-0.122***			-0.039*	
		(0.024)			(0.021)	
$\ln \text{Loans}_{it}$			-0.169***			-0.042*
			(0.041)			(0.021)
Observations	19.8M	19.8M	19.8M	4.8M	4.8M	4.8M
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Real}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes

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 A5: Effect of Loan Guarantees on Real Outcomes - Micro Firms

	Capital	Wage-bill	Labor	Sales		Exit in	
					t = 0	t = 1	t = 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure$_i\times$ Post$_t$	0.021**	0.020	0.012	0.020**			
	(0.008)	(0.012)	(0.011)	(0.009)			
Exposure$_i$					-0.0113***	-0.0203***	-0.0229***
					(0.0031)	(0.0036)	(0.0048)
Observations	586,592	253,763	255,118	595,705	74,729	74,729	74,729
Fixed Effects							
Firm	Yes	Yes	Yes	Yes	-	-	-
Size-bin × Quarter	Yes	Yes	Yes	Yes	-	-	-
Leverage-bin × Quarter	Yes	Yes	Yes	Yes	-	-	-
Industry × Quarter	Yes	Yes	Yes	Yes	-	-	-
City × Quarter	Yes	Yes	Yes	Yes	-	-	-
Size-bin	-	-	-	-	Yes	Yes	Yes
Leverage-bin	-	-	-	-	Yes	Yes	Yes
Industry	-	-	-	-	Yes	Yes	Yes
City	-	-	-	-	Yes	Yes	Yes

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 A6: Drivers of Real Effects - Micro Firms

	Δ Capital				Δ Wage-bill			
	> 0	$> p90$	< 0	$< p10$	> 0	$> p90$	< 0	$< p10$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure$_i$	0.0097***	0.0000	-0.0118***	-0.0185***	-0.0043	-0.0119***	0.0060*	-0.0123*
	(0.0020)	(0.0017)	(0.0019)	(0.0028)	(0.0028)	(0.0030)	(0.0031)	(0.0062)
Observations	73,373	73,373	73,373	73,373	29,314	29,314	29,314	29,314
Fixed Effects								
Size-bin	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Leverage-bin	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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 industry level. Observations are expressed in millions.

Table A7: Heterogeneous Effect of Loan Guarantees on Small Firm Financial Performance - Industry Contact in Bottom Deciles of Pre-Covid Debt

	High-Contact			Low and Non-Contact		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Exposure}_i \times \text{Post}_t$	-0.022***			-0.016***		
	(0.004)			(0.005)		
$\text{Treated}_i \times \text{Post}_t$		-0.130***			-0.099***	
		(0.021)			(0.031)	
$\ln \text{Loans}_{it}$			-0.182***			-0.101***
			(0.036)			(0.032)
Observations	14.7M	14.7M	14.7M	7.0M	7.0M	7.0M
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Real}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes

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 A8: Allocation of Guaranteed Loans

	Share of SBLG		Share of SBL	
	Banks (1)	MFIs (2)	Banks (3)	MFIs (4)
Size (pre-Covid Debt):				
Small	0.13	0.22	0.07	0.17
Medium	0.16	0.43	0.19	0.34
Large	0.71	0.35	0.74	0.50
Micro-firm	0.24	0.60	0.18	0.35
Small-firm	0.76	0.40	0.82	0.65
Industries:				
High-Contact[a]	0.46	0.60	0.59	0.64
Less- and Non-Contact[a]	0.54	0.40	0.41	0.36
Manufacturing	0.12	0.09	0.10	0.07
Retail, Hotel, Transp.[b]	0.29	0.46	0.44	0.50
Rest	0.59	0.45	0.46	0.43
Lender share:	0.75	0.25	0.48	0.52

Table A9: Heterogeneous Effect of Delinquency on Small Firm Financial Performance - Bottom Deciles

Panel A						
	MFI share = 1			MFI share $\in (1, 0.5]$		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure$_i \times$ Post$_t$	-0.028***			-0.024**		
	(0.008)			(0.009)		
Treated$_i \times$ Post$_t$		-0.225**			-0.163**	
		(0.084)			(0.065)	
ln Loans$_{it}$			-0.427**			-0.171***
			(0.169)			(0.050)
Observations	9.5M	9.5M	9.5M	1.3M	1.3M	1.3M
Panel B						
	MFI share $\in (0.5, 0)$			MFI share = 0		
	OLS	IV		OLS	IV	
Exposure$_i \times$ Post$_t$	-0.021***			-0.009***		
	(0.001)			(0.002)		
Treated$_i \times$ Post$_t$		-0.161***			-0.061**	
		(0.009)			(0.021)	
ln Loans$_{it}$			-0.123***			-0.034***
			(0.018)			(0.009)
Observations	1M	1M	1M	2.7M	2.7M	2.7M
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Real}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes

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 A10: Heterogeneous Effect of Delinquency on Small Firm Financial Performance - Micro-credit

Panel A						
	MFI share = 1			MFI share $\in (1, 0.5]$		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure$_i\times$ Post$_t$	-0.024***			-0.021**		
	(0.008)			(0.009)		
Treated$_i\times$ Post$_t$		-0.204**			-0.154**	
		(0.084)			(0.068)	
ln Loans$_{it}$			-0.355**			-0.149***
			(0.135)			(0.050)
Observations	13.4M	13.4M	13.4M	1.9M	1.9M	1.9M
Panel B						
	MFI share $\in (0.5, 0)$			MFI share = 0		
	OLS	IV		OLS	IV	
Exposure$_i\times$ Post$_t$	-0.022***			-0.009***		
	(0.001)			(0.002)		
Treated$_i\times$ Post$_t$		-0.172***			-0.065**	
		(0.010)			(0.021)	
ln Loans$_{it}$			-0.135***			-0.035***
			(0.016)			(0.009)
Observations	1.5M	1.5M	1.5M	4.6M	4.6M	4.6M
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Real}}(f)\times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)\times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes

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 A11: Heterogeneous Effect of Delinquency on Small Firm Financial Performance - High-Contact

Panel A						
	MFI share = 1			MFI share $\in (1, 0.5]$		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure$_i \times$ Post$_t$	-0.027***			-0.022**		
	(0.008)			(0.010)		
Treated$_i \times$ Post$_t$		-0.229**			-0.150**	
		(0.085)			(0.067)	
ln Loans$_{it}$			-0.421**			-0.155***
			(0.162)			(0.054)
Observations	10.1M	10.1M	10.1M	1.6M	1.6M	1.6M
Panel B						
	MFI share $\in (0.5, 0)$			MFI share = 0		
	OLS	IV		OLS	IV	
Exposure$_i \times$ Post$_t$	-0.010			-0.001		
	(0.007)			(0.003)		
Treated$_i \times$ Post$_t$		-0.057			-0.003	
			(0.035)			(0.013)
ln Loans$_{it}$			-0.055			-0.002
			(0.016)			(0.009)
Observations	1.4M	1.4M	1.4M	3.2M	3.2M	3.2M
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Real}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f) \times$ Quarter	Yes	Yes	Yes	Yes	Yes	Yes

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.

Appendix B: Additional Figures

Figure A1: Geographical Distribution of Financial Institutions

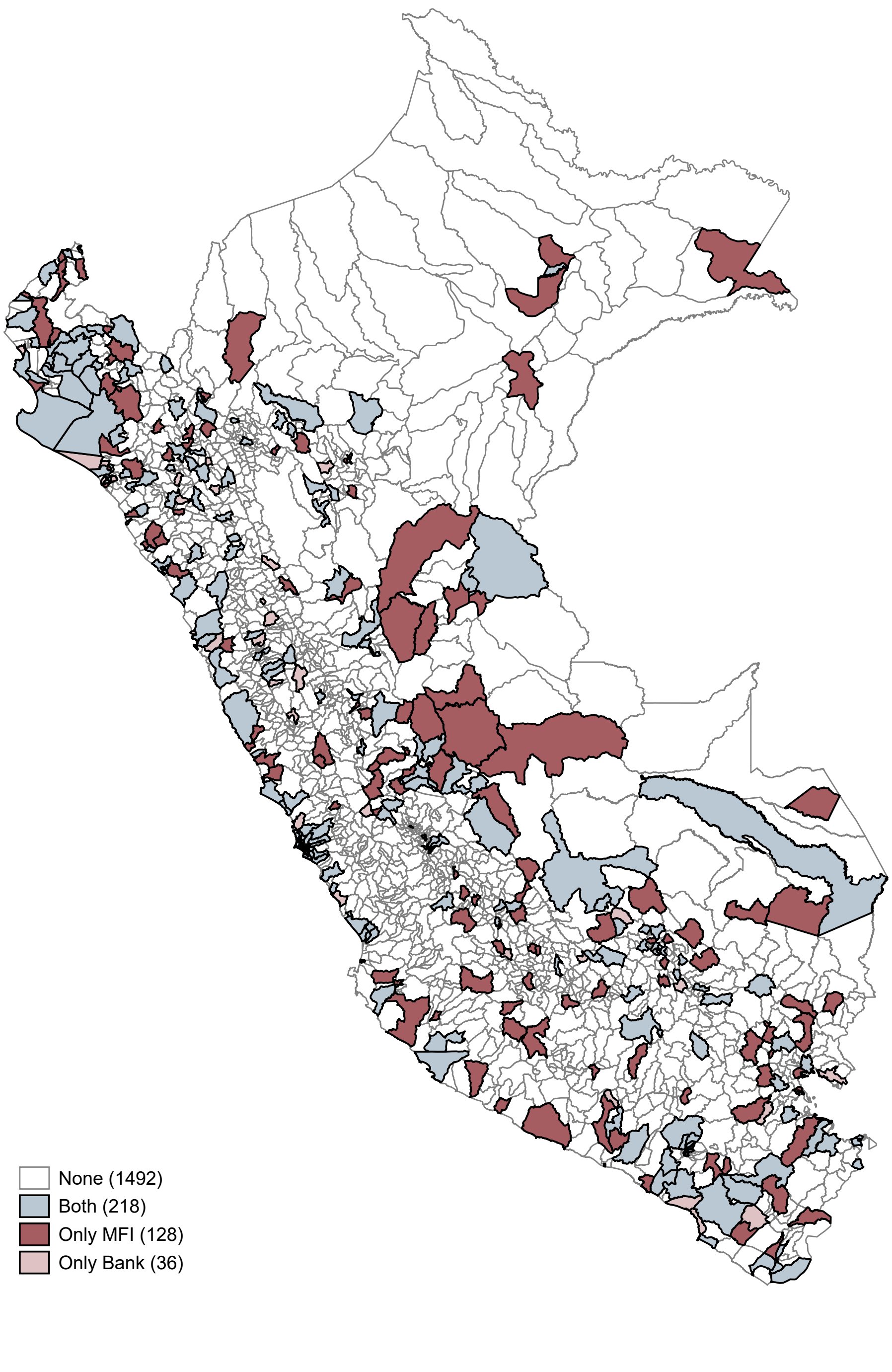
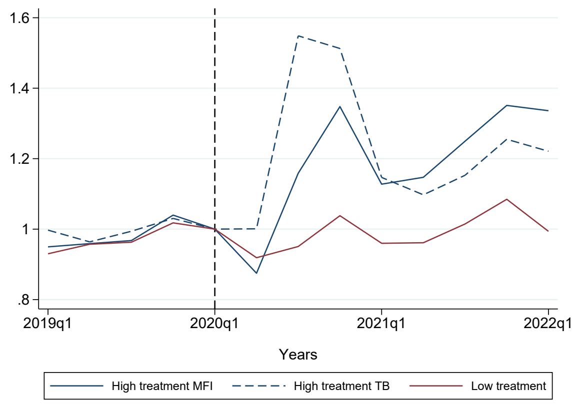
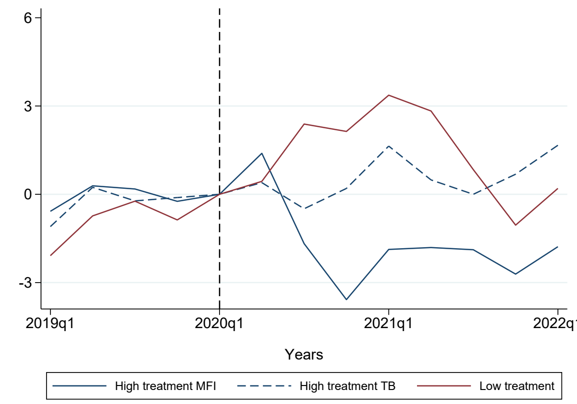


Figure A2: Credit, Delinquency and Bank Treatment



(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 (2). 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 A3: Balance of covariates

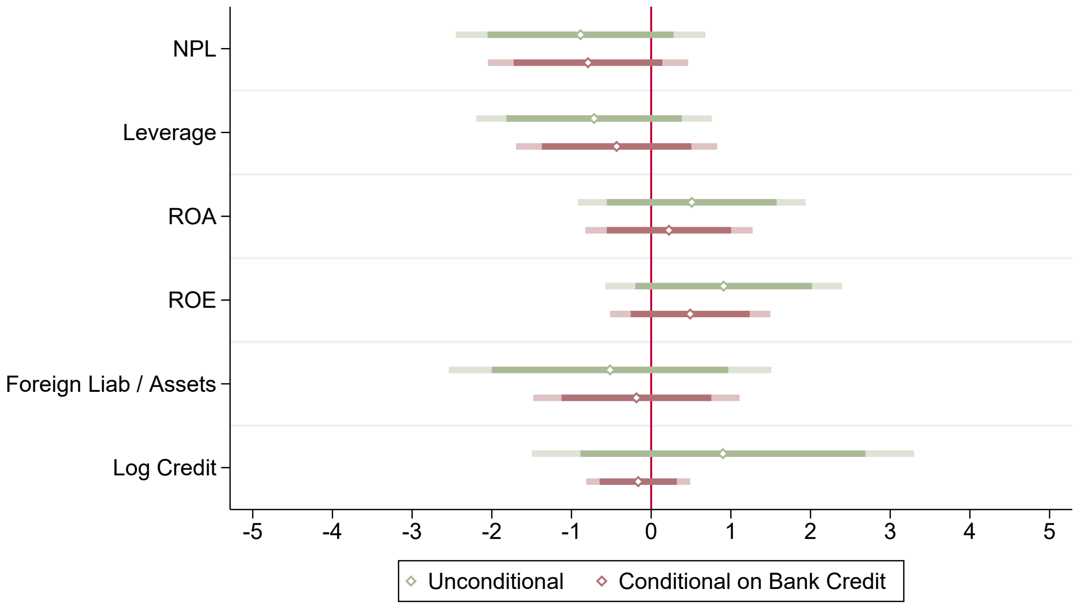
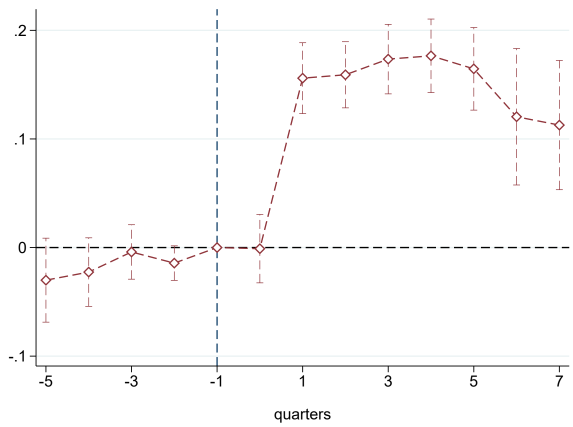
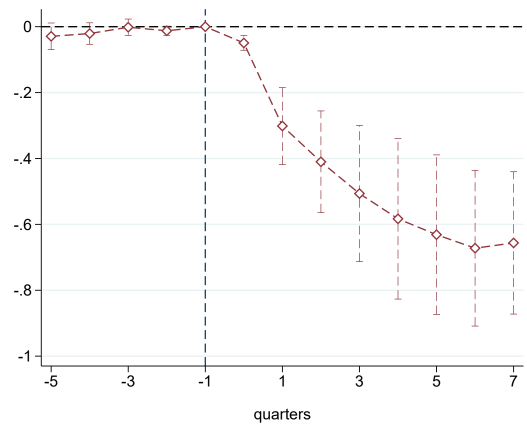


Figure A4: Lending Relationships and Credit



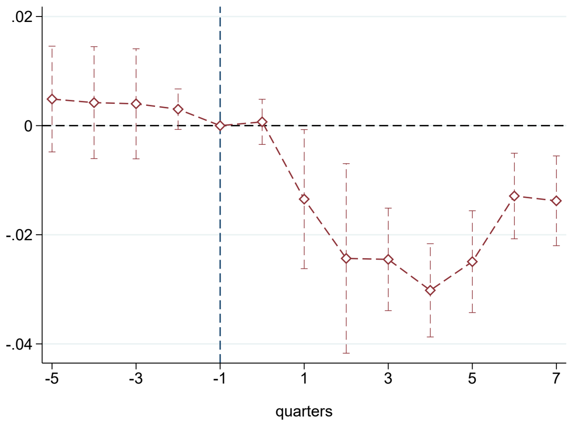
(a) Total Loans



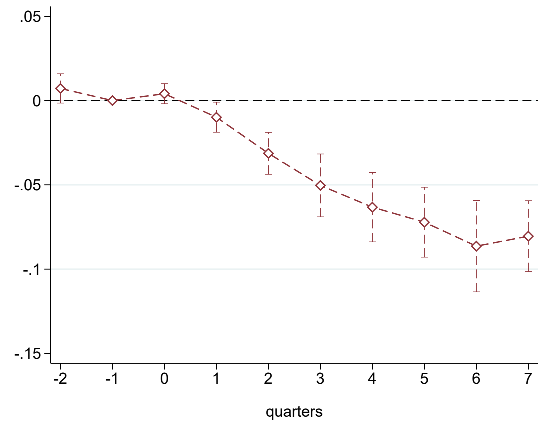
(b) Non-Guaranteed Loans

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 A5: Lending Relationships and Delinquency Rates



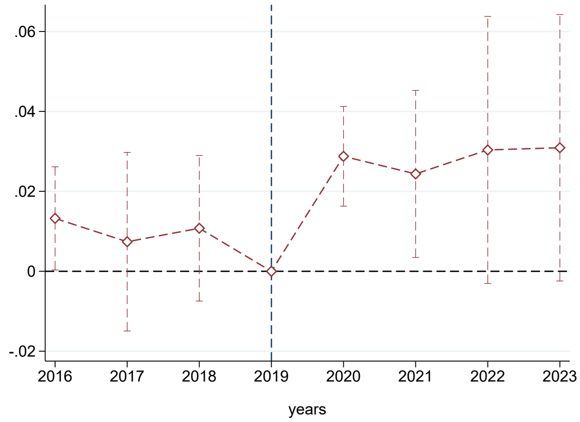
(a) Delinquency Rates



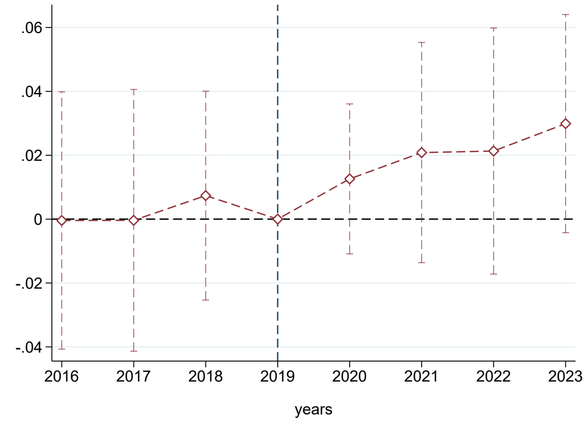
(b) Exit Rate

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.

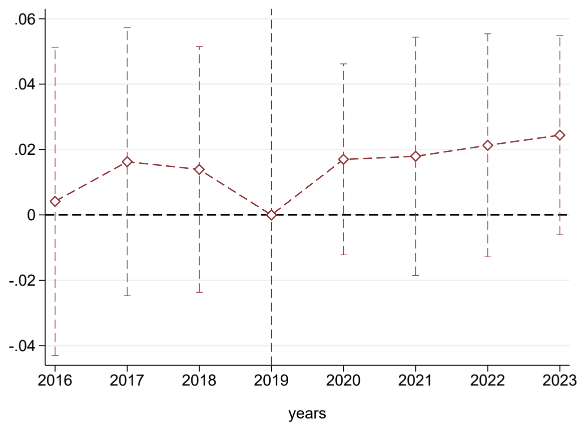
Figure A6: Lending Relationships and Real Outcomes



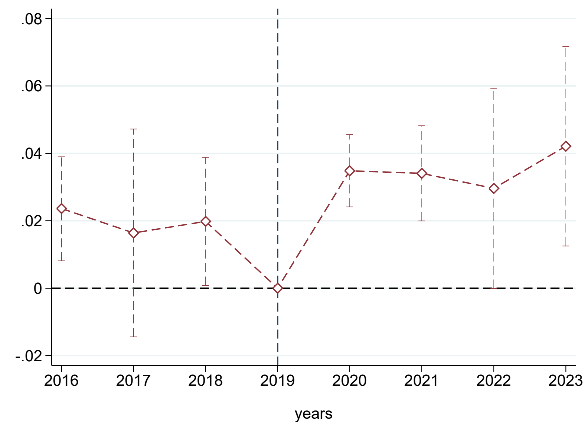
(a) Capital



(b) Wage-bill



(c) Num. Workers



(d) Sales

This figure plots the annual 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.

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:

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

Where $\Pr\left(d|n\right)$ denotes the probability of being delinquent in $t+1$ conditional on being non delinquent in t, and $\Pr\left(d|d\right)$ 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 $\Pr\left(d|n\right)$ was affected by the program. Thus, we have the following delinquent debt in $t+1$, under the program:

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

Where $\Pr\left(d|n,T\right)$ denotes the probability of being delinquent in $t+1$ conditional on being non delinquent in t and being treated, and $\Pr\left(d|n,C\right)$ 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:[13]

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

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

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

Since guaranteed loans represented 40 percent of current small business loans (see Table 2), 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 **??** 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:

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

Finally, we have:

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

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

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